Universidade do Minho
Escola de Engenharia

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Group Recommender Systems for Tourism: Overcoming the Cold-Start Problem and Conflicting Preferences by using Artificial Intelligence and Serious Games

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Work performed under the supervision of:
Professor Paulo Novais
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To Júnior and Mafalda, I got this far because of you!

To the amazing people who carried me to the light at the end of the tunnel.

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Porto, December 22, 2024



(Patrícia Raquel de Jesus Araújo Alves)

ACKNOWLEDGEMENTS

Although it doesn't seem, I'm not always keen on routines and the ordinary, and I'm known for being perseverant and "stubborn". Sometimes I like to experience different paths, aim for the highest stakes, and do things differently from the common. So, as they are personal, I decided to give a personal touch in the acknowledgements to my "personal agents".



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PREFACE

I never really liked memorizing material for tests, although having a very good memory (well, now it's not that good...too much sleep deprivations and insomnias...:')). But I have always enjoyed reading and researching, and I love science, the elementary, the beginning of things. Although to study Medicine was in the top of my list in my adolescence, as I have always wanted to be a Surgeon and help others, I realized I wouldn't have the stomach for some things. That is why I chose to study Chemistry at FCUP in 1998. I just loved to absorb that knowledge, the theory of everything, to be in the lab, making experiments and writing reports on the results.

I am so passionate for computers that, during the Chemistry course, I had already programmed in Pascal my own MS-DOS application for controlling my finances, and at the course's second year, I was thinking of changing to the Informatics Engineering course at FEUP, but I was enjoying Chemistry so much... So, I said to myself I had to finish what I started! My mother has always told me to never give up and always do my best, so I continued in Chemistry until the end. And I never regret that decision, I learned so much and met spectacular professors, friends and staff!

I was the so-called computer geek (I still am), always participating in LAN parties and game events with my friends, playing Unreal Tournament 99, and other first-person shooters like Counterstrike, and Quake. And of course, all the Tomb Raider and Myst series :)

I have always been eager to learn more about different areas. So, I also completed a technological specialization course in Microbiology in the meantime. After graduating in Chemistry in 2003, I was planning to do a master's in Astronomy and/or Archeology. I am an Astronomy enthusiast! Oh Archeology... However, my oldest child was born soon after, and when I thought I could proceed with my "knowledge spree", my mother said, "young lady, now you have to provide for yourself." And so, I did, I worked in several places, including two years at Glintt HS, a healthcare software company. However, I felt the need to know more about programming and informatics. So, I quit my job to pursue that objective. From 2009-2014 I attended the Integrated Master's in Informatics and Computing Engineering at FEUP. I really enjoyed the course and learned a lot, having forced myself to do some works alone so I could learn more.

After that, I ended up working as a Scrum Master and Software Engineer at the Shared Services of the Ministry of Health (SPMS). However, I felt "trapped" in the industry field, because I am a person always eager to learn new things and I know I have the capability and the need to go further. Thus, the idea of creating an innovative application using games and Artificial Intelligence, for helping and motivating tourists on their trips, sprouted. My head was full of ideas, which I started to transpose to the paper. In 2018, an opportunity to work as a research fellow on a related project at GECAD arose. I needed to return to the academic world. I wanted to do more! To research! So, the path took me to this Ph.D... I engaged in the Doctoral Program in Informatics (PDINF) at University of Minho, being very grateful for the FCT grant! I felt accomplished! In 2019, I was invited to be a guest assistant professor at ISEP, and contrary to what I expected, I adore teaching!! I love to transmit knowledge and see my students strive!

Now, I am fully committed to research and teaching, doing what I have always wanted. It's a dream come true. Like Steve Jobs once said "...have the courage to follow your heart and intuition. They somehow already know what you truly want to become. Everything else is secondary".

It's not all roses, though. Although I am very happy with my professional accomplishments, I felt my personal life had paused during the Ph.D. So many things happened... the CoViD-19 pandemics for instance, which significantly delayed my work... Although I had many good moments, many complicated and stressful ones also happened. I can say the greatest strength came from my children. Countless times I left my Ph.D. in the background to spend time with and accompany them, but I felt it was never enough. I worked the double of time in every "free" slot and I would never change that!

Although this last six years have been exhausting and the anguish of handing in the thesis was growing, with many sleepless nights, unexpected delays, a lot of hard work, twenty mentees to supervise in this last year... I finally made it! What a sense of accomplishment and relief!!

Patrícia Alves

Porto, December 22, 2024

RESUMO

A evolução tecnológica e Humana nos últimos 25 anos levou a uma abundância avassaladora de informação e bens, dificultando o processo de escolha. Isto levou ao desenvolvimento de Sistemas de Recomendação (RS), que visam ajudar os utilizadores a escolher itens alinhados com as suas preferências em domínios como a música, filmes, turismo e notícias. Contudo, surgem desafios, especialmente em contextos de grupo, onde as preferências divergentes e conflitos são frequentes. Isto é particularmente evidente no turismo, que envolve experiências emocionais. Os Sistemas de Recomendação para Grupos (GRS) surgiram para resolver esses problemas, mas desafios como o problema de arranque a frio (*cold-start*), configurações demoradas, intrusividade, balanceamento das preferências de grupo e falta de atenção às necessidades individuais persistem.

Para enfrentar os desafios mencionados, o principal objetivo deste trabalho foi desenvolver um protótipo de GRS baseado na personalidade. Primeiro, foi realizado um estudo de larga escala (n=1035 participantes), que revelou que certas preferências turísticas são procuradas por personalidades específicas, contribuindo com novos modelos baseados em personalidade para prever essas preferências. De seguida, foi implementado o protótipo de GRS, usando uma arquitetura de microserviços, incluindo um Microserviço Multi-Agente onde foi criado um algoritmo de *clustering* dinâmico baseado na personalidade, d-means, que agrega turistas com personalidades semelhantes, criando os melhores *clusters* em tempo real sem precisar de conhecer o número inicial de *clusters*. Os modelos e algoritmo d-means eliminam a necessidade de dados de interação ou classificações prévias para as recomendações iniciais, resolvendo o problema do *cold-start*. Os *clusters* ajudam a resolver a heterogeneidade e preferências conflituosas, agregando turistas com personalidades semelhantes no mesmo subgrupo quando são solicitadas recomendações para um grupo. As recomendações são depois refinadas usando o algoritmo Apriori, que extrai regras dos utilizadores agrupados. Por fim, foram desenvolvidos dois jogos sérios, demonstrando ser possível determinar implicitamente traços de personalidade em menos de 5 min, eliminando a necessidade de questionários de personalidade suscetíveis ao viés de desejabilidade social e dados de interação com o RS, o que pode ser uma reviravolta na história dos RS baseados na personalidade.

Palavras-chave: *Clustering* dinâmico, *cold-start*, jogo sério, personalidade Big Five, Sistema de Recomendação para Grupos

ABSTRACT

The technological and Human evolution in the last 25 years has led to an overwhelming abundance of information and goods, complicating the choice process. This led to the development of Recommender Systems (RS), aiming to help users choose items aligned with their personal preferences across an increasing range of domains like music, movies, tourism, and news. However, challenges arise, especially in group settings, where differing preferences and conflicts are common. This is especially evident in tourism, which involves emotional experiences. Group Recommender Systems (GRS) came to address those issues, but challenges like the cold-start problem, time-consuming configurations, intrusiveness, balancing group preferences, and the lack of concern for individual necessities persist.

Building on that, this work's main purpose was to develop a personality-based GRS prototype to tackle the referred challenges. First, a large-scale study (n=1035 participants) was conducted, having found that certain tourist attractions and travel-related preferences & concerns are sought by particular personalities, contributing with new models to predict tourist preferences based on the tourists' raw Big Five personality. Then, the GRS prototype was implemented following a microservices architecture with a Multi-Agent Microservice, where a novel personality-based dynamic clustering algorithm, d-means, was developed, which is a clustering algorithm for aggregating similar personality/preferences tourists, creating the best clusters in real time without needing to know the number of initial clusters. The models and the clustering algorithm eliminate the need for previous interaction data and ratings to provide the initial recommendations, solving the cold-start problem. The clusters also help solve heterogeinity and conflicting preferences, as the most similar personality tourists go into the same subgroup when requesting a recommendation for an excursion group. The recommendations are then refined by using the Apriori algorithm that extracts rules from the clustered users. Finally, two short-duration mobile serious games were developed, showing it is possible to implicitly determine granular personality traits in less than 5 min, eliminating the need for personality questionnaires prone to social desirability bias and great amounts of interaction data with an RS, which can be the twist needed in the history of personality-based RS.

Keywords: Big Five personality, cold-start, dynamic clustering, Group Recommender System, serious game

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ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
ALGORITMI	Research unit of the School of Engineering – University of Minho, that develops R&D activity in Information and Communications Technology and Electronics.
API	Application Programming Interface
AR	Augmented Reality
ASOC	Applied Soft Computing
BFI	Big Five Inventory
CEOS.PP	Centre for Organizational and Social Studies of the Polytechnic Institute of Porto
CFA	Confirmatory Factor Analysis
CORE	COmputing Research & Education
DB	Database
DSRM	Design Science Research Methodology
EFA	Exploratory Factor Analysis
ESWA	Expert Systems with Applications
FCUP	Faculty of Sciences of the University of Porto
FEUP	Faculty of Engineering of the University of Porto
FFM	Five Factor Model
FIPA	Foundation for Intelligent Physical Agents
FIPA-ACL	FIPA Agent Communication Language
GDPR	General Data Protection Regulation
GECAD	Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development
GPS	Global Positioning Service
GRS	Group Recommender System
HTTP	Hypertext Transfer Protocol
IF	Impact Factor
IPIP	International Personality Item Pool
IPP	Polytechnic Institute of Porto
ISCAP	Porto Accounting and Business School
ISEP	Superior Institute of Engineering of Porto
JADE	Java Agent DEvelopment framework
LAN	Local Area Network
LASI	Intelligent Systems Associate Laboratory
LBS	Location-Based Services
LLM	Large Language Models
MAMS	Multi-Agent Microservice
MAS	Multi-Agent System
MAE	Mean Absolute Error
MIT	Massachusetts Institute of Technology
ML	Machine Learning

MS	Microservice
MS-DOS	Microsoft Disk Operating System, originally used in IBM personal computers
NEO-FFI	Neuroticism-Extraversion-Openness Five Factor Inventory
NEO PI-R	Neuroticism-Extraversion-Openness Personality Inventory Revised
NLP	Natural Language Processing
OCEAN	Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism
PEGA	Personality-Guided Preference Aggregator
POI	Point of Interest
Q&A	Questions and Answers
REST	REpresentational State Transfer
RMSE	Root Mean Squared Error
RS	Recommender System
SEM	Structural Equation Modeling
SPMS	Shared Services of the Ministry of Health (Serviços Partilhados do Ministério da Saúde)
TCCM	Theory, Context, Characteristics, Methodology
TIPI	Ten Item Personality Inventory
UMinho	University of Minho

Part I

EXEGESIS

"As long as the centuries continue to unfold, the number of books will grow continually, and one can predict that a time will come when it will be almost as difficult to learn anything from books as from the direct study of the whole universe. It will be almost as convenient to search for some bit of truth concealed in nature as it will be to find it hidden away in an immense multitude of bound volumes."

Denis Diderot, "Encyclopédie" (1755)

1

INTRODUCTION

It is undeniable we are living in an era of consumption and that the number of products available has become overwhelming since online markets appeared. If even before the appearance of the World Wide Web knowing what to recommend to someone was a difficult task, we can imagine how even more difficult it is today. There are many more products, like books, films, music, news, or even tourist attractions, and they can be accessed in ways that were impossible before international traveling and the Internet.

The development of Recommender Systems (RS) came to help with this overwhelming amount of information, changing the users experience and knowledge in a variety of domains, such as entertainment, online shopping, tourism, and many others. Not only do they try to help users make personalized choices, but they also suggest unknown products that can be interesting to the users. The same can be said for groups of people, for whom Group Recommender Systems (GRS) have been developed.

Despite the benefits RS brought[2], there are many issues that still need to be addressed, which are even more complex when groups of people, like large (casual) groups, are involved. This is especially caused by the groups' heterogeinity and conflicting preferences (Boratto & Carta, 2010), which make the choice process more difficult, negatively affecting the group members' satisfaction. The GRS open issues are well known in literature and Jameson (2004) was one of the first to address them, identifying five main challenges:

1. How can the group members' individual preferences be obtained?
2. Should the group members be aware of the other members' preferences?

2 For simplicity, from this point on, RS will refer to both individual and group RS, and GRS only to Group Recommender Systems.

3. How can the group members' preferences be combined and not manipulated, so recommendations that satisfy all members can be generated?
4. How can recommendations be presented and explained in a suitable and effective way to each group member?
5. How can the group members be supported in the choice and negotiation process to obtain the final recommendation?

An example of a very complex and challenging area is leisure tourism (Delić, Nguyen, & Tkalčič, 2020; Garcia, Sebastia, & Onaindia, 2011; Sertkan, Neidhardt, & Werthner, 2019). It involves emotional and sensorial experiences, making the tourists' preferences very subjective. Knowing personal information about a tourist is therefore crucial to provide more personalized and suitable recommendations. And what other personal information could be better than personality? It is well evidenced in literature that personality is strongly related to the users' preferences in a variety of domains such as music, books, or movies (Tkalcic & Chen, 2015). And in the tourism area? That is one of the questions that was intended to unravel during the doctoral journey.

The user's context, such as location, weather conditions, time of day, mood, or device being used can also be important to provide more relevant recommendations. By incorporating contextual information, RS can deliver more intelligent, personalized and situationally appropriate suggestions (Adomavicius & Tuzhilin, 2011; del Carmen Rodríguez-Hernández, Ilarri, Hermoso, & Trillo-Lado, 2017). Using the user's context in mobile devices opens new opportunities in the areas of travel and tourism, providing more personalized content (Ricci, 2010) and information, anytime and anywhere (Gavalas, Konstantopoulos, Mastakas, & Pantziou, 2014).

Many prototypes of GRS for tourism are being proposed, usually recommending a list of Points of Interest (POI) to visit (Abolghasemi, Engelstad, Herrera-Viedma, & Yazidi, 2022; Amato, 2023; Castro, Quesada, Palomares, & Martinez, 2015; da Cruz, Durao, & Rossetti, 2024; Delic, Neidhardt, Nguyen, Ricci, et al., 2016; Garcia, Sebastia, Onaindia, & Guzman, 2009; Song et al., 2024), with some already starting to concern for the tourists' interaction and satisfaction with the choice process, by taking advantage of the social-web (Cantador & Castells, 2012; Delic, Emamgholizadeh, Nguyen, & Ricci, 2024; Delic, Neidhardt, Nguyen, Ricci, et al., 2016; T. N. Nguyen & Ricci, 2018). However, various limitations persist, such as time-consuming configura-

tions (Ardissono, Goy, Petrone, Segnan, & Torasso, 2003; Borràs, Moreno, & Valls, 2014), large amount of previous interaction data to make the first recommendations (cold-start problem) (Bengali & Veldt, 2023; Ezugwu et al., 2022), complex methods for aggregating preferences and that do not satisfy all group members yet (Delic et al., 2024; Najafian, Herzog, Qiu, Inel, & Tintarev, 2020), excessive intrusiveness involved in building tourists' profiles (Adomavicius & Tuzhilin, 2005), which is the case of personality-based RS that acquire the tourists personality via questionnaires (Dhelim, Chen, Aung, Zhang, & Ning, 2023), which are known for being subject to social desirability biases and false responses (Bhatia & Ryan, 2018; Pedregon, Farley, Davis, Wood, & Clark, 2012), not accurately characterizing the tourists and using broader personality dimensions instead of more granular traits that better characterize a person (Costa & MacCrae, 1992). Additionally, there is often a lack of consideration for tourists' interests during planning and tours, such as fostering a sense of freedom, reducing the fear of getting lost, enhancing companionship, and promoting socialization, all while maintaining a personalized experience.

To know the tourists' preferences and more granular personality traits in a non-intrusive, less time-consuming, and more engaging manner is a challenge. Gamification and Serious Games can be the twist needed in the RS history (Dunn, Wiersema, Ham, & Aroyo, 2009; Xu, Buhalis, & Weber, 2017). Gamification has been shown to enhance user engagement and motivation in various activities, whether it's learning, working, or exploring a city (Hamari, Koivisto, & Sarsa, 2014; Hamari et al., 2016; Mortara et al., 2014; Xu, Tian, Buhalis, Weber, & Zhang, 2016). A gamified RS can help users to engage in and use more the application. Serious Games are games designed for purposes beyond just entertainment (Djaouti, Alvarez, & Jessel, 2011; Michael & Chen, 2005). They are being successfully used in various fields such as education, healthcare, military training, and city planning to provide meaningful learning experiences and practical skills (Arif, Ayunda, Diah, & Garcia, 2024; Susi, Johannesson, & Backlund, 2007; Yang et al., 2024). These games combine elements of game design, technology, and educational principles to engage users in activities that are both enjoyable and educational. So, what if we use Serious Games to implicitly determine the users' personality?

This work intended to propose a new approach to solve the cold-start problem without needing great amounts of previous data to provide the initial recommendations; to implicitly acquire the

tourists' more granular personality traits in order to better characterize them and avoid the social desirability bias associated with personality questionnaires; and at the same time show concern for their interests by using intelligent agents to improve the initial recommendations; as well as aggregate tourists so they can perform joint activities without conflicting interests.

1.1 Motivation

The main motivations behind this work were related to the improvement of group recommender systems for tourism, so the tourists' experience when visiting a location could be maximized, namely:

- To solve the cold-start problem in GRS, so preliminary recommendations can be offered without the need for previous interactions data with the system;
- To overcome the group's members' heterogeneous and conflicting preferences, and the alienation by minority, ensuring that all group members have an opportunity to give their opinion without unduly prioritizing one over the others;
- To show concern for the individual users' needs, as not everyone has the same capabilities and travel-related preferences;
- To build the users' initial profile with the minimum possible intrusiveness;
- To overcome sparsity issues common to recommender systems;
- To find how a group can be aided in reaching the final choice without the emotional contagion phenomenon, so the recommendations received are fair and satisfactory for all the group members;
- How to promote the sense of community and companionship in excursion groups, so it becomes pleasant and a good experience to travel in an excursion group.

1.2 Objectives and Research Questions

To try to address the referred GRS issues and potentiate the tourists' experience and involvement during their stay in a country, this doctoral work encompassed the design and development of a mobile GRS for tourism prototype, focusing on the process of accompanying groups of tourists in the planning stage, by using their personality, intelligent agents and serious games. For that, the following objectives (O) were proposed:

O1. To study and design the most suitable architecture for the GRS prototype;

O2. To study and develop a Multi-Agent System (MAS) of personalized agents modeled with the tourists' profile (demographics, personality, physical limitations, and fears/phobias);

O3. To determine the tourists' personality in a non-intrusive and less time-consuming way, so their tourist attractions preference, travel motivations, and personal preferences & concerns when travelling can be automatically predicted, and therefore solve the cold-start problem;

O4. To study how the GRS prototype can generate personalized and intelligent recommendations considering the tourists' profile;

O5. To take advantage of the MAS and the agents' interaction to intelligently connect group members with similar interests in order to overcome the group's heterogeinity and conflicting preferences, promoting socialization.

Building on the proposed objectives and the existing research, the following research questions (RQ) arose:

RQ1) Is it possible to effectively learn the users' personality in a non-intrusive and less time-consuming way by using serious games?

This research question led to two relevant sub-questions:

RQ1.1) Does personality predict preferences for tourist attractions, travel motivations, and personal preferences & concerns when travelling?

RQ1.2) If so, which personality dimensions or traits are antecedents of which tourist attractions, travel motivations, and personal preferences & concerns when travelling?

RQ2) Is it possible to generate personalized and relevant recommendations based on the tourists' personality?

RQ3) Can the cold-start problem be solved just by using the tourists' personality?

RQ4) How can tourists in an excursion be efficiently aggregated according to their preferences, so it becomes more beneficial to them than to stay in the main and heterogeneous group?

1.3 Research Methodology

To conduct the proposed work, a system of principles, practices, and procedures, known as Design Science Research Methodology (DSRM), was followed. Proposed by Peffers et al. (2007), it is

intended to produce and present a valuable, rigorous and publishable research in the domain of Information Systems. This methodology provides an iterative process for doing Design Science Research, and is comprised of six steps, illustrated in Figure 1.1: (1) problem identification and motivation; (2) definition of the objectives for a solution; (3) design and development; (4) demonstration; (5) evaluation; and (6) communication.

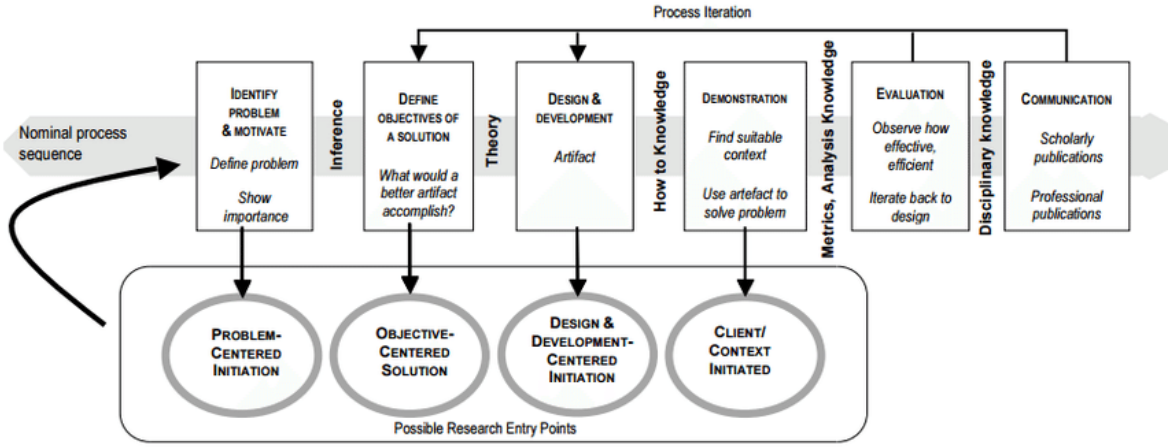


Figure 1.1. Diagram of the Design Science Research Methodology. Retrieved with permission from Peffers, Tuunanen, Rothenberger, and Chatterjee (2007).

According to Hevner, March, Park, and Ram (2004), the most important in a thoroughly performed Design Science Research in Information Systems is that it must involve a process to design artifacts to address observed problems, which must be relevant to the solution of yet unsolved and important business problems. The artifacts, which may be constructs, models, methods and instantiations, should be developed based on existing theories and knowledge, and their "utility, quality, and efficacy" (Hevner et al., 2004) meticulously evaluated, in order to solve the defined problem(s), and effectively communicated to the proper audiences.

Although the methodology does not need to be performed in the referred sequential order, it was the order followed to accomplish the proposed research work. So, following the first step, problem identification and motivation, the research problems were clearly identified, and the value of the proposed solutions justified, to help understand the reasoning behind the comprehension of the problem. A thorough literature review was performed on the different addressed areas of research. Along the path, according to the needs of the research, further literature reviews were conducted in an iterative manner. These "step backs" were performed between the writing of each paper for the thesis, as new concepts were being addressed and/or updated.

The second step, definition of the objectives for the solution, consisted in the rationalization of the objectives from the initially identified problems for the GRS prototype, being the state of the art found the base resource for that reasoning.

The artifacts (step 3) necessary to solve the identified problems and fulfill the proposed objectives consisted in the:

- conceptualization, design, and development of several models, namely: (1) a model to categorize the possible tourist attractions, (2) a model to relate personality to the preference for those tourist attractions, (3) another model to relate personality to travelling motivations, and finally, (4) a model to relate personality and travel-related preferences & concerns;
- conceptualization and design of algorithms to predict the tourists' preferences and solve the cold-start problem;
- conceptualization and design of algorithms to effectively aggregate tourists with similar preferences in an excursion group and solve the groups' conflicting preferences and heterogeneity;
- conceptualization, design and development of the Group Recommender System prototype, including the implementation of the referred models and algorithms, to provide POI recommendations just by knowing the tourists' personality, and maximize the group's members tourist experience;
- development of algorithms to improve the initial recommendations;
- design of short-duration serious games as proof of concept to implicitly determine the users' personality.

The produced artifacts are reflected in the papers that compose this thesis. Besides being grounded by the literature review, the artifacts design primarily stemmed from data collected from a questionnaire administered in a large scale study (see Paper 2 in Chapter 4, and Paper 3 in Chapter 5).

Demonstrations of the developed models and GRS prototype to the academic community were undertaken in different iterations of the research work, showing how the artifacts solved the identified issues, represented by Papers 4 and 6 (Chapter 6 and Chapter 8, respectively).

Functional and integration tests along the development process determined the need to iterate back to step 3 to try to improve the models, algorithms, and the GRS prototype. The prototype was

also evaluated for performance, scalability, sensitivity, accuracy, and user satisfaction after its development, corresponding to DSRM step 5, and is presented in Paper 5 (Chapter 7). This included experimentation and case studies with real users. In another iteration, the serious games developed were also tested and evaluated in experiments with real users, which is addressed in Paper 7 (Chapter 9).

The communication step accompanied the whole process of the doctoral work, which involved communicating the importance of the identified problems and proposed solutions, the utility, novelty and effectiveness of the designed and developed artifacts to other scholars, through the writing of the mentioned scientific papers, published and publishable, in the areas of User Modeling, Human-Computer Interaction and Recommender Systems.

The work presented in this thesis was conducted at the Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD), research center of the Superior Institute of Engineering of the Polytechnic of Porto (ISEP, IPP), Portugal, in association with the ALGORITMI Research Centre, a research unit of the School of Engineering of the University of Minho (UMinho), Braga, Portugal. Due to the CoViD-19 pandemics, part of the work was conducted remotely. This doctoral work was supported by the FCT research grant 2020.06129.BD and by the European Social Fund. Before being awarded the FCT grant, I was a research fellow of the Grouplanner project (under grant POCI-01-0145-FEDER-29178). As some of the doctoral work was used for the Grouplanner project, the GRS prototype adopted the "Grouplanner" name.

1.4 Thesis Structure

This thesis is based on a compilation of published and publishable papers, also known as "compilation thesis" or "article-based thesis" (Gustavii, 2012; Morrison, 2017; Rowe, 2015). It follows the "sandwich format" (Menk Dos Santos, 2019) and comprises three parts: Part I, the exegesis, which is composed of two chapters, this introduction and a contextualization on the most relevant addressed topics; Part II, the compilation of the papers that includes 6 published papers, 2 in journals and 4 in conferences, and another paper, currently in review, submitted to a journal, corresponding to seven chapters in total; and finally, Part III, which corresponds to the main conclusion, limitations found and future directions.

In Part II, the seven written papers are presented as is, constituting each one a chapter, starting in Chapter 3. For readability, the papers' list of references were compiled at the end of the thesis in a global list of references (Gustavii, 2012; Menk Dos Santos, 2019), as well as the respective appendices. The seven papers included were produced during the several stages of the research project and constitute the detailed main storyline of the doctoral work. The concepts, ideas, and process behind the papers are shortly described next.

Paper 1. Modeling a Mobile Group Recommender System for Tourism with Intelligent Agents and Gamification

This was the first paper written for the thesis project and contributes to objectives O1 and O2. It represents the first ideas thought up for the GRS prototype which I was thrilled to start idealizing. This first concept was important for brainstorming and determining the conducting wire for the proposed research. It involved the first topics addressed in the work, such as to better understand RS, what already existed in literature to address recommendations for groups, and especially for groups of tourists.

A thorough literature review on RS and GRS was conducted, what aspects should be considered, and what the main limitations were. A very important and actual problem related to RS was acknowledged for the first time, the cold-start problem. This highlighted the path by unveiling the importance of personality in predicting user preferences, leading to the conclusion that more information on personality was needed.

During the research, it was found that game components were being used to improve the users interaction in non-game applications, learning the term gamification, which I immediately found a very interesting topic due to my involvement in the videogames world. This introduced the idea of how it could be used to improve a RS, as it was shown to be a success among students, workers, and others (de CA Ziesemer, Müller, & Silveira, 2014; Hamari et al., 2014). However, some features idealized in the paper ended up being projections of future projects outside the scope of the current work, such as the user's avatar or virtual pet, and the use of Augmented Reality (AR). The gamification of the prototype was initially planned but was later removed from the scope of the doctoral work due to the complexity involved.

With the information gathered, the GRS started to be idealized, and the first conceptual model was designed. This study opened the path needed to determine what factors would be more important to improve group recommendations, and what psychological aspects would be relevant to personalize recommendations.

Paper 2. Modeling Tourists' Personality in Recommender Systems: How Does Personality Influence Preferences for Tourist Attractions?

The work involved in the writing of this paper was very challenging and inspiring, as it also involved research in the Psychology area. It was a very important research and determinant for the doctoral work. It involved extensive research on what personality was, how it could be characterized, and the main models used in literature, and contributes to objective O3, and research questions RQ1.1, RQ1.2, and RQ2.

A thorough literature review on the influence of personality in the users' preferences in a variety of domains was performed, especially in the tourism industry, and the use of personality in RS was explored. I also learned the term Psychology of Tourism and got fascinated by the area. This took to a challenge, related to research questions RQ1.1 and RQ1.2. How could the relationship between the raw five personality dimensions and the tourists' preferences be determined, instead of using tourist typologies like the most existing works?

Delving the most important terms used for classifying tourist attractions, the most relevant terms were chosen in brainstorming meetings with two co-authors, one of them a psychologist and Grouplanner's research fellow, Pedro Saraiva, and an ontology started to be idealized. The terms chosen were drawn in a mind map, which was named the "Fish Ontology" due to its shape and can be consulted in Appendix A. Then, to find the relationship between tourist preferences and the tourists' personality, a survey to gather ground-truth data was conducted, which was also challenging. The survey involved hard work and persistence, as the questionnaire comprised 196 questions, and not everyone was willing to answer for free[3].

To define the "personality vs tourist preferences" model, many weeks of model adjustments and calculations were needed. As a result, we constructed a model that proved what I expected, that

3 The questionnaire can be consulted at https://www.gecad.isep.ipp.pt/grouplanner/dissemination.html, under the "UMUAI APPENDIX" pane.

the raw personality dimensions could be used to predict tourist preferences. However, the model's fit was only satisfactory, meaning the sample size needed to be larger to increase the model's fit, which was already being idealized as future work (see Paper 3).

Having this paper accepted in one of the top conferences on the user modelling area at the time was very gratifying as it recognized the importance of the work done.

Paper 3. Group recommender systems for tourism: how does personality predict preferences for attractions, travel motivations, preferences and concerns?

This paper continues the work presented in Paper 2, also focusing in answering to research questions RQ1, RQ1.1 and RQ1.2, and objectives O3 and O4, by improving the previously obtained "Personality vs Tourist Attractions Preference" model with a larger and more heterogenous sample, and extending the prediction to travelling motivations, and travel-related preferences & concerns, as we also intended to consider more personal concerns and interests, including weather preference, fears/phobias and physical limitations, to maximize the tourists' experience.

The research here presented results from a long and exhaustive study (from 2020 to 2022)[4] focused in discovering how personality relates to the choice of (a wide range of) tourist attractions, travelling motivations, and travel-related preferences & concerns, as most of the works found in literature were based on tourist roles/typologies and/or do not use the Big Five[5] personality dimensions to predict objective relationships between personality and the referred travel aspects. The questionnaire from the previous study was used, and, with many persistence, the sample was duplicated, resulting in a total of n=1035 viable responses.

In this work, objective relationships between all the Big Five personality dimensions, and some respective traits, and the preference for a wide range of tourism categories, travelling motives, travel-related preferences & concerns, and weather preferences were found, contributing with knowledge and hopefully a solid base for researchers of RS for tourism to automatically model

4 Where I had the pleasure of exchanging messages with Paul Costa, regarding some doubts about the Revised NEO personality inventory (NEO PI-R) (Costa & MacCrae, 1992). Thank you for your sympathy and suggestions on work to follow.
5 Model most widely recognized to represent the five personality dimensions (Dhelim, Aung, Bouras, Ning, & Cambria, 2021; Digman, 1990; Matz, Chan, & Kosinski, 2016).

tourists based on their personality. The results were used to propose recommendation algorithms to be used in the GRS prototype.

These findings allow to solve the cold-start problem and create groups with similar preferences, and therefore less conflicting preferences, so more accurate and personalized recommendations can be provided, being, to the best of our knowledge, the firsts to provide an exhaustive prediction of travel aspects preference based on the tourists' raw personality, also contributing to research questions RQ3 and RQ4.

This paper was published in one of the top journals in the user modeling area at the time and is presented in Part II.

Paper 4. Grouplanner: A Group Recommender System for Tourism with Multi-Agent Microservices

Meanwhile, the GRS prototype concept initially proposed was improved, and started to be implemented at the beginning of 2021. This involved thorough requirements elicitation and prototyping, the architecture and domain model design, and the design and implementation of personality-based recommendation algorithms, considering the findings of Papers 2 and 3.

In February of 2022, the prototype started to be altered, where the main change was to transform the MAS architecture into a Multi-Agent MicroService (MAMS), joining the best of a Multi-Agent System and Microservices, where the agents would be directly accessed through Representational State Transfer (REST) endpoints. So, the architecture model proposed in Paper 1 was improved and is briefly presented in this demo paper[6] and more completely in Paper 5.

This paper contributes to objectives O1, O2, and O4, and research questions RQ2 and RQ3.

This demonstration was very important for the research work and for me personally, being awarded the best demo paper prize of the IBM Demonstration Award at PAAMS'22, which was a recognition of the work done so far.

6 The demonstration video can be watched at https://www.youtube.com/watch?v=sS3Zc9kf0NA

Paper 5. Are Heterogeinity and Conflicting Preferences No Longer a Problem? Personality-Based Dynamic Clustering for Group Recommender Systems

The algorithms for the recommendations and formation of subgroups proposed in Paper 3 were thoroughly analyzed and significantly improved, being implemented accordingly in the GRS prototype. The points of interest ratings were no longer needed to provide the first recommendations, as the recommendations were solely based on the tourists' personality, by using the personality models proposed in Paper 3 to predict the travel preferences, solving the cold-start problem. To further personalize the recommendations and show concern for the tourists' specific needs, fears/phobias and disabilities, if any, were also considered and implemented in the recommendation algorithms.

A new personality-based dynamic clustering algorithm, d-means, was also conceptualized and implemented in the MAMS, by adapting the k-means algorithm, so the tourists could be aggregated according to their personality using a high similarity threshold (≥ 0.80). This adaptation was reasoned to eliminate the need to know the number of clusters a priori, as is mandatory by the existing clustering algorithms, to eliminate noise and outliers, which are a common problem in clustering algorithms, and to solve group's conflicting preferences and heterogeinity. This is a novelty in the RS area, assigning each tourist to a cluster in real-time without needing to know the number of clusters before.

The idea of using association rules, namely the Apriori algorithm, to further predict the clustered tourists' preferences came up. This idea was designed to help improve and refine the initial recommendations by the Recommendation Engine, using the tourists' profile and travel history.

To also improve the recommendations, the weather conditions at the excursions' destination and dates were also considered, using a weather API, provided by Sistrade at the time, as we were jointly working in a new project, the smarTravel project[7].

The work here presented contributed to research questions RQ2, RQ3, and RQ4, and objectives O1 to O5. To have this work accepted by Expert Systems with Applications is very rewarding and motivating, and represents an important milestone in my doctorate.

7 More information at https://smartravel.sistrade.com/

Paper 6. Improving Group Recommendations using Personality, Dynamic Clustering and Multi-Agent Microservices

This paper represents a demonstration of the work published in Paper 5, presented at the 17th ACM Conference on Recommender Systems (RecSys'23), and contributed to objectives O1 to O5, and research questions RQ2, RQ3, and RQ4.

RecSys is the premier international forum for the presentation of works related to RS. "It has become the most important annual conference for the presentation and discussion of recommender systems research" (RecSys, 2023), and is sponsored by great companies like Netflix Research, Huawei, Amazon Science, Google, Meta, among others.

A poster representing the work (see Appendix C) as well as a demonstration video[8] were created for the conference[9].

This conference had been in my mind since the beginning of my doctorate and was another milestone I really wanted to accomplish due to the conference's reputation in the RS area. To have this demo accepted was therefore a very important conquest for me.

Paper 7. "You Want to Play a Game?" Detecting Two Personality Traits with Short-Duration Mobile Games.

This is the last paper that composes this thesis and is currently under review in an international journal. It presents the work related to the concept of using serious games to capture the tourists' personality, as I not merely wanted to try to capture the tourists' personality implicitly, but equally the most granular Big Five personality traits. Not only to create a more immersive, motivating and fun way of capturing the tourists' personality, but also to solve the problems related to self-reporting questionnaires, such as the social desirability bias and fake responses.

As proof of concept, I chose to design two games, each one intended to specifically acquire one of the 30 Big Five traits (Costa & MacCrae, 1992). In a brainstorming session with two of the co-authors, João Trindade and Gonçalo Monteiro, also my mentees and smarTravel's fellow stu-

8 The video can be consulted at https://youtu.be/up0A3B_e6zU
9 The GRS prototype user manual can be consulted at https://www.gecad.isep.ipp.pt/grouplanner/assets/files/grouplanner_user_manual.pdf

dents[10], who were also used to play different types of video and mobile games, we decided for cautiousness and achievement-striving, as they were related to the Conscientiousness dimension, which we find very interesting, and because they seemed to be easier to measure in a first concept.

However, the design of the games was defying, where the cautiousness trait revealed to be the most complex to acquire, as not many related works could be found in literature, involving more imagination. Several situations that we thought could cause the players to behave in a more careful way were designed, inspired by several games played in the past, like Prince of Persia and Tomb Raider, among others. The idea of the achievement-striving game was also inspired in classic platformers, like Prehistorik, Sonic, and Super Mario Bros, and more recent games like Gran Turismo for the trophies' mechanics.

The game design ideas were debated in other brainstorming sessions, including Pedro Saraiva, who also enjoys playing video and mobile games, contributing knowledge from the behavioral area of Psychology. To determine if the minigames were measuring the intended personality traits, experiments with real users were conducted (n=100).

I can say that studying and designing the games was very gratifying and fun for me, as I have always enjoyed playing videogames since my childhood.

In this paper, we show personality traits can be measured with short-duration mobile serious games, and that being able to measure personality traits other than the proposed ones is a plus. This also shows that it might not be possible to measure some traits independently, as they are related to each other. This means that with simple minigames, without many interactions, we can measure someone's detailed personality without being subjected to the social desirability bias and false responses, in less than five minutes. Of course, there is always the possibility of filling in the personality questionnaires, but we already know that many responses can be socially biased or false, which would hinder the characterization of the real true self. The presence of a third person to conduct the questionnaire would be time-consuming and logistically impossible for modeling all users in an RS. This paper contributes to objective O3 and research question RQ1.

10 smarTravel Project supported under the European Regional Development Fund POCI-01-0247-FEDER-179946.

2

MAIN CONCEPTS

To give some initial background to the reader, being careful not to repeat the content addressed in the papers written for the doctoral work, this Chapter summarizes the main concepts behind the work done, such as what is a Recommender System, what are the main types, and some current key limitations. Group Recommender Systems are also presented, as well as the concepts of Multi-Agent Microservices, Personality, Gamification, and Serious Games. Detailed information, contextualization and state of the art is given in the papers that compose Part II.

2.1 Recommender Systems

A Recommender System (RS) is a type of information filtering tool designed to suggest items that are most relevant to a specific user (Ricci, Rokach, & Shapira, 2015), and are currently used in a panoply of domains, like online stores, music, movies, restaurants, tourism, online dating, etc. A RS typically specializes in a particular type of item, where the term "item" refers to what the system suggests to users, such as news to read, a place to visit, or music to listen (see Figure 2.1 Left). As a result, its design, user interface, and the main recommendation technique it employs are all tailored to offer useful and effective suggestions for that specific category of items. These systems are especially helpful when a person needs to select an item from a large and potentially overwhelming number of options provided by a service, a problem known as information overload (Levy, 2008), and already foreseen by Denis Diderot in 1755 (Diderot & d'Alembert, 1776).

This problem was computationally approached for the first time by Elaine Rich (Rich, 1979), who developed the first RS, Grundy, a virtual librarian that suggested books to individual users according to their stereotype. Already at that time, she stated that computers could distinctively treat users according to their personality and objectives, and, therefore, proposed to model users accord-

ing to some inferred demographic characteristics (such as gender, religion, education, political causes, etc.), matching them to predefined stereotypes, like Sports-Person, Feminist, or Intellectual. More than one stereotype could be active at the same time for a particular user, depending on the actions triggered and the stereotype rating. The stereotypes were related using a directed acyclic graph (see Figure 2.1 Right), using the "generalization of" relation. A structure that, if we think, can be equated with an ontology. With a complex structure but with simple calculations, Grundy could make predictions with 72% accuracy.

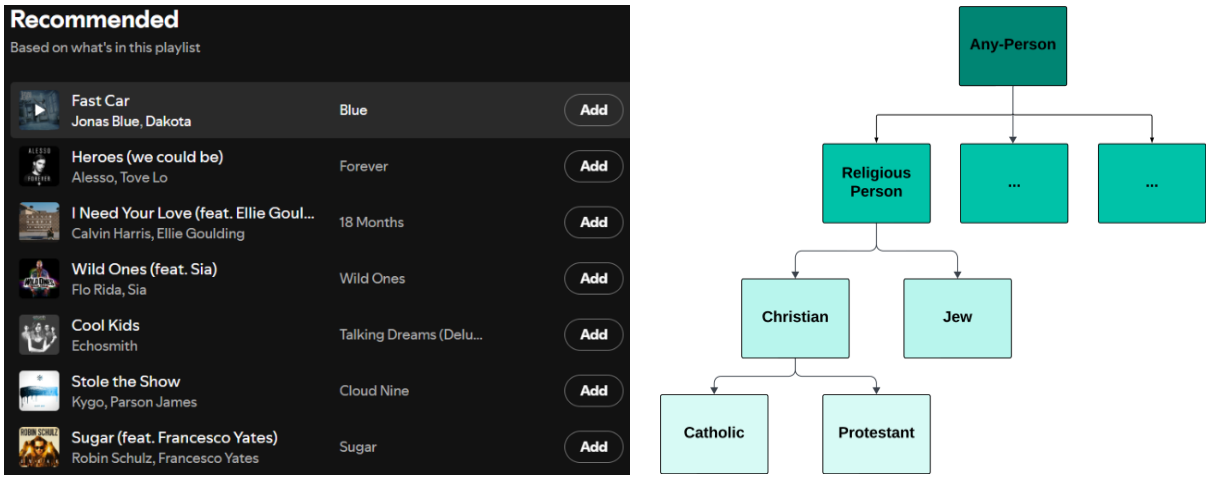


Figure 2.1. (Left) Example of music from a Spotify recommendation list based on a personal playlist; (Right) Part of the Stereotype graph used by Grundy RS, adapted from Rich (1979).

Only more than ten years after another RS was described (Karlgren, 1990). Karlgren presented an algebra for recommendations based on reader's data to measure document proximity in electronic document retrieval systems, discussing their difference between physical bookcases in terms of document clustering. To provide recommendations and enhance the users' chances of finding documents, it used a matrix to define relationships between documents based on interest grades given by the readers (interesting, uninteresting, not seen) and calculated the proximity between documents based on those grades.

Since the 90's, the interest and research on RS started to increase, with many RS being proposed and academically or commercially used, evolving from novelties to essential business tools (Schafer, Konstan, & Riedl, 1999), being an important current research area (Jannach, Pu, Ricci, & Zanker, 2021; Knees, Neidhardt, & Nalis, 2024).

GroupLens is an award-winning example of a RS (Resnick, Iacovou, Suchak, Bergstrom, & Riedl, 1994). It was designed to help users navigate the vast amount of content available on Usenet newsgroups by automating the use of collaborative filtering of the Tapestry mail system (D. Goldberg, Nichols, Oki, & Terry, 1992). GroupLens predicts which articles users will like based on the ratings of other users with similar tastes. The goal of GroupLens is to facilitate users finding articles they will enjoy in the large stream of available content, while also protecting user privacy by allowing ratings to be entered under pseudonyms. The ratings encouraged user engagement, which in turn improved the accuracy of future recommendations. Resnick and Varian (1997) emphasized the potential of RS to enhance user experience by making it easier to find relevant content and highlighted the importance of designing systems that balance user privacy with the need for accurate recommendations, while considering the user engagement and contribution.

In 2005, Adomavicius and Tuzhilin (2005), debated several limitations of the existing RS, such as the cold-start problem (difficulty in recommending items to new users or items with few ratings), scalability issues, and the need for more personalized and context-aware recommendations. They suggested enhancing the representation of user preferences and item characteristics to provide more accurate recommendations; the incorporation of contextual information (e.g., social context) into the recommendation process to make suggestions more relevant (Adomavicius & Tuzhilin, 2011); multi-criteria ratings (e.g., quality, price, usability) to capture a more nuanced understanding of preferences; and less intrusive and more flexible methods.

Gavalas et al. (2014) highlighted the significance of mobile RS in tourism, noting that tourists often find themselves in unfamiliar environments with a plethora of choices. Mobile RS can help alleviate the choice process burden by providing timely, relevant, and personalized suggestions. They emphasize contextual information such as location, time, weather, or the user's activity (e.g., walking, driving) should be considered to provide more relevant recommendations. This is particularly important in tourism, where the context can significantly influence what is recommended. The authors discuss several challenges in creating effective mobile RS for tourism, such as data sparsity and cold start problem (tourists might be visiting a location for the first time, or a new attraction might have just opened); the dynamic users' preferences that can change rapidly based on their

experiences and changing context; the need for context adaptation, which requires advanced algorithms that can process real-time data efficiently; and privacy concerns related to personal data.

Borràs et al. (2014) highlighted the role of AI techniques, including machine learning, MAS, ontologies, and clustering, and a user-centric design, in enhancing the performance of tourism RS and to provide more personalized and relevant recommendations. They suggested the integration of more sophisticated AI techniques and the development of context-aware recommendations.

Other interesting and useful overviews on RS can be found in literature, such as the works of Ricci et al. (2015), Aggarwal (2016), Delić et al. (2020), Jannach et al. (2021), and Y. Li, Liu, Satapathy, Wang, and Cambria (2024) which were some of the "Bibles" for this doctoral work, where an evolution of the knowledge and techniques in the area can be clearly seen, starting from simple user-item rating histories to the use of Generative Artificial Intelligence (such as Generative Adversarial Networks, Large Language Models, Variational Autoencoders, among others) (Ayemowa, Ibrahim, & Khan, 2024; Deldjoo et al., 2024). However, it can also be noticed that the same challenges persist.

The Netflix case is a contributing example for the RS evolution (Bansal & Sharma, 2024; Tuzhilin, Koren, Bennett, Elkan, & Lemire, 2008). In October 2006, Netflix launched the Netflix Prize Competition, a global contest aimed at improving the accuracy of its movie recommendation algorithm, offering a prize of US$1,000,000 (Bennett & Lanning, 2007). The goal was to develop a model that could predict user ratings for films more accurately than Netflix's existing algorithm at the time, called Cinematch, by at least 10%. The competition attracted more than 20k participants from 167 countries (Tuzhilin et al., 2008), fostering advancements in collaborative filtering and other data mining recommendation techniques. The competition concluded in 2009 when a team called "BellKor's Pragmatic Chaos" won by achieving the required improvement. This contest was an inspiration for other Over-The-Top platforms like Prime Video, YouTube, and others, in leveraging recommendation algorithms to drive revenue, warranting an in-depth analysis over the years, leading to further innovations in RS (Bansal & Sharma, 2024). The significance of incorporating contextual information beyond just user ratings was recognized in 2010, enabling the Netflix RS to better understand users' preferences in various contexts, such as time of day and viewing history (Bansal & Sharma, 2024).

The use of accuracy metrics, such as precision, recall, and F-measure are used to evaluate how well the system's recommendations match user preferences (Ezugwu et al., 2022; Gavalas et al., 2014). However, with the RS evolution, from an evaluation perspective, basic metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and precision are being transitioned to A/B testing, like in the Netflix case (Bansal & Sharma, 2024).

2.1.1 The Cold-Start Problem

The cold-start problem is a well-known and researched issue in RS and it refers to the challenges faced by RS when dealing with new users, new items, or both, due to a lack of historical data (Bobadilla, Ortega, Hernando, & Bernal, 2012; Schafer, Frankowski, Herlocker, & Sen, 2007; Schein, Popescul, Ungar, & Pennock, 2002). There are three primary types of cold-start issues:

New User Cold-Start: Occurs when a new user joins the system and the system has insufficient data about their preferences or behavior. Without enough ratings or interactions from the new user, the system struggles to make accurate recommendations;

New Item Cold-Start: Arises when a new item is introduced to the system. If the item has not yet been rated or interacted with by users, the system lacks information about how to recommend it effectively to users;

New System Cold-Start: Refers to the challenge of starting up a new RS with no initial data or user interactions, combining the challenges of both the New User and New Item scenarios, as all users and items are novel. The system must rely on limited information or external data sources to begin making recommendations.

Addressing the cold-start problem often involves leveraging alternative methods such as using content-based recommendations, integrating external data, or employing hybrid approaches that combine different recommendation techniques.

2.1.2 The Sparsity Problem and Curse of Dimensionality

In an RS, sparsity refers to the condition where the user-item interaction matrix is largely empty, with many possible interactions (such as ratings or preferences) being unobserved or missing (Schafer et al., 2007). In other words, it indicates that most users have interacted with only a small

fraction of the available items. Sparsity is a common issue in recommender systems and can impact their performance (Aggarwal, 2016; Altman & Krzywinski, 2018). For example, if most users have rated only a few items, it becomes challenging to make accurate recommendations for items that have not been rated or to identify patterns in user preferences.

Data sparsity aggravates with high-dimensional spaces, which is directly related to the "curse of dimensionality" (Altman & Krzywinski, 2018). The expression "curse of dimensionality" was created by Bellman (1957) and is well-known in the mathematics and machine learning domains. It refers to the various challenges that emerge when analyzing and working with data in high-dimensional spaces. As the number of dimensions (or features) increases, the volume of the space grows exponentially, complicating tasks like data analysis, visualization, and machine learning by increasing sparsity, computational demands, and the risk of overfitting.

Addressing sparsity often involves techniques to improve data coverage or handle incomplete data effectively. According to Adomavicius and Tuzhilin (2005), to address the issue of rating sparsity, one approach is to incorporate user profile information when determining user similarity. For instance, users could be deemed similar not only based on their similar ratings of the same tourist attractions but also if they belong to the same demographic group. The authors give the example of Pazzani (1999), who used the users' demographic information, such as age, gender, education, employment, and area code, to recommend restaurants. This filtering technique is also known as "demographic filtering". This shed some light on how to solve the sparsity issues in the developed GRS prototype, which is thoroughly explained in Paper 5 (Chapter 7).

2.1.3 Diversity, Novelty, and Serendipity

In a RS, diversity refers to the inclusion of a wide range of different items in a recommendation list (Aggarwal, 2016; Zhao et al., 2023) and should be a priority (Ricci, 2022). This means that instead of suggesting similar items based on a user's past preferences, the system aims to offer a variety of options that span different categories, genres, or topics. The goal is to enhance the user experience by exposing them to new and varied content, which can prevent the recommendations from becoming monotonous and help users discover new interests. For instance, imagine Joana is using a travel app to find tourist attractions. If the app only recommends famous wine cellars like Caves Cálem and Caves Ferreira in Porto, Portugal, it might get "repetitive". However, a diverse

RS would suggest a mix of attractions such as monuments, natural wonders, historical sites, cultural experiences, unique attractions, etc. This way, Joana can get a variety of options that can make her travel experience more exciting and enriching. She might discover a hidden gem or a new favorite destination that she wouldn't have considered otherwise.

As for novelty in RS, it is the ability to suggest items that users have not previously encountered but are still relevant to their interests (Aggarwal, 2016; Castells, Hurley, & Vargas, 2021; Kotkov, Medlar, & Glowacka, 2023). This concept is crucial since, by introducing novel items, RS can help users discover new content, preventing them from being confined to a narrow set of familiar items. Novel recommendations can make the user experience more engaging and satisfying, as users are more likely to explore and interact with new and interesting content (Ping, Li, & Zhu, 2024). While popular items are often recommended, focusing on novelty ensures that less popular but potentially interesting items are also suggested, providing a more diverse range of options.

Serendipity is an interesting feature that RS should also have, and it means "lucky discovery" (Aggarwal, 2016). It refers to the ability to suggest items that are not only relevant and novel but also pleasantly surprising to the user (Kotkov et al., 2023; Menk, Sebastia, & Ferreira, 2017). This means the recommendations are unexpected and delightful, often leading to discoveries that the user might not have found on their own (Ziarani & Ravanmehr, 2021). Contrary to novelty that simply means that the user has not encountered the recommendation before, serendipity is a more stringent criterion. While all serendipitous recommendations are novel, not all novel recommendations are serendipitous (Aggarwal, 2016). For example, imagine Junior is planning a trip to Paris and has mostly been looking at popular tourist attractions like the Eiffel Tower and the Louvre. One day, the RS suggests a hidden gem, offering a delightful and memorable experience that he wouldn't have found on his own: a small, charming bookstore called Shakespeare and Company, located near the Seine River. He decides to visit it and ends up spending hours exploring its unique collection of books and enjoying the cozy atmosphere.

2.1.4 Types of Recommender Systems

Depending on how the recommendations are made, there are three main approaches that can be used as basis to the design of RS (Adomavicius & Tuzhilin, 2005; Aggarwal, 2016):

Content-Based Filtering: This approach suggests items to users based on the characteristics of the items and the user's past interactions or preferences. It relies on the attributes of items (like genre, description, keywords) and compares them to what the user has previously liked or interacted with. For example, in tourism, content-based recommenders might suggest attractions like ones the user has visited before.

Collaborative Filtering: Collaborative filtering was coined for the first time by D. Goldberg et al. (1992). This approach recommends items based on the preferences and behaviors of other users. It operates under the assumption that if users agreed on items in the past, they would likely agree again in the future. For example, if two users have rated several places similarly, the system might recommend a place one of them liked to the other. Collaborative filtering is divided into two main types: user-based filtering, which recommends items to a user by finding similar users (neighbors) who have similar tastes or preferences; and item-based filtering, which recommends items by finding similar items based on the preferences of all users, i.e., finds items that are like those the user has previously liked or rated highly and recommends those. Amazon was one of the pioneers in implementing recommendation technology on a large scale (Linden, Smith, & York, 2003).

Collaborative recommendation algorithms can be further categorized into two broad types: memory-based (also known as heuristic-based), which use the entire user-item ratings database to make predictions; and model-based, which involve creating/learning a model from the user-item interactions (e.g., using machine learning techniques like matrix factorization, cluster models, Bayesian networks, and deep learning techniques) to make predictions (Breese, Heckerman, & Kadie, 2013).

Hybrid Approaches: These systems combine multiple recommendation techniques, such as content-based and collaborative filtering, to leverage the strengths of each other and provide more accurate and robust recommendations, and other machine learning techniques, such as deep neural networks like in YouTube (Covington, Adams, & Sargin, 2016), deep learning, natural language processing, and computer vision like in Netflix (Bansal & Sharma, 2024). Hybrid recommender systems can be enhanced with knowledge-based techniques, such as case-based reasoning, to improve recommendation accuracy and to overcome some

of the limitations, such as issues with new users and new items, faced by traditional recommender systems, as unlike collaborative or content-based methods, knowledge-based techniques do not rely on historical user data. Instead, they use explicit knowledge about user needs and preferences and item features to generate recommendations, which is useful for domains where user preferences are highly specific or change infrequently, like in the tourism, real estate, or automobiles domains (Aggarwal, 2016). As pointed by Smyth (2007) and referred by Aggarwal (2016), knowledge-based RS are frequently seen as closely related to content-based RS, leading to questions about whether a clear distinction exists between the two types of methods.

Further details on the different types of RS can be consulted, for example, in the RS handbooks of Adomavicius and Tuzhilin (2005), Ricci et al. (2015), and Aggarwal (2016).

It is clear that RS have significantly evolved since their first appearance, and that many issues are still open, such as data sparsity and the cold-start problem, where the lack of sufficient data on new users or new items can make it difficult for the system to provide accurate recommendations. Each RS type has its own strengths and weaknesses, and the approach to use often depends on the specific use case and the nature of the available data.

Considering the existing types of RS and the issues identified, a hybrid recommender system prototype was conceptualized and developed for the doctoral work. It uses user-based collaborative filtering with demographic filtering, context-awareness, knowledge-based to some extent, and model-based algorithms such as clustering and association rules. The development process is described throughout the papers in Part II, along with proper justifications.

2.2 Personality-Based Recommender Systems

Throughout the last two decades, personalization became the core feature for the effectiveness of RS in a wide range of domains (L. Chen, Wu, & He, 2016; Rashid et al., 2002; Tkalcic & Chen, 2015; Tondello, Orji, & Nacke, 2017), with several trying to predict the users' preferences based on their personality (Dhelim et al., 2023; Eldeswky, Elazab, Bolock, & Abdennadher, 2023; Hu & Pu, 2009; Perik, De Ruyter, Markopoulos, & Eggen, 2004; Roshchina, 2012; Tkalcic & Chen, 2022; Tkalcic, Kunaver, Tasic, & Košir, 2009; W. Wu, 2017). Nunes, Cerri, and Blanc (2008) pro-

posed the use of personality traits to recommend a president candidate for voters in the elections in France. In an experiment, the participants had to evaluate two candidates and the ideal president using the IPIP-NEO-300 personality questionnaire. Comparing the results to the participants actual votes, when using the 30 personality traits the recommendations were 100% accurate. When using only the 5 personality dimensions, the recommendations were 80% accurate.

W. Wu, Chen, and Zhao (2018) used the BFI to assess the users' diversity preference for different aspects of life's topics in a popular Chinese social network, such as music, movies, sports, etc. Personality similarity was then used in collaborative filtering and greedy re-ranking techniques to make recommendations of topics.

Dhelim, Ning, Aung, Huang, and Ma (2020) developed Meta-Interest, a personality-based product recommender system. They combined data-mining techniques, such as text-mining in social-networks, with personality and preferences similarity to match the items to recommend in a news social network. They used the short version of the Big Five Inventory (BFI), the Ten Item Personality Inventory (TIPI) (Gosling, Rentfrow, & Swann Jr, 2003), to determine the users' personality.

PEGA is a Personality-Guided Preference Aggregator model used for making recommendations to ephemeral groups, proposed by Ye et al. (2023). They use the users' individual Big Five personality to calculate the weighted group preferences and make the recommendations according to those weights.

Many other personalized RS that consider the users' personality have been developed (Dhelim et al., 2021; Waris, Fakhar, Gulsoy, Yalcin, & Bilge, 2024). However, to the best of our knowledge, the existing RS obtain the users' personality from explicit personality questionnaires, or implicitly by learning from their interactions with the continuous use of the system, like data mining social chats or posts. That is, they have time-consuming configurations and/or excessive intrusiveness, or they need to data mine a great amount of information in order to learn the user's behavior and interests. Also, the measured personality is based on the broadest five dimensions instead of the more granular traits, and some use less accurate questionnaires, such as the TIPI. To overcome these limitations, as a proof of concept, we developed short-duration serious games to implicitly determine granular personality traits, which are described in the work composing Paper 7 (Chapter 9).

2.3 Group Recommender Systems

Group recommender systems are tools designed to suggest items to a group of users rather than just a single individual. These systems consider the preferences of all members in the group to generate a recommendation aiming to better satisfy the group as a whole. The goal is to find a balance between individual preferences to provide suggestions that are acceptable, or even enjoyable, for the entire group.

GRS emerged as a natural extension of personalized RS, which have been widely used since the mid-1990s with the rise of platforms like Amazon and Netflix, where to provide personalized recommendations was essential for helping users navigate vast amounts of content (Jannach et al., 2021). However, it soon became evident that many real-world situations involve groups of people making joint decisions, such as friends deciding on a movie or families choosing a vacation destination (Jameson, Baldes, & Kleinbauer, 2003).

The earliest research on GRS began in the early 2000s. One of the pioneering studies was PolyLens (O'connor, Cosley, Konstan, & Riedl, 2001), a GRS which adapted personalized recommendation techniques to cater to group preferences. This work emerged as part of a broader effort to extend collaborative filtering techniques, which were initially developed for individual users, to group contexts. Many foundational concepts from personalized RS, like collaborative filtering and preference aggregation, were adapted and expanded to create algorithms that could accommodate multiple users' preferences (Jameson & Smyth, 2007; Masthoff, 2003). Since then, the field has grown significantly, with applications spanning entertainment, travel, e-commerce, and even collaborative work environments (Delic & Masthoff, 2018; Masthoff, 2015).

While GRS have made significant advancements, they still face several challenges (Álvarez Márquez & Ziegler, 2016; Delic & Masthoff, 2018; Delic, Neidhardt, Nguyen, & Ricci, 2018; Delić et al., 2020; Ricci, 2022). The most fundamental issue is how to combine the preferences of individual group members. This can be done using methods like averaging ratings or selecting the most popular choice within the group. However, these methods often fail to capture the nuances of diverse preferences, leading to suboptimal results for certain group members. The nature of group interactions is complex, including negotiation, compromise, and the influence of dominant personalities, where group members influence each other's preferences and choices, and understanding

these dynamics is crucial for developing effective GRS (Delic et al., 2018). This gives rise to another challenge, ensuring fairness and balancing the satisfaction of all group members. Simply selecting a "majority rule" approach can alienate minority preferences within the group. Designing algorithms that give voice to all members without disproportionately favoring any one individual remains a key issue. The users' satisfaction, not just with the final recommendation but with the choice-making process itself, is very important, which is not easy to predict. For example, the consideration of cognitive and emotional aspects has been shown to improve the accuracy in the satisfaction evaluation and prediction (João Carneiro, Saraiva, et al., 2019).

It is also common, and even more in large (occasional) groups, the existence of heterogeinity and conflicting preferences among the group members. For instance, one person might want to visit a monument, while another prefers to do wild nature activities. Resolving these conflicts in a way that maintains harmony and provides an agreeable recommendation is difficult. Also, as the number of group members increases, the complexity of calculating a recommendation that balances everyone's preferences grows. This becomes computationally demanding, especially in large groups.

The composition of groups often changes over time. A system that works well for a group of friends may need to adjust when one member is replaced or a new person joins in. Handling these dynamic shifts in group composition while maintaining relevance in recommendations is an ongoing challenge.

Group choices often depend heavily on context. For example, the same group might prefer different restaurant recommendations depending on whether it's a casual night out or a special occasion. Designing systems that can account for such context-specific preferences is complex and requires integrating contextual data.

In real-world scenarios, group preferences may evolve as discussions unfold. For instance, after some negotiation, group members might soften their initial preferences or change their minds entirely. GRS need to adapt in real-time to these changes, which presents a significant technical challenge, although it can be a controversial subject whether the group's members should be influenced or not by the others (Delic & Masthoff, 2018; Delic, Neidhardt, Rook, Werthner, & Zanker, 2017).

GRS represent an exciting and necessary evolution in recommendation technology, but they still face important challenges. While we have come a long way since their inception in the early 2000s, challenges related to preference aggregation, fairness, and real-time adaptability remain areas of active research and development. As these systems continue to improve, they hold great potential to enhance choice-making for groups in a wide range of contexts.

2.3.1 Examples of GRS in Industry

Several GRS prototypes, in different domains, can be found in literature, being INTRIGUE (Ardissono et al., 2003), Travel Decision Forum (Jameson et al., 2003), CATS (McCarthy, Salamó, et al., 2006a), and e-Tourism some of the first (Sebastia, Garcia, Onaindia, & Guzman, 2009) in the tourism domain. The GRS proposed by Sojahrood, Taleai, and Cheng (2023), Abolghasemi, Khadka, et al. (2022), and CHARM, developed by Delic et al. (2024), are some examples of recent ones. These and other works are detailed in the papers that compose this thesis.

Several industries have also implemented GRS to cater to the collective preferences of multiple users. For instance, Spotify offers a group session feature, Spotify Jam sessions[11] (previously Spotify Blend), where users can merge their listening habits with friends or family to create collaborative playlists or enjoy shared sessions in real-time.

Facebook Events[12] incorporates elements of group recommendation, particularly when suggesting locations or activities for social gatherings. The platform uses data from group members, such as liked events, previous activity, or interactions with similar posts, to recommend events or places that might interest the entire group.

Both TripAdvisor and Airbnb offer recommendations for groups traveling together, providing suggestions for accommodations, activities, and dining. For example, when multiple users input their preferences, the platforms can recommend vacation rentals or tourist attractions that suit the collective tastes of the group.

11 More details on https://community.spotify.com/t5/Your-Library/Spotify-Takes-Listening-With-Friends-to-Another-Level-with-Jam/td-p/5641808
12 https://www.facebook.com/events/

Google Maps' Group Planning[13] feature allows users to share lists of places they want to visit (e.g., restaurants or touristic sites) and collectively vote on which place to go. The system recommends places based on shared preferences within the group.

Booking.com uses collaborative filtering and group recommendation techniques to suggest accommodations that suit groups traveling together. The system takes into account the preferences of each individual in terms of price, location, and amenities, providing options that are acceptable to all.

Peach[14] is a group food ordering app, where it offers recommendations for restaurants that fit the collective tastes of the group. It aggregates individual preferences and dietary restrictions to make group ordering more efficient and satisfying for everyone. As an example, company teams ordering lunch through Peach can get restaurant recommendations that fit various dietary needs, such as vegan, gluten-free, or popular choices within the team.

These examples illustrate how GRS are gradually being incorporated into real-world applications, enhancing collaborative choice-making in various contexts such as entertainment, travel, dining, and social planning.

2.3.2 Aggregation Strategies

As previously mentioned, to know how to combine the users' individual preferences is crucial in a GRS. Many aggregation strategies have been developed, some inspired by Social Choice Theory (Masthoff, 2015). They help balance the diverse preferences of individual group members to generate a recommendation that is acceptable to the entire group. This ensures that the recommendation is not overly biased towards one member's preferences (Felfernig et al., 2023). Aggregation strategies should aim to make fair recommendations by considering the preferences of all group members. This helps avoid situations where the majority's preferences overshadow those of the minority (Dueñas-Lerín, Lara-Cabrera, Ortega, & Bobadilla, 2023). By aggregating preferences, the system can streamline the recommendation process, making it more efficient and less time-consuming (Lin, Zhang, Yang, Song, & Peng, 2021). This is particularly important when dealing

13 https://www.businessinsider.com/google-maps-group-planning-polling-feature-how-to-use-2018-9
14 https://www.peachd.com

with large groups. Effective aggregation strategies can adapt to changes in group members' preferences over time, ensuring that the recommendations remain relevant and satisfactory. Properly aggregated recommendations can enhance overall group satisfaction by ensuring that the selected items or activities are enjoyable for everyone involved (Masthoff, 2015).

Masthoff (2015) explains eleven aggregation strategies, categorized by Senot et al. (2010) into three major types: (1) majority-based strategies, like plurality voting, which use the most prevalent items; (2) consensus-based strategies, like average or fairness, which take into account all group members' preferences; and (3) borderline strategies, like dictatorship or least misery, which only consider a subgroup. Table 2.1 summarizes the eleven aggregation strategies (more details in Masthoff (2015)).

Table 2.1. Aggregation strategies used in GRS, adapted from Masthoff (2015). Reproduced with permission from Springer Nature.

Aggregation Strategy	Description
Approval voting	Counts the individuals with ratings for the item above an approval threshold (e.g. 6)
Average	Averages individual ratings
Average without misery	Averages individual ratings, after excluding items with individual ratings below a certain threshold (say 4)
Borda count	Counts points from items' rankings in the individuals' preference lists, with bottom item getting 0 points, next one up getting one point, etc.
Copeland rule	Counts how often an item beats other items (using majority vote[a]) minus how often it loses
Fairness	Items are ranked as if individuals are choosing them in turn
Least misery	Takes the minimum of individual ratings
Most pleasure	Takes the maximum of individual ratings
Most respected person (Dictatorship)	Uses the rating of the most respected individual
Multiplicative	Multiplies individual ratings
Plurality voting	Uses 'first past the post': repetitively, the item with the most votes is chosen

a If most group members rate item X higher than item Y, then item X is preferred over item Y.

2.4 Multi-Agent Systems and Multi-Agent Microservices

Due to the complexity associated to groups of tourists, several strategies are being proposed to improve recommendations, like the use of Multi-Agent Systems (Borràs et al., 2014; Ravi, Devarajan, Sangaiah, Wang, & Subramaniyaswamy, 2021; Z. Wang, Yu, Zheng, Ma, & Zhang, 2024). These systems are composed of multiple interacting agents, each one capable of autonomous action to achieve specific goals, being able to communicate, coordinate, and collaborate to solve complex problems. By using MAS, each agent can be optimized for specific tasks, leading to

greater efficiency and performance (Van der Hoek & Wooldridge, 2008; Wooldridge & Jennings, 1995). MAS can easily adapt to changing environments by adding, removing, or modifying agents without needing to retrain the entire system, making them suitable for a wide range of applications like RS. The capability of decentralized control ensures that the system continues to operate even if some components fail. By distributing tasks among multiple agents, MAS can effectively manage and filter large amounts of data, providing more relevant recommendations (Dorri, Kanhere, & Jurdak, 2018; Mahmood, El-Bendary, Platoš, Hassanien, & Hefny, 2014).

MAS are a powerful approach for enhancing the performance and adaptability of RS. Their remarkable similarities with microservices (MS) make them a perfect combination. Multi-Agent MS sprouted from this similarity and combine the principles of MAS and MS architecture to create a more dynamic and flexible system (W. Collier, O'Neill, Lillis, & O'Hare, 2019). The MS architectural style structures an application as a collection of loosely coupled services. Each service is fine-grained and the protocols are lightweight, typically HTTP/REST. As MS allow the deployment of modular and scalable independent services, with independent databases, different programming languages can be used for each one (Villamizar et al., 2015). MAMS integrate these two concepts by deploying agents within microservices, where each microservice can host one or more agents, exposing their functionalities through REST endpoints. With this approach, agents can interact with each other and with external systems more efficiently through standardized communication protocols; and the system can easily scale by adding or removing microservices without affecting the overall architecture (Jagutis, Russell, & Collier, 2023). By leveraging the strengths of both MAS and microservices, MAMS can provide faster and more intelligent responses to user requests (Z. Liu, Yu, Fan, & Chen, 2022). This combination makes MAMS a powerful approach for building complex, adaptive, and scalable systems. Table 2.2 and Table 2.3 show the comparison between both MAS and MAMS principles, showing the referred commonalities, which are thoroughly explained in W. Collier et al. (2019).

Several Multi-Agent platforms exist (Pal, Leon, Paprzycki, & Ganzha, 2020). After a thorough research, ActressMAS was chosen for developing the GRS prototype's MAMS (see Paper 4, Chapter 6), for being a simple framework with an easy learning curve. Additionally, it is one of the few agent frameworks that utilize the C# programming language, making it more compatible with the

.NET framework, chosen for the prototype development. ActressMAS is built on the Actor model and leverages .NET asynchronous operations for its implementation. To ensure a transparent and efficient parallel and sequential execution, in ActressMAS the "agents are stored in a concurrent or 'normal' C# dictionary" (Leon, 2022). The agents are alive in an environment, executing in turns, and communicate with each other using messages. The messaging system uses a simple syntax, based on the FIPA's Agent Communication Language (ACL) standard and the JADE framework messages implementation. The parallel execution can benefit from the multiple processor cores now available, and is performed by using .NET Tasks, which use a thread pool that allows the execution of thousands of agents at the same time.

Table 2.2. Comparison of the microservice principles to MAS. Adapted from W. Collier et al. (2019), licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

Principle	Microservices	MAS
Bounded Context	A microservice represents a single piece of business functionality.	An agent can play a single or multiple roles in a system.
Size	Microservices should be small enough to ensure maintainability and extensibility.	Size/complexity is not an issue in MAS research and often depends on the target domain.
Isolated State	Sharing of state information is minimized across services.	State is local and private to an agent. This is often viewed as essential for an agents autonomy.
Distribution	Services are spread across multiple nodes.	Agents are logically distributed, but it is also expected that they will be spread over multiple nodes.
Elasticity	The application is designed to allow addition and removal of required resources at runtime.	The ability to add/remove agents at runtime is a central feature of MAS.
Automated Management	Management operations like failure handling and scaling are automated.	Management operations are not central to agents, but are sometimes considered.
Loose Coupling	Systems are decomposed into loosely coupled sets of highly-cohesive colocated services.	Agents are autonomous and loosely-coupled problem solvers.

2.5 Personality

Personality refers to the unique patterns of thoughts, feelings, and behaviors that distinguish an individual from others. As defined by Allport (1961) "Personality is the dynamic organization within the individual of those psychophysical systems that determine his characteristics behavior and thought". They are seen as "the characteristics or blend of characteristics that make a person unique" (Weinberg & Gould, 2023), and they are considered stable during most of an individual's lifetime independently of the situation (McCrae & Costa Jr, 1997).

Table 2.3. Comparison of the MAS principles to microservices. Adapted from W. Collier et al. (2019), licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

Principle	Microservices	MAS
Autonomy	Microservices operate without the direct intervention of humans and have some kind of control over their internal state (and actions?).	Agents operate without the direct intervention of humans and have some kind of control over their actions and internal state.
Social Ability	Interaction between microservices is typically achieved using messages based on RESTful APIs and HTTP.	Agents interact with other agents using some kind of Agent Communication Language.
Reactivity	Microservices respond to incoming HTTP requests in a timely fashion.	Agents perceive their environment and respond in a timely fashion to changes that occur in it.
Proactivity	Microservices do not take the initiative.	Agents don't just respond - they take the initiative.

The assessment of personality has evolved significantly over time, but some of the earliest methods date back to ancient civilizations. Early attempts to understand personality can be traced back to ancient Greece, where Hippocrates and later Galen proposed the theory of the four humors (Dumont, 2010). They believed that personality traits were influenced by bodily fluids: blood, phlegm, black bile, and yellow bile (Goldstein & Hersen, 2000). In the 19th century, phrenology became popular. This pseudoscience, developed by Franz Joseph Gall, involved measuring bumps on the skull to predict personality traits and mental abilities (Van Wyhe, 2002).

The 19th and early 20th centuries saw the development of more scientific approaches. Hans Eysenck's theory of personality emphasized that personality traits are largely influenced by biological factors (Hans Jurgen Eysenck, 1958; Hans J Eysenck, 1966, 1982). A notable strength of Eysenck's theory is its consideration of both nature and nurture. It posits that our personality is shaped by an interplay between biological predispositions and the influences of conditioning and socialization during childhood. He proposed our personality is shaped by our genetic makeup, which determines our temperament. Eysenck identified three major dimensions of personality: Extraversion vs. Introversion, Neuroticism vs. Stability, and Psychoticism. Eysenck believed that these dimensions could be measured and used to predict behavior, making his theory one of the foundational models in personality psychology.

Alfred Binet and Théodore Simon created the first intelligence test, which indirectly contributed to personality assessment by highlighting individual differences (Siegler, 1992; Zazzo, 1993). In the early 20th century, projective tests like the Rorschach Inkblot Test (Hertz, 1936) and the Thematic

Apperception Test (Murray, 1943) were developed. These tests aimed to uncover unconscious aspects of personality by analyzing responses to ambiguous *stimuli*.

The mid to late 20th century saw the rise of objective personality tests, such as the Minnesota Multiphasic Personality Inventory (Hathaway & McKinley, 1951). The trait theories proposed by Gordon Allport and Raymond Cattell, led to the creation of personality inventories like the 16 Personality Factor Questionnaire (16PF), and the Neuroticism-Extraversion-Openness Personality Inventory (NEO PI) by McCrae and Costa (1985). Later, in 1992, Costa and MacCrae (1992) published the revised 240-item NEO PI (NEO PI-R), which included newly added dimensions, Agreeableness and Conscientiousness, representing the Big Five dimensions:

> *Agreeableness:* This dimension reflects how well a person gets along with others. Individuals high in agreeableness tend to be compassionate, cooperative, and eager to help. They are often seen as warm, friendly, and considerate, trusting, altruist, kind, and affectionate. People with low agreeableness might be more competitive, critical, or less concerned with others' feelings.
>
> *Conscientiousness:* This dimension measures a person's level of organization, dependability, and work ethic. Highly conscientious individuals are disciplined, goal-oriented, and detail-focused. They are reliable and tend to plan ahead. On the other hand, those with low conscientiousness might struggle with organization, procrastinate, and be more impulsive.

Table 2.4 shows the five dimensions and the respective facets (or traits) with corresponding adjectives that were used by Costa and McCrae to describe each dimension.

As NEO PI-R was considered too long for several research purposes, the authors created a shorter version, the 60-item NEO-FFI (Costa & MacCrae, 1992). John, Donahue, and Kentle (1991) also developed a short inventory to measure the five dimensions, the Big Five Inventory, composed of 44 items, that represent short phrases based on the dimensions' adjectives. The BFI can be consulted in Appendix B. Other personality inventories have been developed ever since, many of which can be consulted in the International Personality Item Pool (IPIP) website[15].

15 https://ipip.ori.org/

These personality tests use standardized questions and scoring methods to assess various personality traits and psychopathologies. For example, in the BFI, the subject needs to answer in a 5-point Likert scale to the 44 items, from 1 (strongly disagree) to 5 (agree strongly). As some questions are reverse scored, it means their score needs to be reversed in the interpretation phase, i.e., a response of 1 needs to be changed to 5, 2 to 4, 4 to 2, and 5 to 1. Then, the final score for each dimension is the sum of the registered scores.

Table 2.4. Costa and MacCrae (1992) NEO PI-R personality dimensions' facets, adapted from John and Srivastava (1999).

Big Five dimensions		Facets (and correlated trait adjectives)
E	Extraversion vs. introversion	Gregariousness (sociable) Assertiveness (forceful) Activity (energetic) Excitement-seeking (adventurous) Positive emotions (enthusiastic) Warmth (outgoing)
A	Agreeableness vs. antagonism	Trust (forgiving) Straightforwardness (not demanding) Altruism (warm) Compliance (not stubborn) Modesty (not show-off) Tender-mindedness (sympathetic)
C	Conscientiousness vs. lack of direction	Competence (efficient) Order (organized) Dutifulness (not careless) Achievement striving (thorough) Self-discipline (not lazy) Deliberation (not impulsive)
N	Neuroticism vs. emotional stability	Anxiety (tense) Angry hostility (irritable) Depression (not contented) Self-consciousness (shy) Impulsiveness (moody) Vulnerability (not self-confident)
O	Openness vs. closedness to experience	Ideas (curious) Fantasy (imaginative) Aesthetics (artistic) Actions (wide interests) Feelings (excitable) Values (unconventional)

As evidenced, different personality traits and scales have been proposed in literature by several researchers in the area of Psychology (Lewis Robert Goldberg, 1971), involving thousands of traits or terms, creating difficulties in the researchers communications (John & Srivastava, 1999), such as scales having the same name but measuring different concepts, and the opposite. As well pointed by John and Srivastava (1999), "what personality psychology needed was a descriptive

model, or taxonomy, of traits". After decades of studies, a consensus on a general taxonomy was reached, involving several researchers in uncovering and refining the five personality dimensions, being widely accepted nowadays (Digman, 1990; Matz et al., 2016). This five-factor structure was replicated by several researchers in lists originated from Cattell's 35 variables (John & Srivastava, 1999), and is known as the "Big Five" for representing the broadness of each dimension (Lewis R Goldberg, 1990), where each dimension encapsulates a wide array of distinct, more specific personality traits.

According to Costa Jr, McCrae, and Kay (1995), in the Big Five or Five-Factor Model (FFM) of personality, also known as OCEAN, the five personality broad dimensions can be described as:

Openness to Experience: This dimension features characteristics such as imagination, insight, and a broad range of interests. People high in openness are often more adventurous and creative.

Conscientiousness: Previously described.

Extraversion: This dimension encompasses excitability, sociability, talkativeness, assertiveness, and high amounts of emotional expressiveness. Extraverts are often outgoing and gain energy from social interactions.

Agreeableness: Previously described.

Neuroticism: This trait is characterized by sadness, moodiness, and emotional instability. Individuals high in neuroticism experience mood swings, anxiety, irritability, and sadness.

These five dimensions are considered relatively stable over time and across different cultures, providing a comprehensive framework for understanding personality, and was therefore the model chosen for the doctoral study.

2.6 Gamification

Nowadays who hasn't played a mobile game? Almost every owner of a mobile device did, and games are increasingly being developed for every taste. The application of gaming and game elements to a non-gaming context, i.e., gamification, such as education, health, business, or tourism, to engage, motivate, and influence behavior, is the cutting-edge concept (Lehtoranta, Xi, & Hamari, 2024; Oliveira et al., 2024; Xu et al., 2016; Y. Zhang, Xi, Liang, & Hamari, 2024). By incorporating

aspects typically found in games, such as points, levels, challenges, rewards, and competition, gamification seeks to make activities more enjoyable, interactive, and rewarding for participants. While gamification is not about turning everyday tasks into full-fledged games, it aims to use the psychology of games to enhance user engagement and productivity in various fields. In fact, it is demonstrated that gamification increases the users' engagement and incentive while learning, working or visiting a city (Barna & Fodor, 2018; Cheng & Chau, 2022; Hamari et al., 2014; Hamari et al., 2016; Xu et al., 2016; Yang et al., 2024). Commercial applications like Kahoot! (A. I. Wang & Tahir, 2020) and Duolingo (Shortt, Tilak, Kuznetcova, Martens, & Akinkuolie, 2023) are two well-known successful examples that incorporate points, levels, and badges to motivate the users/students, helping them to stay engaged while learning new subjects or languages.

Gamification is being eulogized as the next generation method for marketing and customer engagement (Hamari et al., 2014), and it is increasingly being used by tourism organizations to promote their products and motivate tourists (Xu et al., 2016). For example, the mobile app Geocaching was developed to motivate tourists interacting with a tourism destination, by performing a treasure hunt, and can be used in different parts of the world[16].

The motivation to play a game is very important in the design of specific games (Xu et al., 2016), like for the tourism domain, since it is clearly evidenced that the role of the context to be gamified influences the gamification success (Hamari et al., 2014). Xu et al. (2016) concluded that if designed properly, games can clearly enhance the tourists experience before, during and after a visit, increase their satisfaction, and even their brand awareness and loyalty to a destination. The authors present game design elements and best practices to leverage tourism marketing.

Since tourism is an experience industry (Pine, Pine, & Gilmore, 1999), we believe gamification can help in the design of less time-consuming and interesting/fun configurations in a RS for tourism. Hence, if a tourist knows he can get better recommendations if he plays a game to help build his profile, he will be more motivated to play it. Thus, a RS for tourism could become more challenging and exciting if gaming components, like badges for accomplishing certain tasks or mini games to

16 https://www.geocaching.com/play

gather the tourists' profile, were added to it. This could be a potential feature for the proposed GRS prototype, as proposed in Paper 1 (Chapter 3).

2.7 Serious Games

The biggest challenge in designing personality-based RS is capturing the users' personality (Tkalcic & Chen, 2015). Explicit techniques, like personality questionnaires, can be used, but are intrusive and time-consuming, and not everyone has the patience and willingness to answer such intimate questions, which many times results in magnified responses due to social desirability bias, and false responses (Pedregon et al., 2012). This poses a challenge for RS that rely on questionnaires to determine the users' personality. To address this issue, researchers are exploring methods to gather user personality data implicitly, like audio and/or visual approaches, wearable devices, smartphones, text, social media, or games (Finnerty, Lepri, & Pianesi, 2016; Quwaider, Alabed, & Duwairi, 2023). However, we can see that the concept of serious games to gather personality is still green in the area of RS, and researchers have not yet found a way that motivates and challenges the users to complete their profile. Predicting someone's personality with sufficient accuracy, without requiring numerous interactions or continuous input from the user, and doing so unobtrusively, presents a significant challenge, as is detailed in Paper 7 (Chapter 9).

This doctoral work proposed to solve that challenge by using short-duration serious games as a proof of concept, taking advantage of the capability that games have in motivating and challenging the users. Since it is possible to predict someone's personality by analyzing her gaming behaviors (Berdun & Armentano, 2018; Mayer, 2018; Quwaider et al., 2023; Van Lankveld, Spronck, Van den Herik, & Arntz, 2011; Yee, Ducheneaut, Nelson, & Likarish, 2011; Yi, Zhou, Xiao, Qing, & Mayer, 2020), to use games for predicting the users' personality and other traceable aspects is a great leverage, which can be used by personality-based RS to help build the user's profile. Understanding player behavior in video games (known as player modeling) is also beneficial for marketing strategies, procedural content generation, and game design (Anadón, Sanahuja, Traver, Lopez, & Ribelles, 2021).

Serious games are a recent category of games designed for purposes beyond mere entertainment (Michael & Chen, 2005; Susi et al., 2007), having demonstrated to be advantageous compared to

traditional games, especially in an era where the new generation is surrounded by technology and easily gets bored by the traditional (Tsionas & Satratzemi, 2023). While they incorporate elements of traditional gameplay, such as rules, objectives, challenges, and rewards, their primary focus is on education, training, or solving real-world problems. These games are being successfully used in fields like education (e.g., "Minecraft: Education Edition"[17] (Bar-El & E. Ringland, 2020) and "Civilization" (Mol, Politopoulos, & Ariese-Vandemeulebroucke, 2017)), healthcare (e.g., Adventure Game (Venturini, Faralla, & Innocenti, 2013) and Foldit (Cooper et al., 2010)), business, military (e.g., America's Army (Nieborg, 2004)), and public policy, to engage users in learning or skill-building through interactive experiences.

As mentioned before, in this work, one intention was to implicitly determine the users' personality. Several works that try to unobtrusively determine the users' personality by using serious games are already being developed (see Paper 7, Chapter 9). For instance, the story-based serious game "Learn C", developed by Tsionas and Satratzemi (2023), was developed to help students learn the C programming language, and at the same time, to model the students' personality. They found extraversion and openness could be effectively measured with the game. However, to the best of our knowledge, the existing works still need many users' interactions and input to characterize them, take too much time to be played, are not that accurate, or only determine the broader five dimensions of personality, instead of the more granular 30 traits. So, the challenge is to develop an immersive and appealing game that can learn more granular personality traits in a short time.

To implicitly acquire someone's personality poses other challenges, such as the privacy, confidentiality, and anonymity of the user's personal data, which must be considered and assured in the design of this type of games, particularly in relation to sensitive data such as their personality, as mandatory by the General Data Protection Regulation (GDPR) in Europe.

17 https://education.minecraft.net/en-us/get-started/school-leaders

Part II

THE PAPERS

"Mistakes are the building blocks of wisdom"

Martha Rodgers, in Castle

3

MODELING A MOBILE GROUP RECOMMENDER SYSTEM FOR TOURISM WITH INTELLIGENT AGENTS AND GAMIFICATION



An image representing a conceptual GRS where the users are represented by agents.

Generated with AI, Image Creator in Bing, October 2024

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Abstract

To provide recommendations to groups of people is a complex task, especially due to the group's heterogeneity and conflicting preferences and personalities. This heterogeneity is even deeper in occasional groups formed for predefined tour packages in tourism. Group Recommender Systems (GRS) are being designed for helping in situations like those. However, many limitations can still be found, either on their time-consuming configurations and excessive intrusiveness to build the tourists' profile, or in their lack of concern for the tourists' interests during the planning and tours, like feeling a greater liberty, diminish the sense of fear/being lost, increase their sense of companionship, and promote the social interaction among them without losing a personalized experience. In this paper, we propose a conceptual model that intends to enhance GRS for tourism by using gamification techniques, intelligent agents modeled with the tourists' context and profile, such as psychological and socio-cultural aspects, and dialogue games between the agents for the post-recommendation process. Some important aspects of a GRS for tourism are also discussed, opening the way for the proposed conceptual model, which we believe will help to solve the identified limitations.

Keywords: Group Recommender Systems, Mobile Tourism, Context-Awareness, Gamification, Multi-Agent Systems

3.1 Introduction

Since 1992 (D. Goldberg et al., 1992) that Recommender Systems (RS) have been studied to help individual users make better choices (Jameson et al., 2015; Resnick & Varian, 1997) thus recommending items that intend to better satisfy the users tastes in various domains, each one with its specific challenges, like recommending a movie to watch, a music to listen, a place to visit, a restaurant to lunch, etc. But if to generate accurate individual recommendations is complex, to provide accurate recommendations to groups is even more. The tourism domain has many particularities and is an interesting challenge. To support groups of tourists plan and get accompanied in their excursions can be a very complex task, especially due to the group's heterogeneity and conflicting preferences (T. N. Nguyen & Ricci, 2018). Millions of tourists participate in planned tours every day, some travel alone, others in groups, but are their needs, interests and curiosity satis-

fied? Do they enjoy the tours they engaged in? Boratto and Carta (2010) state how a group is formed influences its modeling and the predicted recommendations. Groups formed occasionally for a common aim, like travelling together to a specific destination, and that may or may not be acquainted to each other (Boratto & Carta, 2010) causes this heterogeneity to go deeper. Group Recommender Systems (GRS) are being designed for helping in situations like those, and if they use the capabilities of a mobile device, they can brutally improve the users' experience, bringing new possibilities to explore, like the users' context (del Carmen Rodríguez-Hernández et al., 2017), i.e., the information that surrounds him (Lamsfus, Wang, Alzua-Sorzabal, & Xiang, 2015).

In this paper, we introduce a conceptual model that intends to improve the tourists experience in a GRS for tourism by showing concern for their interests, facilitate the post-recommendation process, by proposing the use of an argumentation-based dialogue model between intelligent agents, agents that will accompany the tourists during the tour. Gamification techniques are also proposed to acquire the tourists' profile and motivate them during the tour.

In the next section we present a brief state-of-the-art in GRS for tourism and discuss some current issues. Section 3 introduces dialogue games between intelligent agents and gamification as ways of enhancing the choice process and the tourists' involvement in GRS for tourism, respectively. This section also explains the connection between choice and decision, and how important explanations are in a recommendation. The conceptual model of the GRS for tourism is presented and shortly explained. Section 4 summarizes the contents addressed in the paper and describes what will be done as future work.

3.2 Group Recommender Systems for Tourism

GRS have become an important and challenging theme in the field of RS (Castro et al., 2015; Delic & Masthoff, 2018; Masthoff, 2011, 2015; McCarthy, Salamó, et al., 2006b) since the group members' preferences can vary, and therefore, to reach a solution that satisfy all the members can be hard to accomplish. It is of extreme importance to guarantee that none of the group members gets too dissatisfied, dissatisfaction that can spread within the group due to the emotional contagion phenomenon (Delic & Masthoff, 2018). For instance, suppose a travel agency in China that has vacation packages for groups of tourists, with a set of different types of Points of Interest

(POI) to visit in a certain country. It is known that Chinese tourists usually travel in groups, either by option or because of impositions (Nasolomampionona, 2014). Families, individuals, friends can subscribe a package. But does the package has POI that satisfy all the subscribed members? Although they share the same culture, not all members have the same personality and preferences, but they had no other choice than to choose a predefined package. A vacation that seemed exciting can easily become toilsome. A GRS capable of providing personal and contextual recommendations can be the perfect solution.

Many interesting prototypes of GRS for tourism have and are being proposed to help groups of tourists in the planning of vacations or excursions, usually presenting a list of POI to visit. For instance, looking at some of the first GRS for tourism, *INTRIGUE* (INteractive TouRist Information GUidE) was proposed in 2003 by Ardissono et al. (Ardissono et al., 2003) to help (heterogenous) groups of tourists find sightseeing destinations and itineraries in Italy. It is a GRS for mobile and desktop devices where a group member configures the group size, their preferences and characteristics. The group is then divided into subgroups according to those configurations, and recommendations are given to each subgroup grounded by explanations that address potential conflicting requirements.

CATS (Collaborative Advisory Travel System) aims to help a group of friends in planning a ski-holiday (McCarthy, McGinty, Smyth, & Salamó, 2006; McCarthy, Salamó, et al., 2006b) using a face-to-face collaborative platform (the DiamondTouch interactive tabletop) that uses critiques as a way of giving feedback to recommended POI and iteratively find a final choice.

Garcia et al. (Garcia et al., 2009) developed a GRS for tourist activities, based on the group's tastes, demographic data and places visited in former trips, by extending the *e-Tourism* tool they previously developed for individual tourists. This tool is composed by the *Generalist Recommender System Kernel* (GRSK), which is a domain-independent taxonomy-driven search engine that manages the group recommendation. It is responsible for aggregating, intersection and incrementally intersection the users' preferences and present a final list of items to recommend.

Travel Decision Forum is a GRS that uses animated characters to represent the group members (Jameson et al., 2003). The authors state that mutual-awareness and communication are important in order to reach a consensus in the post-recommendation process. For that, the group

members configure their preferences incrementally and collaboratively, being able to see the other members' preferences. Since the choice of preferences can be influenced by a person's motivations, the authors implemented a simple way for the members to configure their motivational orientation regarding the other members. This is a very important factor in social interactions that other GRS do not consider, and that we will further discuss later in this paper.

It is perceptible that due to technological limitations at the time, the first GRS were totally dependent of the users' interactions and configurations. Indeed, since the mobile technology was still emerging, the users felt offended for having a "too intelligent" application and argued they could think and decide for themselves, not accepting a too much automatization of the system (Van Setten, Pokraev, & Koolwaaij, 2004). However, fifteen years later, the minds "evolved", the users' requirements changed, and many would like to have a more automated system that could think and decide for them, at least regarding recommendations...

In the early 2000's, wireless internet access was very limited and very expensive, but now, that is no longer a problem. The rapid evolution of the wireless internet connections, its throughput, stability, price and massification, also shifted the way (G)RS were being designed and many ideas/approaches found in literature were discontinued. This is a positive reinforcement for creating new and better (G)RS.

For example, the very recent work by T. N. Nguyen and Ricci (2018) consists on a chat-based GRS for mobile devices that also allows the group members to become part of the choice process. It is similar to WhatsApp in the way users in a group can exchange messages between them, with the additional features of allowing the users to rate previously visited POI and define their mood, so a higher importance is attributed to the user in the preferences aggregation in case he is in a bad mood, tired, etc. The users can classify the recommended POI by liking/disliking them or by classifying one as the best, or comment on them with text and emoticons. This evaluation allows the system to infer users' constraints based on the attributes of the classified POI, and incrementally update the information on a recommended POI with additional explanations, based on those restrictions. Although the system provided higher perceived recommendation quality than the standard benchmark, this approach may not be practical for large and/or occasional groups, since the tested groups were very small, composed of 2 or 3 members. We think it can be very confusing for

a group of 20 or more people to chat and exchange opinions in an efficient way. Something else is needed.

3.2.1 Important Aspects to Consider in a GRS for Tourism

To support groups in travel planning is not a simple process and to generate a list of recommendations based on the users' context and preferences is not enough. Other factors need to be considered for a GRS to effectively serve its purposes. For instance, in 2003, Jameson et al. (2003) made the intelligent observation that the recommendation process does not end when a list of recommendations is presented to the user. The users need to decide what to choose from the list, so all the group members get (minimally) satisfied. The authors went even further by stating that it would be short-sighted not to include post-recommendation processes in the design of a (G)RS, like ways of persuading the other group members to follow a certain recommendation a user finds better. If the process of reaching the final choice has not been delegated to one of the group members, communication and possibly negotiation will be needed between the group members (Jameson et al., 2003). This falls into the same line of thought that the users need to be somehow involved in the recommendation process, and as mentioned before, a full automatization may not be the perfect solution.

It is evidenced that many people like to know the preferences of other group members, leaning to choose similar preferences (Jameson et al., 2003), either because they would like to please other member(s) or because they tend to avoid conflicts if they previously know what the other users think, like in a real face-to-face scenario. This awareness leads to a sort of collaboration that can help reach a faster consensus. However, this type of behavior is not so linear. Like in a decision-making process, the group members in a choice process can have different intentions, which influence their behaviors and choices. Jameson et al. (2003) address motivation as a way of influencing the choice process. However, motivation is what compels us to fulfil or not our intentions. So, a person's intentions are in the core of a choice, powered by her motivations, and we believe both need to be accounted for. For instance, Phoebe can have an intention to visit a country, but because she cannot go with her boyfriend, she doesn't feel motivated to go, and therefore she won't go unless he does.

As RS can be seen as "tools for helping people to make better choices" (Jameson et al., 2015), how choices are made (the psychology of choice) and how the process of making choices can be supported is of extreme importance (Jameson et al., 2015). Some GRS are already considering group decision-making (GDM) as an indispensable factor for their success. McCarthy et al. (McCarthy, Salamó, et al., 2006b) developed a face-to-face collaborative GRS for planning skiing vacations. The users reach a consensus by critiquing the items in a list of recommendations during the choice process. Castro et al. (2015) proposed a consensus driven GRS, which implements a consensus reaching process used for group decision-making, to iteratively piece together individual recommendations before delivering the group recommendations. The authors concluded that applying a consensus reaching process to group recommendations undoubtedly improved the results and that GRS could benefit from the use of GDM approaches. Marques, Respício, and Afonso (2016) developed a mobile GRS that uses group collaborative decision-making by using votes. The users model their preferences into the system and give weights to existing restaurants recommendation' platforms. The users have then to democratically elect a restaurant from the generated list of recommended restaurants.

Another extremely important aspect for a RS are the explanations it provides. For instance, Tintarev and Masthoff (2015) dedicated a paper to the explanation of recommendations in RS. Explanations can be used with many purposes like: to expose the reasoning behind a recommendation, to gain the users trust and loyalty, to persuade users to buy a recommended item, to increase satisfaction, to help users make better and faster decisions, etc. (Tintarev & Masthoff, 2015). The users like to feel the system is not a black box or a computerized oracle that gives advices (Herlocker, Konstan, & Riedl, 2000) and that they understand the system. This is even more true when decisions with some impact are involved, like when choosing a honeymoon destination: "Why is the system suggesting I should go to Galápagos in my honeymoon?". Explanations are also very helpful to detect errors in recommendations (Herlocker et al., 2000; Tintarev & Masthoff, 2015), like suggesting Galápagos as a vacation destination because the user visited many websites related to Galápagos since he is researching on Galápagos penguins.

The GRS found in literature are also intrusive in the ways they present the recommendations and are not focused in the tourists' personal interests allied to their context. This causes the tourists to

ignore recommendations or ignore the remaining group members. For instance, suppose a group of tourists is visiting a monument with tall towers at some point, and that a member is afraid of heights. The GRS should be capable of warning her that she should not climb those towers because of her fear, avoiding the tourist's discomfort. Or, suppose a tourist is constantly ignoring notifications presented by the GRS in the morning. The GRS should be capable of detecting that the tourist does not like notifications and stop showing them at that time of day.

3.3 Intelligent Agents, Dialogue Games and Gamification to Enhance a GRS

We believe the post-recommendation process can be improved by using intelligent agents and techniques from group decision-making and consensus reaching. So, we propose to solve some of the issues presented before by applying formal dialogue games (McBurney & Parsons, 2009), for agent communication and interaction using argumentation, between intelligent agents modeled to represent the group members. We intend to model each agent with the respective tourist's profile and context, acting on his behalf. So, each agent will consider the respective tourist's preferences, personality, socio-cultural aspects, mood, intentions, etc., to choose the POI to visit from the list, engaging in a real time conversation with the other agents by using argumentation. The agents argumentation will also be based on the dynamic argumentation model developed in our previous work (João Carneiro, Alves, Marreiros, & Novais, 2019; João Carneiro, Martinho, Marreiros, Jimenez, & Novais, 2018), and will use dialogues of different types, such as negotiation and deliberation (Walton & Krabbe, 1995), to propose solutions and reach a final consensus on the list of POI to visit that better suits the group's interests and intentions. We believe this strategy can be helpful for large groups, since the agents automatic dialogues will minimize the time the tourists will need to spend in the system to reach a consensus, and will avoid the confusion inherent to chats of large groups of people, simplifying and making the choice process more organized. For example, suppose a group of 30 members where 5 of them are from the same family. The agents from the same family can deliberate together on the POI to visit before dialoguing with the other agents, and then negotiate the POI with the other agents.

The proposed argumentation-based dialogue model will be capable of proposing recommendations and at the same time, due to its self-nature, be capable of explaining the reasons behind those recommendations. We believe this will allow the tourists to feel part of the process and understand

it. The dialogue model will also have a high level of expressiveness, meaning the agents will be capable of acting according to different intentions and motivations in the same dialogue, mirroring their tourist, as mentioned in our previous works (Joao Carneiro, Martinho, Marreiros, & Novais, 2018; João Carneiro, Saraiva, Martinho, Marreiros, & Novais, 2018).

Since the tourists will exchange messages in real-time with other tourists in the group, the content of those messages will be studied, content that will influence their agents' dialogues. For that, we will rely on machine-learning techniques such as text-mining and natural language processing, in order to study the human dialogues and produce important information in terms of their meaning and the sentiment existent in them.

3.3.1 The Conceptual Model

Figure 3.1 shows the architecture for the conceptual mobile GRS. We chose microservices because they allow a better modularity, scalability and the services can be deployed independently, each one with its own database. This means the most suitable programming language(s) can be used for each service, a better faults isolation, continuous delivery and components spread across multiple servers, among others (Villamizar et al., 2015). The communication between the microservices will be asynchronous and through the REST protocol. The API Gateway will be the single-entry point into the system, simplifying the mobile clients' requests and serving as a load balancer for the microservices. The microservices will include the:

3.3.1.1 Multi-Agent Service

This service will be responsible for modeling the intelligent agents according to the tourists' information (profile and context), and other agents necessary to the process, by using the JADE Framework. Here is where the dialogue games between the agents, to choose the POI to visit, will also be processed. The agents are also intended to learn the tourists' behavior and context, automatically improving their profile, so better and more proactive recommendations/notifications can be made to the group and/or the individual tourist.

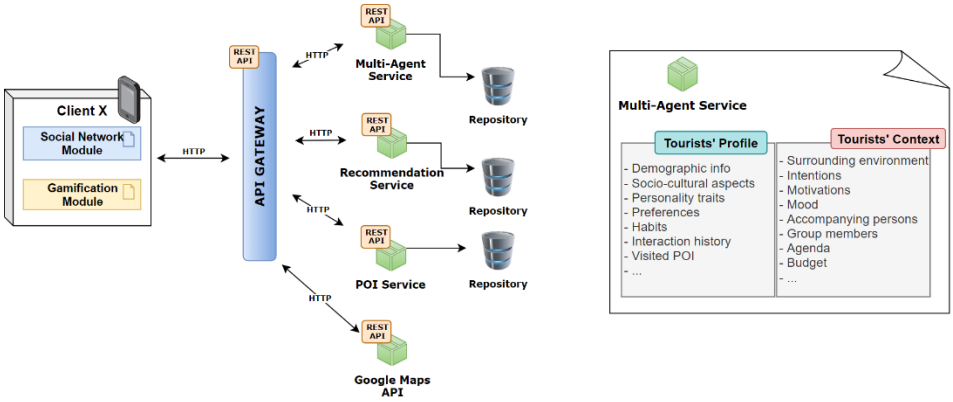


Figure 3.1. (Left) Architecture of the conceptual mobile Group Recommender System. (Right) Information about the tourists, available in the Multi-Agent Service.

Machine-learning classification algorithms will be applied to form (if possible) subgroups of agents/tourists with similar profiles and interests. This can minimize the group's heterogeneity and conflicts of interest, facilitating the consensus reaching in the post-recommendation process and the generation of more precise recommendations to the (sub)groups. This aggregation also intends to promote more socialization and the creation of bounds between the group members. For instance, suppose a group of 50 tourists where 6 of them play Pokémon Go. By comparing the tourists' personality, the agents find out 5 of them have a high openness to experience, agreeableness and low neuroticism. The agents can suggest those members to meet after lunch, at the hotel entrance, to search for Pokémon in the surroundings. Also, suppose the whole group went to visit a monument. If the agents know the personality traits and mood of the tourists, they can suggest a quest for some group members to complete, where they will receive instructions that will make them perform joint tasks to better know the monument, like taking a picture from some important window or collect a certain object that represents the monument's history, promoting their socialization and opening ways of creating bounds between them.

3.3.1.2 Recommendation Service

This service is intended to iteratively run the recommendation algorithm(s) based on the tourists' profile, context and the results obtained from the agents dialogues, presenting the processed recommendations in each iteration, until a final recommendation is accepted by the tourist, in the case of individual recommendations/notifications, or the group/subgroup, in the case of group recommendations/notifications. Since our focus is to work on the post-recommendation process that will lead to a consensus on the places to visit and on making more interesting the tourists'

experience from the planning to the tour itself, we won't detail on the recommendation algorithm(s).

3.3.1.3 POI Service

This service will be fed by the Google Maps API, or similar, and will be responsible for retrieving all the available POI that match the tour requirements. The list of POI will then be fed into the Recommendation Service so recommendation lists can be generated for the group or subgroups of tourists.

3.3.1.4 The Social Network Module

The proposed GRS will try to embed a Social Network similar to Facebook, composed of secret groups that represent the whole group of tourists for a specific tour, the group of their respective agents, and the subgroups automatically created. The dialogues between the agents will be seen in their respective group, and at the same time, the tourists can post comments in the other available groups. This network is intended to communicate with the Multi-Agent Service, and vice-versa. The list of POI to visit will be presented to the tourists after each agents' dialogue iteration, until they agree in a final itinerary, by posting comments and giving likes/dislikes.

Another important aspect is that our approach is intended to be applied to all group sizes, and not only large ones, because the context in which the group members are is as much important as their profiles. For example, a small group can be formed by 5 hairdressers of different personalities, who do not know each other, but are going to the same congress, i.e., are in the same context, and one of them decides to use the GRS to find other hairdressers to visit the cultural heritage in the congress's country.

3.3.1.5 The Gamification Module

Personalization is a key factor for the success of RS in tourism (Gavalas & Kenteris, 2011; Ricci, 2002; Schmidt-Belz, Nick, Poslad, & Zipf, 2002). The more information about the tourist is known better recommendations can be made. Information like the tourists' demographics, personality traits, socio-cultural aspects, habits and preferences can be critical factors for the system's effectiveness. Personality has been evidenced to improve the recommendations made to groups and can even help in the cold-start problem (de CA Ziesemer, Müller, & Silveira, 2014; Feil, Kretzer,

Werder, & Maedche, 2016; Tkalcic & Chen, 2015), since it is demonstrated that personality is strongly related to the users preferences and therefore, correlating the users' personalities and their preferences can help find the preferences of users with similar personalities. For instance, tourists with a high Openness to Experience tend to be more appreciative of the significance of intellectual and artistic pursuits (Friedman & Schustack, 1999) and will probably be more interested in visiting an art exhibit than tourists with low Openness.

To model the tourists' profile will help form groups with similar interests, minimizing the groups' heterogeneity and conflicts of interest. However, the existing GRS are still intrusive and time-consuming in the ways they gather the tourists' profile. The challenge here will be to gather all that information in a non-intrusive and less time-consuming way, and at the same time, motivating and challenging the tourists. Gamification can be the leverage we are looking for. It is demonstrated that gamification improves the users' involvement and motivation while learning, working, among other tasks (de CA Ziesemer et al., 2014; Hamari, 2013; Hamari et al., 2014; Hamari et al., 2016). For instance, it has been showed that challenging games motivate students to be more concentrated and committed to the studies, learning significantly better (Hamari et al., 2016). The use of achievement badges proved to affect the students' behavior motivating them to study (Hakulinen, Auvinen, & Korhonen, 2015). In their work, Mortara et al. (Mortara et al., 2014) present the state-of-the-art of serious games for cultural heritage and state that this approach can be of a tremendous value to learn about the history of a location, its inhabitants and their behaviors. Hence, a GRS for tourism could become more challenging and exciting if we add gaming components to it, like badges for accomplishing certain tasks or mini games to gather the tourists' profile.

Gamification techniques can also be used to personify the agent that represents the tourist in the Multi-Agent Service, transforming it into an Augmented Reality (AR) avatar, visible through the mobile device screen[18]. The avatar would be like the tourist's companion and can play an important role in the system by accompanying the tourist throughout the whole process, helping to decide the itinerary for the group he belongs to, and motivating the tourist during the tour by presenting intelligent information (push-notifications) and proposing personalized challenges according to the

18 Or possibly another device, like Google Glasses®, but that is another chapter, not to be addressed in this work.

tourist's intentions and interests. Why an avatar? It is evidenced that representing the tourist with an avatar can help him feel empathy towards the system (Mortara et al., 2014).

Location-based AR games can have a tremendous potential, and they can be a smarter way of catching the tourists' attention to visit a country's heritage. We propose to transform the whole trip process into a sort of a location-based AR game, where the tourists will have to complete certain personalized "quests" in the POI they visit, using AR features. We hope this will also increase their interest in knowing and learning about a country's heritage, and in a more exciting way.

3.4 Summary and Future Work

In this work, we discuss on a novel approach for a Group Recommender System for tourism using agents and gamification. The aim is not to focus on a better algorithm for generating a list of recommendations, but to facilitate the consensus in the post-recommendation process so higher quality and more satisfactory choices can be made, and to enhance the tourists' experience during the whole process, from the planning to the tour itself. We intend to accomplish this by taking advantage of dialogue games using argumentation for the post-recommendation process, between intelligent agents modeled with the tourists' profile and context, and by introducing gaming components in the system that will encourage the tourists' interaction in a more appealing way. The tourists' profile and context will be used to provide more intelligent and personalized recommendations and notifications during the whole tour, to groups of any size. We believe the dialogue games between the agents will be a smarter way of explaining the recommendations to the tourists.

Travelling is an emotional experience (Delic, Neidhardt, Nguyen, & Ricci, 2016) and therefore, personalization and gamification are becoming a crucial factor for the success of GRS in tourism. In fact, gamification techniques and personalized services will be a major trend for the future of tourism (Xu et al., 2016). To motivate the tourists in planning the group tour and configure their profile and context, either implicitly or explicitly, we propose the use of gamification techniques like mini games, badges, trophies, and rankings of the best achievements. An AR avatar is also proposed to represent the tourist's agent and accompany him through the whole process, including during the tour, being responsible for providing personalized and contextual recommendations and push-notifications for the tourist's well-being.

The proposed approach will be thoroughly explained in our future work, and will include, among other tasks, the realization of questionnaires to different cultures in order to develop the model to correlate personality traits with (culture related) touristic preferences, and the development of mini games to implicitly acquire the tourists' personality, preferences and context. The gathered information will be used to model the agents representing the tourists and their avatar. The Social Network prototype will be developed for the post-recommendation choice process and to enable the tourists' online interaction. Intelligent push-notifications, recommendations, other mini games and tasks during the tour will be designed based on the tourists' profile and context. Experiments with real users will be conducted to test the viability of the proposed work and the users' satisfaction.

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4

MODELING TOURISTS' PERSONALITY IN RECOMMENDER SYSTEMS: HOW DOES PERSONALITY INFLUENCE PREFERENCES FOR TOURIST ATTRACTIONS?



An image representing distinct tourist attractions and the tourists' different personalities.

Generated with AI, Image Creator in Bing, October 2024

Paper Title	**Modeling Tourists' Personality in Recommender Systems: How Does Personality Influence Preferences for Tourist Attractions?**
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Abstract

Personalization is increasingly being perceived as an important factor for the effectiveness of Recommender Systems (RS). This is especially true in the tourism domain, where travelling comprises emotionally charged experiences, and therefore, the more about the tourist is known, better recommendations can be made. The inclusion of psychological aspects to generate recommendations, such as personality, is a growing trend in RS and they are being studied to provide more personalized approaches. However, although many studies on the psychology of tourism exist, studies on the prediction of tourist preferences based on their personality are limited. Therefore, we undertook a large-scale study in order to determine how the Big Five personality dimensions influence tourists' preferences for tourist attractions, gathering data from an online questionnaire, sent to Portuguese individuals from the academic sector and their respective relatives/friends (n=508). Using Exploratory and Confirmatory Factor Analysis, we extracted 11 main categories of tourist attractions and analyzed which personality dimensions were predictors (or not) of preferences for those tourist attractions. As a result, we propose the first model that relates the five personality dimensions with preferences for tourist attractions, which intends to offer a base for researchers of RS for tourism to automatically model tourist preferences based on their personality.

CCS Concepts: Information systems ~ Recommender systems • Human-centered computing ~ User centered design

Keywords: Recommender Systems; Personality; Tourist Preferences; Affective Computing; Leisure Tourism

4.1 Introduction

Recommender Systems (RS) are being studied in various domains to help users make better choices (Adomavicius & Tuzhilin, 2005; Resnick & Varian, 1997), being one widely studied the travel and tourism domain. Travelling is an emotional experience (Delic, Neidhardt, Nguyen, & Ricci, 2016) and therefore, personalization is a key factor for the success of RS in tourism (Gavalas & Kenteris, 2011; Ricci, 2002; Schmidt-Belz et al., 2002). The more information about the tourist is known better recommendations can be made. Artificial Intelligence techniques, like Multi-Agent Systems, have been applied to RS to try to enhance the tourists' experience and proactively make

suggestions based on the tourists' context and profile (Batet, Moreno, Sánchez, Isern, & Valls, 2012; Borràs et al., 2014; Ceccaroni, Codina, Palau, & Pous, 2009; Lorenzi, Loh, & Abel, 2011). To personalize agents with the tourists' profile (Mortara et al., 2014), to accompany them throughout the process by presenting intelligent information and proposing personalized challenges, according to the tourists' psychological aspects and interests, can improve their experience and satisfaction. For instance, personality has been shown to improve (group) recommendations and can even help with the cold-start problem (Feil et al., 2016; Tkalcic & Chen, 2015). Studies show personality is strongly related to the users' preferences (Tkalcic & Chen, 2015), and in the case of recommendations to groups, correlating the users' personalities and their preferences can help match users with similar interests, minimizing the groups' heterogeneity and conflicts of interest in (occasional) groups of tourists. Several studies exist on the relation between personality and tourist preferences, however, the ones available only focus on specific types of travelling or tourist roles (Delic, Neidhardt, & Werthner, 2016; Eachus, 2004; Jani, 2014b; Masiero, Qiu, & Zoltan, 2019; K. Y. Poon & Huang, 2017; Schneider & Vogt, 2012), or mainly target the Extraversion and Openness to Experience personality dimensions (Bujisic, Bilgihan, & Smith, 2015; C.-Y. Li, Lu, Tsai, & Yu, 2015). So, what combination (if any) of personality dimensions influence the choice of certain tourist attractions?

In order to start overcoming those limitations, we engaged on a large-scale study to determine the relation between the Big Five personality dimensions and preferences for tourist attractions. First, an intensive research was conducted so that a questionnaire to collect as much information as possible about the respondents' personality, tourist and personal preferences, travel motivations and socio-demography could be constructed. The questionnaire was sent in a first round to Portuguese individuals from the academic sector and their respective relatives/friends, obtaining a sample of 508 valid responses. After analyzing and treating the responses, all personality dimensions were found to be predictors of different preferences for tourist attractions. As a result, we propose a model that relates all five personality dimensions with preferences for a wide range of tourist attractions, in the hope we can help researchers of RS for tourism to automatically model tourist preferences based on the tourists personality.

The remainder of the paper is structured as follows: Section 2 describes some related work on personalized Recommender Systems and Psychology of Tourism. Section 3 presents the methodology used, Section 4 the results and their respective analysis, along with the proposed models that relate Preferences for Tourist Attractions and how personality traits influence those preferences, and finally, Section 5 reflects on the contents addressed in the paper and describes what will be done as future work.

4.2 Background

4.2.1 Personality and Recommender Systems

Throughout the last two decades, personalization became the main concern for the effectiveness of RS (L. Chen et al., 2016; Rashid et al., 2002; Tkalcic & Chen, 2015; Tondello et al., 2017). Therefore, to know personal information about the user is crucial for building a robust profile. The researchers increased interest in developing more personalized and accurate RS created the need to consider other research areas such as Psychology. Psychological aspects, such as personality, moods and emotions, are being perceived to influence the variance in the user preferences and behavior in RS (Tkalčič, De Carolis, de Gemmis, Odić, & Košir, 2016), and their consideration is evidencing to show better results than generic approaches (Gretzel, Mitsche, Hwang, & Fesenmaier, 2004; Nunes et al., 2008; Tondello et al., 2017). Many personalized RS that take into account the users motivations (Jameson et al., 2003), mood (del Carmen Rodríguez-Hernández et al., 2017; T. N. Nguyen & Ricci, 2018), or personality (Hu & Pu, 2009; Perik et al., 2004; Roshchina, 2012; Tkalcic et al., 2009; Wecker, Kuflik, & Stock, 2016) have been developed.

As defined by H. Eysenck and Rein (1998), "personality is the sum-total of the actual or potential behavior-patterns of the organism, as determined by heredity and environment". Each individual has her own behavior patterns, which are considered relatively stable over time across different situations (McCrae & Costa Jr, 1997). These patterns were summarized into five universal personality dimensions by Costa and MacCrae (1992): Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, being the Five Factor Model (FFM), or Big Five, recognized as the most widely accepted model to represent them (Digman, 1990; Matz et al., 2016).

Each factor is defined by six traits/facets (Costa & MacCrae, 1992), resulting in a total of 30 traits, which are more granular and can be used to better characterize a person (see Table 4.1).

Table 4.1. Personality dimensions and their respective six traits (adapted from Costa and MacCrae (1992)).

Neuroticism	Extraversion	Openness to experience	Agreeableness	Conscientiousness
Anxiety	Friendliness	Imagination	Trust	Self-efficacy
Anger	Gregariousness	Artistic interests	Morality	Orderliness
Depression	Assertiveness	Emotionality	Altruism	Dutifulness
Self-consciousness	Activity level	Adventurousness	Cooperation	Achievement-striving
Immoderation	Excitement seeking	Intellect	Modesty	Self-discipline
Vulnerability	Cheerfulness	Liberalism	Sympathy	Cautiousness

As noted by Tkalcic and Chen (2015), personality can be useful in different areas of RS, since it is strongly related to the users' preferences (Cantador & Fernández-Tobías, 2014). Users with similar personalities tend to choose similar items or contents (Cantador, Fernández-Tobías, & Bellogín, 2013). For example, extraverts who are dependent on warmth and gregariousness tend to enjoy popular music, and persons who score high on excitement seeking tend to enjoy rock music (Cantador et al., 2013; Rawlings & Ciancarelli, 1997). In games, extraverts are more inclined to group activities than solo activities (Yee et al., 2011). Even certain features of Instagram pictures are related to personality traits (Ferwerda, Schedl, & Tkalcic, 2015). Personality is therefore a powerful characteristic of humans that can be used to help predict their preferences in a wide range of domains, but it is still an under explored topic in RS (Cantador & Fernández-Tobías, 2014). And how about the tourism domain? Is personality strongly (or weakly) related to tourist preferences, or only certain personality dimensions are? These are the research questions we propose to answer.

4.2.2 Psychology of Tourism

Research on psychology of tourism is rapidly growing, since it is evidenced that psychological aspects are related to the choice of specific destinations (Jafari, 1987; Passafaro et al., 2015; S. C. Plog, 1974). But which ones? Several researchers tried to answer that question, some by proposing tourist typologies based on psychological aspects, others by trying to find relationships among personality traits and tourist behaviors or preferences.

4.2.2.1 Tourist Typologies

E. Cohen (1972) was one of the first researchers to propose a tourist typology, composed of four types: the organized mass tourist (least adventurous, lazy, prefers package-tours, is more orga-

nized and prefers familiarity to novelty), the individual mass tourist (similar to organized mass but the tour is not fully preplanned, has a certain control over his time and itinerary and is not bound to a group), the explorer (trip self-arranged, likes to meet locals and speak their language without totally immersing herself), and the drifter (extremely independent, has no time schedules or itinerary, lives with the locals, likes novelty at maximum and familiarization at minimum).

Plog is another renown researcher who studied the psychology of travel in tourism (S. C. Plog, 1974). He argued that travel destinations attract specific types of people (S. Plog, 2001) and proposed two main psychographic dimensions to characterize tourists' travel behavior: Allocentrics, who are more nature related, adventuresome, curious, like to explore the world around them, practical, outgoing, self-confident, seek for novelty and new experiences; and Psychocentrics, who are self-inhibited, anxious, non-adventuresome, prefer the familiar in travel destinations, especially if they can drive to them, and places where they can relax. The two dimensions are in the opposite extremes of a normally distributed continuum, being this scale later extended (S. C. Plog, 1991, 1994). Plog's model became widely known, and many researchers used or even tried to improve/extend it, some by correlating Plog's two dimensions with Extraversion (Hoxter & Lester, 1988; M. S. Jackson, Schmierer, & White, 1999), activation theories (Nickerson & Ellis, 1991), or sensation seeking, powerlessness and generalized anxiety (Griffith & Albanese, 1996). However, no significant correlations to actual tourist behavior were found.

M. Jackson, White, and White (2001) proposed four types of tourists: the explorer, the adventurer, the guided and the groupie, combining the orthogonal scales of Allocentrics-Psychocentrics and Introversion-Extraversion, model which was later studied by M. S. Jackson and R. Inbakaran (2006). As also suggested by Nickerson and Ellis (1991), the authors found Extraversion and Allocentrism were independent constructs. The same cannot be said of Openness to Experience and Allocentrism, which showed to be correlated (M. S. Jackson & R. Inbakaran, 2006).

However, the existence of ambiguity between the dimensions of both Plog's and M. Jackson et al. (2001) models, led Eachus (2004) to propose a modification to those typologies so a more objective measure of tourist preferences could be used: Adventurous preference, Beach preference, Cultural preference, and Indulgent preference. To do that, they used the Brief Sensation Seeking Scale (BSSS) (Hoyle, Stephenson, Palmgreen, Lorch, & Donohew, 2002) to predict their proposed

Holiday Preferences Scale. They found that people with high sensation seeking values tend to prefer Adventurous and Beach holidays and not Indulgent holidays. No significant correlations were found between Sensation Seeking and Cultural holidays, but older people were more likely to prefer Cultural holidays than younger.

Based on the Cohen's individual mass tourist type (E. Cohen, 1972), Wickens (2002), proposed five micro-types of tourists according to a survey conducted in Chalkidiki (Greece): the Cultural Heritage type, who were more interested in the cultural, natural and historical aspects of the region; the Raver type, who were attracted by sensual and hedonistic pleasures, prefer to spend more time at the beach and its night clubs; the Shirley Valentine type, who were seeking for a romantic experience with a "charming Greek gentleman"; the Heliolatrous type, who just wanted to relax and sunbath; and the Lord Byron type, who had the ritual to return every year to the same destination, because they enjoyed the familiarity, nostalgia and felt like home.

Interestingly, Gretzel et al. (2004) proposed 12 travel personalities and found strong correlations between their respective activities. For instance, Shopping Sharks type was related to tourists more interested in shopping, nightlife, and dining.

4.2.2.2 Personality as Predictor of Tourist Preferences.

However, and as pointed by several authors, the existing research on tourism behavior is mostly descriptive instead of predictive (M. Jackson et al., 2001; Schneider & Vogt, 2012) which is a limitation that needs to be overcome, i.e., what personality dimensions or traits are predictive of the tourists' typologies or behaviors/preferences found in literature? For example, some researchers focused on adventure tourism (Addison, 1999; Millington, Locke, & Locke, 2001), developing adventure tourism typologies such as "hard adventure" and "soft adventure" typologies (Lipscombe, 1995). Since most studies failed to determine the psychological antecedents of soft (e.g.: hiking, hunting, scuba diving) and hard (e.g.: climbing, cave exploring) adventure travelers (Schneider & Vogt, 2012), Schneider and Vogt (2012) applied Mowen's (Mowen, 2000) 3M Model of Motivation and Personality for consumer behavior, to explain the behavior of soft and hard adventure travelers. They found the interest in cultural experiences, need for arousal (excitement seeking) and need for material resources were predictors of hard adventure travel, and the interest in cultural experiences and competitiveness of soft adventure travel.

C.-Y. Li et al. (2015) also studied the impact of sensation seeking and extraversion in the behavior of three types of tourists: familiarized mass tourists, organized mass tourists and independent tourists. They found extraversion did not significantly predict the tourists' behavior in neither of the three types, but sensation seeking did, being the highest level for independent tourists, followed by organized mass tourists and then familiarized mass tourists. They also concluded extraversion and sensation seeking were measuring different things.

Kvasova (2015) studied how personality influences tourists' eco-friendly behavior. No association between Extraversion and eco-friendliness was found, but individuals with high Agreeableness were strongly related to eco-friendly behavior, followed by Conscientiousness and Neuroticism, confirming several past studies on the same area of research (Hirsh, 2010; Markowitz, Goldberg, Ashton, & Lee, 2012; Milfont & Sibley, 2012). Regarding Openness to Experience, individuals with high imagination were negatively associated to eco-friendliness but individuals with high intellect were positively associated.

A study on how Extraversion and Openness to Experience influenced the tourists satisfaction with a set of different tourist experiences was performed by Bujisic et al. (2015). Results showed that individuals with higher level of Openness to Experience tended to be more satisfied with aesthetic and escapist experiences than those with lower level. In contrast, individuals with lower Openness to Experience were more satisfied with entertainment and educational experiences compared to the ones with higher level. Extroverts tended to be more satisfied with educational and escapist experiences.

More recently, K. Y. Poon and Huang (2017) used Plog's psychographic model (S. C. Plog, 1994) to study how travel personality affected peer-to-peer accommodation ("couch-surfing") preferences in the AirBnB platform. They found Allocentrics (adventurous and risk-taking) who travelled alone, with partner, or with friends, were more prone to use AirBnB than Psychocentrics, or Allocentrics when travelling with family.

Masiero et al. (2019), beside other factors, studied how personality could influence long-haul tourists to visit a stopover destination. For measuring personality they used the BSSS (Hoyle et al., 2002) and concluded sensation seekers were more inclined to stopover visits. Also, travelers more interested in entertainment (shopping, casinos, cinemas, theme parks, theater, etc.), nature (sea-

scape, coasts, islands, beaches, landscapes, parks, mountains, flora and fauna), and cultural (historical/archaeological sites, museums, architecture and industrial sites, city sightseeing) attractions were more prone to a first-time visit to a stopover destination, contrary to tourists with preference for sport activities who were less likely to visit a stopover destination.

Although many studies on psychology of tourism for different sectors can be found, many are about typologies of tourists, which as mentioned before, are descriptive of the tourists' behavior and do not predict how that behavior impacts the choice of tourist preferences. Others try to predict how psychological aspects influence tourist behavior or preferences, but most of them only rely on Sensation Seeking and/or Extraversion scales, which do not cover all Big Five's dimensions. Few studies try to correlate all Big Five dimensions to tourist behaviors or preferences (Katifori, Vayanou, Antoniou, Ioannidis, & Ioannidis, 2019; Kvasova, 2015), being the works of Delic, Neidhardt, and Werthner (2016) and Jani (2014b) worth mentioning, where they studied how the Big Five correlated to a variety of tourist roles. For example, Sun Lover type was related to high neuroticism individuals, Archeologist to extraverts, and Drifter to less conscious people (Delic, Neidhardt, & Werthner, 2016). However, none, to the best of our knowledge correlates the five personality factors to the choice of a wide range of specific tourist attractions. With this work, we intend fill that gap by proposing a model to predict the preference for a wide range of tourist attractions based on the tourists' five personality dimensions. This research is motivated by the evidences found in literature, from which it is possible to deduce that the tourist typologies do not fully match the tourists' preferences for tourist attractions, since many different combinations of intensity for the personality traits exist and therefore a single typology may not be enough for a certain tourist as well as not all the attractions present in a typology may be suitable for that tourist. This is supported by the results found by Gretzel et al. (2004).

4.3 Methodology

In order to investigate how personality dimensions impact the choice of tourist attractions, we first studied the terms used for classifying the most significant tourist attractions. As defined by Lew (1987) "tourist attractions consist of all those elements of a "nonhome" place that draw discretionary travelers away from their homes. They usually include landscapes to observe, activities to participate in, and experiences to remember." To be considered an attraction, a phenomenon

must have three components: “a tourist, a site to be viewed and a marker or image that makes the site significant” (MacCannell, 2013). Based on these definitions and the categorizations of attractions by Lew (1987), the “Thesaurus on Tourism and Leisure Activities” (UNWTO, 2001) and Moreno, Valls, Isern, Marin, and Borràs (2013), we selected the most common tourist attractions terms.

An online questionnaire comprised of five sections was then built, which asked about socio-demographic data (26 items), personality characteristics, personal preferences and concerns when travelling (34 items), travel motivations (adapted from Pearce and Lee (2005), with 28 items), and preferences for tourist attractions when going for an ideal vacation destination (since Litvin (2006) showed questioning for the ideal vacation destination matched the traveler personality). The preferences for tourist attractions were based on the previously selected attractions (68 items). Responses to the three last sections were measured using a 7-point Likert scale. The personality was measured using one of the most widely spread personality inventories: Big Five Inventory (BFI, 44-item), which assesses an individual on the Goldberg’s (Lewis R Goldberg, 1990) Big Five dimensions of personality, using a 5-point Likert scale. All responses were mandatory, except the sensitive questions (sexual orientation, religion, health issues) in the socio-demographic section. Control questions in sections 2 to 5 were used to verify the consistency of the responses.

A pilot study with 46 respondents was then conducted in order to test its readability, comprehension, and validity. After some modifications, the final version of the questionnaire accounted for 196 questions.

Using the snowball sample method, the questionnaire was disseminated, in several waves, via email to various mailing lists of academic institutions in the North of Portugal, including professors, scholars (including this paper own authors) and general employees, which were asked to share the questionnaire with their respective relatives/friends. Participants were asked to respond as honestly and truthfully as possible throughout the various sections as if they were actually setting up their profile in a tourism application (e.g.: Booking.com or TripAdvisor) for a proposal of a travel itinerary according to their interests. Although the questionnaire is still ongoing for a larger study, responses were collected for 4 months, from October 2019 to January 2020, gathering a total of n=508 viable responses.

4.4 Questionnaire Results and Analysis

4.4.1 Sample Description

As can be observed in Table 4.2, the sample is characterized by a greater percentage of female respondents (68%), being most of the respondents between 18-55 years old, existing a similar percentage between respondents bellow 25 years, and between 25-39 years (38% and 34%, respectively). The mean age is 33 ± 13 years, since most respondents were from academic institutions, which is also reflected in the great majority of respondents having a higher education level (74%). From the 508 respondents, 23% had already lived in other countries, showing almost one third of the sample had the experience of interacting with other cultures. The marital status of the sample was balanced, showing 53% were on some sort of a relationship, and the other 47% were single or separated. The formation area of the majority reflects the academic institutions to which the questionnaire was sent, being more than half (54%) from "Exact and Engineering Sciences" and 26% from "Social Sciences and Humanities". Has for travelling data, by far the great majority had already visited 3 or more countries in their life (96%), but per year, 79% of the respondents travelled 3 times or less. When in leisure, most of the sample (97%) travels accompanied, which may reflect the majority of respondents being young adults.

4.4.2 Tourist Attractions Preferences

Using IBM® SPSS® Statistics version 26, an Exploratory Factor Analysis (EFA) was performed on the 68 items related to the preferences for tourist attractions by using the principal components extraction method with Varimax rotation and with Keiser normalization (eigenvalue > 1), suppressing coefficients bellow 0.40[19]. Thirteen factors were extracted, most of them aggregating items of the same concepts as expected, but some were scoring with only one item and therefore were eliminated. EFA was run again and factors with low reliability (i.e., Cronbach's Alpha $\alpha < 0.70$) were removed[20], meaning the sample was not heterogeneous enough to measure those items. A final EFA was run resulting in 11 factors, explaining 68% of the total variance, all with a good Cronbach's Alpha reliability, meaning the items on each factor were measuring the same con-

19 This resulted in the elimination of 11 items: A2-Watch natural phenomena, A3-Religious celebrations, A16-Popular celebrations, A19-Botanical gardens, A23-enjoy/buy handicrafts, A25-Funfairs, A30-Picnics, A31-Shopping, A52-City parks, A54-Safaris, A57-Horse riding.

20 This resulted in the elimination of items scoring alone or factors with $\alpha < 0.70$: F6A5-Oceanarium, F4A21-Beaches natural beauty, F11A24-Biking, F13(A38-Impactful constructions, A39-Thematic parades), F12(A58-Hunt/Fishing, A60-Bullfights, A61-Circus), F10A62-Cruise.

cepts. Names for each factor were assigned according to the concepts they represented: F1-Adventure; F2-Nature; F3-Enternainment & Nightlife; F4-Sun, Water & Sand; F5-Museums & Landscapes; F6-Themes & Animal Parks; F7-Cultural Heritage; F8-Sports & Games; F9-Gastronomy; F10-Boat Tours; F11-Health & Well-being (see Table 4.3). The reliability for the entire scale was very good (α = 0.914) which confirmed the items in the scale were all related to the same concepts.

Table 4.2. Sample descriptive statistics (n=508).

		n	%
Age	< 25	194	38
	25-39	171	34
	40-54	105	21
	>55	38	7
Sex	Female	347	68
	Male	161	32
Lived in other Countries	Yes	119	23
	No	389	77
Marital Status	Divorced/Separated	22	4
	Married	131	26
	Non-marital partnership	36	7
	In a relationship	100	20
	Single	219	43
Have children	No	349	69
	Yes	159	31
Higher education	No	131	26
	Yes	377	74
Formation area	Exact and Engineering Sciences	273	54
	Social Sciences and Humanities	132	26
	Life and Health Sciences	41	8
	Other	62	12

The next step was to conduct a Confirmatory Factor Analysis (CFA), using IBM® SPSS® AMOS version 26, to create the first order model to confirm if the observed variables (Attractions) saturated the latent variables, i.e., the extracted factors (Tourist Attractions Preference) and what correlations exist between the 11 factors. For the estimation, the maximum likelihood method was applied. Several adjustments were needed to reach an acceptable fit of the model, such as eliminating four items with a regression weight lower than 0.5 (Marôco, 2010), and correlating errors within the same factors as suggested by the modification indexes, resulting in a final scale with a total of 48 items (see Table 4.3). All factors regression weights were statistically significant in the prediction of their respective items for $p < 0{,}001^{***}$ (two-tailed). The model revealed an acceptable goodness of fit ($\chi 2/df$=3.046; CFI= 0.828; GFI= 0.787; PCFI= 0.737, PGFI= 0.672, RMSEA=

0.064; p[rmsea≤0.05]p< 0.001), suggesting that the items provide a satisfactory fit for the proposed model (see Figure 4.1) (Marôco, 2010).

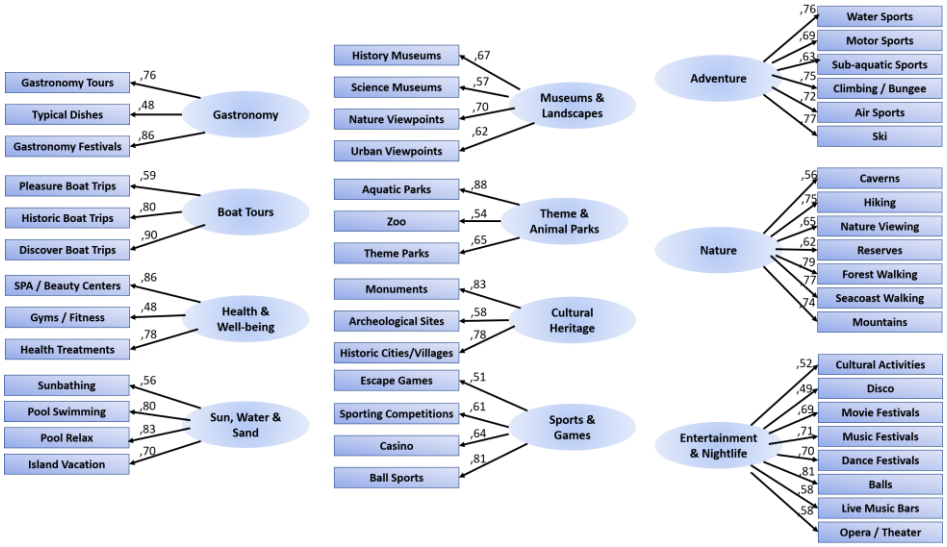


Figure 4.1. Confirmatory Factor Analysis of the Tourist Attractions Preference model obtained with the Exploratory Factor Analysis procedures, showing the normalized regression weights for each item (simplified model, disturbances and covariances omitted).

4.4.3 Personality and Tourist Attractions Preferences

In order to answer the research questions of this study, several other steps were needed. First, the scores for each personality dimension were calculated according to the BFI scoring table (John & Srivastava, 1999). As can be seen in Table 4.4, the average scores for each personality dimension was similar, corresponding to the middle of the respective score range, which means most of the participants responded in average "3-Neither agree nor disagree". These observations are better reflected in Figure 4.2, where in all five dimensions, albeit with different asymmetries, there is a clear concentration of results in the average scores of the scale. A clear majority of participants show moderate values in the Extraversion and Neuroticism dimensions, but in the Agreeableness, Conscientiousness and Openness scores distribution the graphics show a higher kurtosis, i.e., there is a slighter deviation in the scores, where the participants classified themselves more between 3-Neither agree nor disagree and 5-Agree strongly. This higher concentration above midpoint scores may be reflecting some social desirability bias, which is conceivably more pronounced due to self-reporting answers to items that convey the idea of kindness and morality in the case of Agreeableness; self-efficacy, truthfulness and effortful workers/students in the case of Conscientiousness; and probably intellect in the case of Openness to Experience.

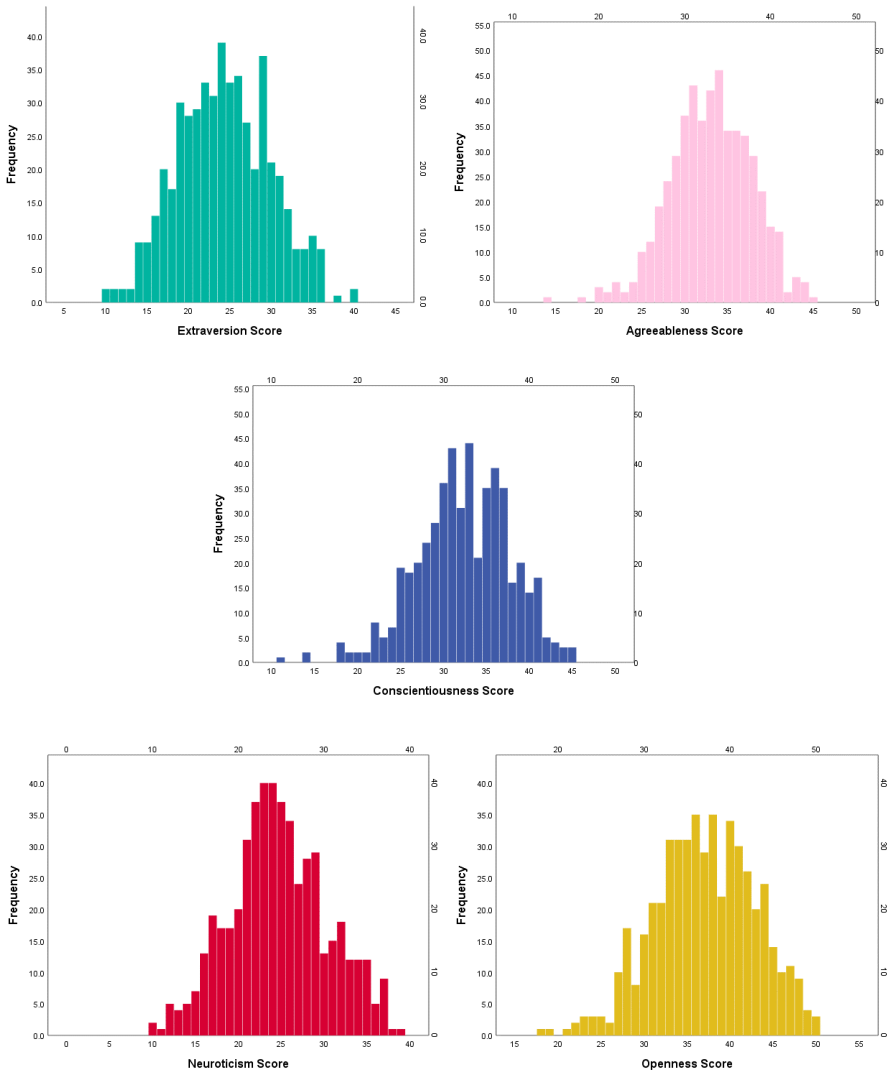


Figure 4.2. Distribution of the five personality dimensions scores among the sample.

The BFI responses to the 44 items were then used to predict preferences for the previously proposed tourist attractions, using Structural Equation Modeling and CFA, applying the maximum likelihood method for estimation. This resulted in our proposed model of "Personality-Tourist Attractions Preference" as shown in Figure 4.3. Although with lower values, the combination of the indicators reveal an acceptable goodness of fit ($\chi 2/df$= 2.486; CFI= 0.712; GFI= 0.680; PCFI= 0.676, PGFI= 0.632, RMSEA= 0.054; p[rmsea≤0.05]p< 0.001), suggesting that the items provide a satisfactory fit (Marôco, 2010), thus confirming the proposed "Personality-Tourist Attractions Preference" model.

By analyzing the model, interesting predictions were found. Individuals with a higher preference for Adventure tend to score higher on Agreeableness but lower on Conscientiousness. This goes in line

with evidences found in literature, where less conscientious people tend to enjoy risky activities (Delic, Neidhardt, & Werthner, 2016; Eachus, 2004; Schneider & Vogt, 2012). Looking at the personality traits described by Costa Jr et al. (1995), this correlation suggests spontaneous individuals get along easily with others.

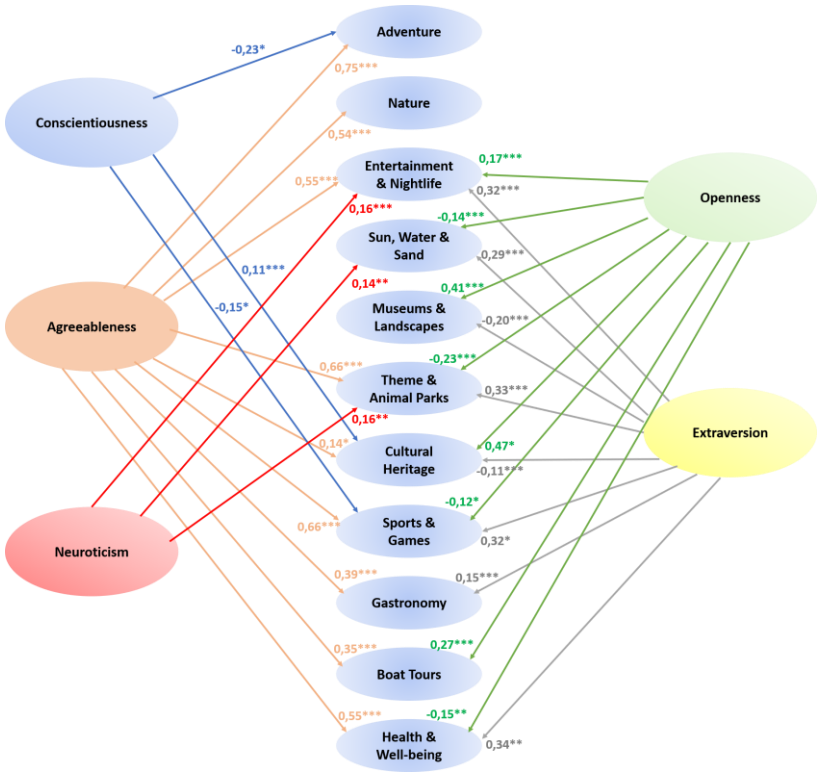


Figure 4.3. Simplified Structural Equation Model for the proposed "Personality-Tourist Attractions Preference" model. For readability, only the statistically significant values are presented (* $p < 0.05$ (2-tailed), ** $p < 0.01$ (2-tailed), *** $p < 0.001$ (2-tailed)).

A higher preference for Nature-related attractions is positively predicted by higher Agreeableness. These individuals tend to be more sympathetic, considerate and altruistic, this may correspond to more concerned and attracted to nature individuals, which may be somehow related to the ecological concern of highly agreeable persons as found by Kvasova (2015).

Entertainment and Nightlife activities are positively associated to all personality dimensions except Conscientiousness. One can presume almost everyone enjoys some form of entertainment or outings, but, once again, there is some risk avoidance as well as a sense of frugality related to conscientious persons that does not seem to combine with futile spending and/or unhealthy habits.

Table 4.3. Varimax rotated component matrix for the proposed tourist attractions, showing the 11 factors extracted using EFA, the estimated correlations between the items and factors, and each factors Cronbach's Alpha reliability.

Factor	Item	Description	Estimated correlations	α
Adventure	A46	Practice climbing or bungee jumping	0,775	0.876
F1	A63	Do air sports (e.g., parachute jump, skydiving, gliding)	0,758	
	A68	Ski	0,750	
	A12	Practice aquatic sports (e.g., sailing, canoeing, diving, jet skiing)	0,744	
	A29	Do motorsports (e.g., karting, motocross)	0,627	
	A37	Observe sub-aquatic environments / marine life (e.g., snorkeling, submarine)	0,575	
Nature	A41	Walk in the forest / woods	0,821	0.857
F2	A11	Do hiking / mountaineering	0,721	
	A42	Take a walk along the river / seacoast	0,662	
	A47	Visit mountain areas / gorges	0,635	
	A36	Visit nature or wildlife reserves	0,632	
	A10	Appreciate natural landscapes	0,625	
	A6	Visit caves/caverns/volcanoes	0,523	
Entertainment &	A44	Go to a dance/ballet festival	0,823	0.849
Nightlife	A43	Go to a music festival/concert	0,743	
F3	A45	Go to balls (dancing)	0,722	
	A48	Go to a live music bar/place	0,683	
	A17	Go to a film festival	0,624	
	A67	Assist to an opera/theater	0,621	
	A8	Attend cultural activities / artistic performances	0,512	
	A9	Go to the disco/nightclub	0,473	
Sun, Water & Sand	A65	Go to the swimming pool to relax	0,797	0.807
F4	A22	Go to the beach (sunbathing/ swimming)	0,725	
	A66	Have vacation on an island	0,648	
	A64	Go to the swimming pool to swim/dive	0,642	
Museums & Land-	A32	Visit museums of historical themes	0,741	0.775
scapes	A34	Visit viewpoints of natural landscape	0,731	
F5	A33	Visit museums of scientific themes (e.g., planetarium, paleontology)	0,670	
	A35	Visit viewpoints of urban landscape	0,637	
Themes & Animal	A15	Go to a Zoo	0,821	0.736
Parks	A13	Go to a theme park (e.g., Disneyland Paris)	0,641	
F6	A27	Go to a water park	0,590	
Cultural Heritage	A7	Visit archaeological sites / ruins	0,737	0.763
F7	A20	Visit monuments (e.g. churches, cathedrals, castles, fortresses, monasteries, palaces, etc.)	0,720	
	A4	Visit the historic cities/villages of the destination	0,657	
Sports & Games	A56	Assist to a sporting competition (e.g., watch a football game	0,764	0.723
F8		from a club of that country)		
	A55	Play at the casino	0,638	
	A53	Play ball sports (e.g., football, handball, volleyball, tennis)	0,601	
	A59	Participate in an escape game	0,572	
Gastronomy	A1	Go to a Gastronomy Festival (food and/or drinks)	0,844	0.742
F9	A40	Participate in a gastronomy tour (typical and/or gourmet dishes, wine tasting)	0,772	
	A18	Taste typical local dishes	0,674	
Boat Tours	A51	Take boat trips for the pleasure of boating	0,626	0.790

Factor	Item	Description	Estimated correlations	α
F10	A49	Take boat trips to know the destination's coast	0,619	
	A50	Take boat trips for the historical value of the route	0,555	
Health & Well-being	A28	Go to a SPA / beauty center	0,582	0.733
F11	A14	Undergo health and wellness treatments (e.g., hydrotherapy centers, mineral water resorts)	0,575	
	A26	Attend gyms / fitness centers	0,556	

Activities like going to the beach or a swimming pool are strongly related to more extraverted, open to experience and neurotic individuals, as also found by Delic, Neidhardt, and Werthner (2016). Extraverts may appreciate the opportunity to be in contact with other people, both new and known acquaintances, and at the same time feel comfortable with their body-image. Individuals with high openness may enjoy the aesthetic experience that comes with appreciating a beach for its natural beauty, along with the meditative state this surroundings may induce, confirming the results found by Bujisic et al. (2015). In turn, neurotics may appreciate these activities for consisting in somewhat predictable vacations, almost a default option in the context of our country, thus reassuring a strong sense of safety and control which is dear to these individuals.

Table 4.4. Personality dimensions mean total scores (BFI-44), n=508.

	Mean	SD	Min/Min range	Max/Max range
Extraversion	24	6	10/8	40/40
Agreeableness	33	5	14/9	45/45
Conscientiousness	32	5	11/9	45/45
Neuroticism	25	6	10/8	39/40
Openness	37	6	18/10	50/50

Visiting museums and landscape viewing are preferred by more open to experience individuals, while extraverted are negatively associated. This goes in line with the findings of Bujisic et al. (2015) and Jani (2014b). Sense can also be made in light of the fact that enjoying historical artifacts or pursuing intimate experiences commonly brought by absorbing impactful sceneries are activities more akin to individual enjoyment and solitude.

The preference for visiting Theme and Animal Parks is positively predicted by persons with higher Agreeableness (probably related to the ones who get along with the ones who enjoy those activities, such as children and adolescents), Neuroticism (the same as the agreeable interpretation) and Extraversion (related to energetic and excitement seeking persons). The preference for Theme and Animal Parks is negatively predicted by Openness to experience, possibly for its standardized, not-so-intellectually-challenging nature. No significant prediction was found for Conscientiousness.

Archeological sites/ruins, monuments and historic cities/villages are also positively sought by agreeable, conscientious and open to experience individuals, but negatively by extraverts, who may not find very exciting that sort of activities as they are averse to sedentarism, confirming the results found by Jani (2014b), but contradictory to the results found by Delic, Neidhardt, and Werthner (2016). This contradiction can be due to the different cultures studied or the sample size, although other reasons can be the cause.

Sports and games are negatively associated to conscientious and open to experience individuals, but agreeableness and extraversion are positively related, which can derive from the cooperativeness, energy, and high activity level inherent to these activities. This confirms what was found for Adventure preferences, and the findings of Schneider and Vogt (2012), who found competitiveness was associated to soft adventure travelers.

Gastronomy experiences are positively valued by more agreeable and extraverted people, which can explain why who appreciates food and wine is usually seen as cheerful and high-spirited. No significant relations were found for the other three personality traits.

Boat tours are preferred by individuals with higher agreeableness and openness to experience, being in line with the results found by Jani (2014b), which is similar to the interpretation given for beach/swimming pool activities and landscape viewing.

Health and well-being are valued by those with higher Agreeableness and Extraversion, but with lower Openness. No significant association was found to Conscientiousness and Neuroticism, which does not mean they do not exist.

The results found demonstrate a strong relation between the five personality dimensions and preferences for tourist attractions, i.e., preferences for specific tourist attractions can be predicted by the tourists' personality meaning they can be used in RS for tourism to automatically model the users preferences.

4.5 Reflections and Future Work

In the domain of travel and tourism, little information is known about the prediction of tourist preferences based on the tourists' personality. This work brought new insights, successfully and strongly relating all the Big Five personality dimensions to preferences for specific tourist attrac-

tions, showing all the extracted tourist attractions factors are relevant and could be predicted by the personality dimensions, constituting, to the best of our knowledge, the first "Personality-Tourist Attractions Preference" model in literature to do so.

Although the model was confirmed with a satisfactory fit, and since this study is part of an ongoing larger study, we believe the model's fit will considerably improve with the increase in size and heterogeneity of the sample, provided the used sample was small for the number of variables to estimate.

It was also found that due to the self-reporting answers in the BFI, some personality dimensions had a higher concentration above mid-point scores, which may reflect some social desirability bias, or that the sample should be more diverse. In fact, most of the respondents had a higher education level, which can explain the greater frequency of higher scores in dimensions like Openness to Experience and Conscientiousness, meaning this study is limited in predicting tourist attractions preferences for individuals with lower education. Also, most respondents were from Exact or Social sciences, meaning the sample was poor on other fields of education, which can also account for the lower variability found in Openness to Experience, Conscientiousness and Agreeableness, since, for instance, individuals with Artistic formation would supposedly positively influence the Openness to Experience overall score.

Also, we cannot forget the questionnaire was conducted in a Portuguese population, and therefore some relationships found between personality and tourist attractions can be culture specific. However, our intention is to conduct the same study on different cultures and compare the results.

Although personality revealed to be a great predictor of tourist preferences, to focus only on the five personality dimensions and not on the more granular thirty traits and on the correlations between them, may limit the preferences prediction. For example, a person considered extraverted may not be a risk taker or like adrenaline-filled activities. It would not be very good if the RS suggested a rollercoaster to the tourist. Since the questionnaire allowed to obtain significant data, it will be further analyzed, along with the incoming data, to determine which of the 30 personality traits can be inferred from the BFI.

It is also evidenced that the personality structure varies substantially across cultures (McCrae & Costa Jr, 1997), and that certain personality traits are more lean to show different emotions according to the social context they are in (Odić, Tkalčič, Tasič, & Košir, 2013). Therefore, to know the personality is not enough, all these variables need to be correlated to provide higher quality recommendations and a greater user experience.

Other psychological aspects, such as mood, intentions, emotions, and motivations have also shown to influence the tourists' preferences (Odić et al., 2013; Tkalčič et al., 2016). Therefore, other psychological aspects will also be a focus in our future work.

It is important to refer that, in addition to psychological factors, other factors, like the geographic and cultural distance should be included in the studies of the relationship between the tourists' personality and destination choice (McKercher, 2006; K. Y. Poon & Huang, 2017).

It is quite evident that personality is not the only responsible for tourist preferences, but it seems undeniable that personality plays an important role in the kind of tourist attractions one chooses to visit.

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5

GROUP RECOMMENDER SYSTEMS FOR TOURISM: HOW DOES PERSONALITY PREDICT PREFERENCES FOR ATTRACTIONS, TRAVEL MOTIVATIONS, PREFERENCES AND CONCERNS?



An image showing different destination possibilities and tourist attractions.

Generated with AI, Image Creator in Bing, October 2024

Paper Title	**Group recommender systems for tourism: how does personality predict preferences for attractions, travel motivations, preferences and concerns?**
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Abstract

To travel in leisure is an emotional experience, and therefore, the more information about the tourist is known, the more personalized recommendations of places and attractions can be made. But if to provide recommendations to a tourist is complex, to provide them to a group is even more. The emergence of personality computing and personality-aware recommender systems (RS) brought a new solution for the cold-start problem inherent to the conventional RS, and can be the leverage needed to solve conflicting preferences in heterogenous groups and to make more precise and personalized recommendations to tourists, as it has been evidenced that personality is strongly related to preferences in many domains, including tourism. Although many studies on psychology of tourism can be found, not many predict the tourists' preferences based on the Big Five personality dimensions. This work aims to find how personality relates to the choice of a wide range of tourist attractions, travelling motivations, and travel-related preferences and concerns, hoping to provide a solid base for researchers in the tourism RS area to automatically model tourists in the system without the need for tedious configurations, and solve the cold-start problem and conflicting preferences. By performing Exploratory and Confirmatory Factor Analysis on the data gathered from an online questionnaire, sent to Portuguese individuals from different areas of formation and age groups (n=1035), we show all five personality dimensions can help predict the choice of tourist attractions and travel-related preferences and concerns, and that only neuroticism and openness predict travelling motivations.

Keywords: Group Recommender Systems; Personality; Tourist Preferences; Travel Motivations; Travel Concerns; Affective Computing

5.1 Introduction

The last two decades have shown that personalization is the key to deliver the best recommendations in Recommender Systems (RS) (L. Chen et al., 2016; K. Y. Poon & Huang, 2017; Tkalcic & Chen, 2015; Tondello et al., 2017). Therefore, the more about the user is known the more accurate and tailored recommendations can be made. But if to provide tailored individual recommendations is complex, to provide them to groups is even more (Masthoff, 2015). The tourism industry has many variables making it a very complex topic, which is aggravated when groups of tourists,

that need a travel plan and to get accompanied in their excursions, are involved, particularly due to the group's heterogeneity and conflicting preferences (T. N. Nguyen & Ricci, 2018), making Group Recommender Systems (GRS) an important and challenging area of RS (Abolghasemi, Engelstad, et al., 2022; Castro et al., 2015; Delic & Masthoff, 2018; Masthoff, 2011; McCarthy, Salamó, et al., 2006b).

The advances in mobile technologies, like smartphones and wearable devices, make it possible to collect users' detailed data (Adomavicius & Tuzhilin, 2011), such as contextual information, identity, preferences and interactions with the mobile device, which in turn can be used to provide and improve recommendations. Also, the emergence and increasing use of social media (e.g., social networks, virtual game worlds, content communities), make it easy to obtain more personal information (Kaplan & Haenlein, 2010). Interestingly, these advances are coincident with the sudden increase of interest for personality computing in the early 2000s (Vinciarelli & Mohammadi, 2014), and consequently to the recent proliferation of personality-aware RS (Dhelim et al., 2021), which can easily be explained by its own definition: "personality is the sum-total of the actual or potential behavior-patterns of the organism, as determined by heredity and environment" (H. Eysenck & Rein, 1998), meaning each individual has her own behavior patterns, which are considered relatively stable over time across different situations (McCrae & Costa Jr, 1997), i.e., "an individual's behavior naturally varies somewhat from occasion to occasion, but... there is a core of consistency which defines the individual's 'true nature'" (Matthews, Deary, & Whiteman, 2003). These behavior patterns were summarized into five universal personality dimensions by Costa and MacCrae (1992): Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, being the Five Factor Model (FFM), or Big Five, recognized as the most widely accepted model to represent them (Dhelim et al., 2021; Digman, 1990; Matz et al., 2016), and therefore were adopted in this study. Each factor is defined by six traits/facets (Costa & MacCrae, 1992), resulting in a total of 30 traits, which are more granular, better characterizing a person (see Table 1).

Personality can be useful in different areas of RS (Ning, Dhelim, & Aung, 2019; Tkalcic & Chen, 2015) to help overcome challenges related to user modeling (Dhelim et al., 2021), since it is strongly related to the users' preferences (Cantador et al., 2013; Martijn, Conati, & Verbert, 2022),

i.e., users with similar personalities tend to choose similar items or contents (Cantador et al., 2013). For example, extraverts who are dependent on warmth and gregariousness tend to enjoy popular music, and persons who score high on excitement-seeking tend to prefer rock music (Cantador et al., 2013; Rawlings & Ciancarelli, 1997). In games, extraverts are more inclined to group activities than solo activities (Yee et al., 2011). Even certain features of Instagram® pictures are related to personality traits (Ferwerda et al., 2015). Being personality an enduring characteristic of humans (Costa & McCrae, 1988), it should be a better predictor of the tourist behavior than demographics like age, income, etc., as they are more liable to change over time (Jani, 2014b).

Table 5.1. Personality dimensions and their respective six traits (adapted from Costa and MacCrae (1992))

Neuroticism	Extraversion	Openness to experience	Agreeableness	Conscientiousness
Anxiety	Friendliness	Imagination	Trust	Self-efficacy
Anger	Gregariousness	Artistic interests	Morality	Orderliness
Depression	Assertiveness	Emotionality	Altruism	Dutifulness
Self-consciousness	Activity level	Adventurousness	Cooperation	Achievement-striving
Immoderation	Excitement seeking	Intellect	Modesty	Self-discipline
Vulnerability	Cheerfulness	Liberalism	Sympathy	Cautiousness

Although personality is still a growing topic in RS (Dhelim et al., 2021; M. Jackson & R. Inbakaran, 2006), it is well evident that personality is a powerful characteristic of humans that can be used to help predict their preferences in a wide range of domains (Cantador & Fernández-Tobías, 2014). For instance, personality has shown to improve recommendations and solve the RS usual problems like the cold-start and data sparsity problems (Dhelim et al., 2021; Feil et al., 2016; Tkalcic & Chen, 2015; Tkalcic, Kunaver, Košir, & Tasic, 2011). And how about the (leisure[21]) tourism domain? Is personality related to tourist preferences? As well observed by M. Jackson and R. Inbakaran (2006), "personality is one of the best known, and potentially the most useful, psychological concepts in tourism". In the case of recommendations to groups, correlating the users' personalities and their preferences can help match users with similar interests, minimizing the groups' heterogeneity and conflicts of interest in (occasional) groups of tourists.

Several studies on the relationship between personality and tourist preferences exist, however, the ones available only focus on specific types of travelling, tourist roles or tourism information search (Delic, Neidhardt, & Werthner, 2016; Eachus, 2004; Ismailov, 2017; Jani, 2014b; Masiero et al., 2019; K. Y. Poon & Huang, 2017; Schneider & Vogt, 2012; Sertkan, Neidhardt, & Werthner, 2020;

21 This work refers only to leisure tourism.

Tan & Tang, 2013), or mainly target the extraversion and openness to experience personality dimensions (Bujisic et al., 2015; C.-Y. Li et al., 2015). So, do all personality dimensions influence the choice of tourist attractions? What is the relationship between the tourists' personality and their preferred tourist attractions? Our previous work showed the proposed tourism categories could be predicted by all the personality dimensions (Alves et al., 2020), but since it was an ongoing study, more responses were still being obtained for future analysis, being the work here presented the continuation of that work.

The correlation between the tourists' personality and preferred tourist attractions can be valuable to automatically model their profile in (G)RS for tourism, solving the cold-start problem and eliminating the need for users to fill long and tedious questionnaires and configurations (Dhelim et al., 2021; Gretzel, Mitsche, Hwang, & Fesenmaier, 2006; Tkalcic et al., 2011). But could personality help find and automatically model other characteristics of tourists, such as their motivations, and travel-related preferences and concerns when travelling in leisure? Can it be used to mitigate conflicting preferences in groups of tourists?

Motivation has long been studied in the area of leisure and tourism (E. Cohen, 1979; Gnoth, 1997; Norman, Daniels, McGuire, & Norman, 2001; Pearce & Caltabiano, 1983; S. C. Plog, 1974; Vigolo, 2017), and is the need that drives someone to travel to a certain destination, or choose a certain tourism activity (Gee, Choy, & Makens, 1984; D.-B. Park & Yoon, 2009). Motivation is a complex topic (Crompton, 1979) and the "starting point for studying tourist behavior" (Pearce & Lee, 2005), being a challenge to study due the diversity of human needs and cultures (S. L. Smith, 2014). Tourism offers and tourism marketing strategies greatly depend on those motivations (Gnoth, 1997; Lo, Cheung, & Law, 2004; Nasolomampionona, 2014), existing many motives that can influence someone to choose a destination/activity, such as to relax, explore the destination, and more. But are these motives a consequence of the tourist's personality? Is there a relationship between the Big Five personality dimensions and motivations for travelling? Based on Pearce and Lee (2005) proposed travel motives, we tried to discover if the tourists' personality could also predict their travel motivations.

But what drives someone to travel may be conditioned by certain travel-related preferences and/or concerns (Alves, Carneiro, Marreiros, & Novais, 2019; Çakar, 2020; Hung, Bai, & Lu, 2016; Morar

et al., 2021). For example, Matthew wants to visit Egypt, but because he cannot go with his girlfriend, he does not feel motivated to go, and so he won't go unless she does. Or suppose someone is in an excursion in Portugal and the group is going to visit Clérigos Tower, but one of the members is afraid of heights and she doesn't want to visit it. Although tourist attractions preference and motivations for travelling are important for (G)RS to present a more tailored tourism offer, travel-related preferences and concerns play an important role in the decision for visiting or travelling to a destination. Therefore, we considered important to study that four travel aspects and discover how/if they are influenced by the tourists' personality.

In short, this study aims to find which tourists' travel aspects can be predicted by their personality, namely, if the choice of tourist attractions, the motivations for travelling, travel-related preferences and concerns are influenced by the tourists' personality (the Big Five personality dimensions), and help tourism GRS researchers automatically model the tourists profile based on their personality without the need for long initial configurations or the users continuous interaction, and therefore help in the cold-start problem; and how those travel aspects, along with personality, can be used to solve conflicting preferences in groups.

Thus, in 2019 (Alves et al., 2020), we started a large-scale study to determine that relationship. To accomplish that, an intensive research on the four travel aspects was conducted so that a questionnaire to collect as much information as possible could be constructed and disseminated. This paper continues that work, exploring the dataset in more detail, having obtained 555 more responses, in a total of n=1035 viable responses. The Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) for extracting and confirming the proposed tourist attractions categories was improved, corroborating the preliminary work (Alves et al., 2020), showing all personality dimensions were predictors of different preferences for tourist attractions. EFA and CFA were then extended to the items associated to the travel motivations, the travel-related preferences and concerns, and related to the Big Five, having found that travel-related preferences and concerns can be predicted by different personality dimensions, but interestingly, only neuroticism and openness to experience were found to be related to the travelling motivations.

As a final result, to help in the cold-start problem, we propose three models that relate the Big Five personality dimensions to a wide range of tourist attractions, travelling motivations, and travel-

related preferences and concerns, and a fourth model, to solve conflicting preferences in groups by creating subgroups of tourists with similar interests. The outcomes are then discussed and evaluated.

The remainder of the paper is structured as follows: Section 2 describes the background and some related work on GRS for Tourism and Psychology of Tourism; Section 3 presents the methodology used; Section 4 the results and their respective analysis, along with the proposed models; Section 5 the proposed models formulations that relate Personality with Preferences for Tourist Attractions, Travelling Motivations, and Travel-related Preferences and Concerns, as well as the algorithms to create subgroups of similar interests; and finally, Section 6 reflects on the contents addressed in the paper and describes what will be done as future work.

5.2 Background and Related Work

5.2.1 Group Recommender Systems for Tourism and Group Decision-Making

To overcome the challenges that (especially casual) groups of tourists bring and to provide a satisfactory list of recommendations are the main concerns of GRS for tourism. Some prototypes of GRS for tourism can be found in literature, like the chat-based GRS of T. N. Nguyen and Ricci (2018) where the system learns from the tourists comments and classifications in the chat, and from the rating of previously visited Points of Interest (POI), to provide a list of recommendations. The tourists then need to reach a consensus on the recommended POI to visit via the chat. This can be a complex task depending on the group's heterogeinity and size. Therefore, the decision-making process is intimately associated to GRS (Delić et al., 2020), as the users in a GRS need to negotiate and reach a consensus on the list of recommended POI to visit (Jameson et al., 2003). Hence, Group Decision-Making (GDM) techniques could help in that part of the process, such as to reach a faster and more satisfying consensus, as no one wants to feel unsatisfied when going for an excursion, dissatisfaction that can easily spread to the group due to the emotional contagion phenomenon (Delic & Masthoff, 2018). There are already GRS that consider GDM as a factor of success in the decision process (Alves et al., 2019), such as the GRS proposed by McCarthy, Salamó, et al. (2006b), Castro et al. (2015), or Marques et al. (2016). For example, Abolghasemi, Engelstad, et al. (2022) proposed a GRS that uses GDM techniques like pairwise scoring methods

(Abolghasemi, Khadka, et al., 2022; Herrera-Viedma, Chiclana, Herrera, & Alonso, 2007), and the Thomas-Kilmann Conflict MODE Instrument (TKI) (Thomas, 2008), which evaluates how someone behaves in a conflict situation, to simulate the users' conflict style in the decision process, as the decision is strongly dependent on the group members personality and conflict solving capabilities.

The consideration of GDM techniques can be the leverage needed to reach a consensus on the final recommendations list, and will be further studied in future works. Predicting the users' preferences based on their personality is the beginning of that path.

5.2.2 Psychology of Tourism

The increased interest on psychology of tourism is undeniable, since it is evidenced that psychological aspects are related to the choice of specific destinations (Jafari, 1987; Passafaro et al., 2015; S. C. Plog, 1974). But which ones? Several researchers tried to answer that question, some by proposing tourist typologies or roles based on psychological aspects, others by trying to find relationships between personality and tourist behaviors or preferences.

5.2.2.1 Tourist Typologies/Roles

Many tourist typologies/roles can be found in literature and represent the role played by tourists while experiencing a destination (Yiannakis & Gibson, 1992). E. Cohen (1972) was one of the first researchers to propose a tourist typology, composed of four types: the organized mass tourist (least adventurous, more organized and prefers familiarity to novelty), the individual mass tourist (has a certain control over his time and itinerary and is not bound to a group), the explorer (trip self-arranged, likes to meet locals and speak their language without totally immersing herself), and the drifter (extremely independent, likes novelty at maximum and familiarization at minimum).

Plog is another renown researcher who studied the psychology of travel in tourism (S. Plog, 2001; S. C. Plog, 1974, 1994). He proposed two main psychographic dimensions, in the opposite extremes of a normally distributed continuum, to characterize the tourists' travel behavior: Allocentrics, who are more nature related, adventuresome, curious, outgoing, self-confident, seek for novelty and new experiences; and Psychocentrics, who are self-inhibited, anxious, non-adventuresome, prefer the familiar in travel destinations, especially if they can drive to them, and places where they can relax.

M. Jackson et al. (2001) proposed four types of tourists: the explorer, the adventurer, the guided, and the groupie, combining the orthogonal scales of Allocentrics-Psychocentrics and Introversion-Extraversion.

Eachus (2004) proposed a Holiday Preferences Scale by modifying both Plog's and M. Jackson et al. (2001) typologies: Adventurous preference, Beach preference, Cultural preference, and Indulgent preference. They found that tourists with high scores in sensation seeking tended to prefer Adventurous and Beach holidays but not Indulgent holidays, and older tourists were more likely to prefer Cultural holidays than younger.

Based on Cohen's individual mass tourist type (E. Cohen, 1972), Wickens (2002) proposed five micro-types of tourists: the Cultural Heritage, the Raver, the Shirley Valentine, and the Lord Byron type.

To enhance the relevance of recommendations in RS, Gretzel et al. (2004) proposed 12 travel personalities and studied how they related to 17 travel activities in Northern Indiana, having found strong correlations between them. The most selected travel personalities were All Arounder, Sight Seeker and Culture Creature. Concerning the relationships found, as also later verified by Delic, Neidhardt, and Werthner (2016), most travel personalities were related to multiple activities, for instance, Shopping Sharks type was related to tourists more interested in shopping, nightlife, and dining. Culture Creatures preferred festivals, museums, and historic sites. Family Guy was not related to gambling, biking, or hunting/fishing. Trail Trekkers were less related to City Slicker, Shopping Shark, and Gamer travel types. Boaters did not consider themselves as Sight Seekers, and Beach Bums did not identify with the History Buff category. The other types corresponded to their respective activities. Later, the same authors studied if the proposed travel personalities could predict the activities and/or places to be recommended by a destination RS (Gretzel et al., 2006), finding travel personalities are "very good proxies for capturing user personality traits and preferences and can be used to make specific destination recommendations" (Gretzel et al., 2006).

As pointed by Gretzel et al. (2006), "it is not clear how easy it is for individuals to select and identify with an existing" typology or how they can actually predict the tourists' behavior. Although being a potential way of describing types of tourists and creating marketing segments, typologies do not allow to understand what personality dimensions and/or traits are behind those preferences, and

therefore are not easy to implement in a (G)RS without the need of certain initial configurations by the user, problem we propose to mitigate by automatically predicting the tourists' preferences for tourist attractions based on their personality.

Personality as Predictor of Preferences for Tourist Attractions/Destinations

As pointed by several authors, the existing research on tourism behavior is mostly descriptive instead of predictive (M. Jackson et al., 2001; Schneider & Vogt, 2012) which is a limitation that needs to be overcome, i.e., what personality dimensions or traits are predictive of the tourists' typologies or behaviors/preferences found in literature?

Crotts (1990) found the more dogmatic (close-minded) the participants were, the less novelty and more familiarity they wanted in their vacations, and the ones that had a greater need for cognition, and tendency to engage in and enjoy thinking sought more for novelty.

According to Bujisic et al. (2015), individuals with higher level of openness to experience tended to be more satisfied with aesthetic and escapist experiences than those with lower level. In contrast, individuals with lower openness to experience were more satisfied with entertainment and educational experiences compared to the ones with higher level. Extroverts tended to be more satisfied with educational and escapist experiences.

Although many studies on psychology of tourism for different tourism sectors can be found, many are about typologies of tourists (Addison, 1999; Lipscombe, 1995; Millington et al., 2001; S. C. Plog, 2002), which as mentioned before, are descriptive of the tourists' behavior and do not predict how that behavior influences the choice of tourist preferences. Others try to predict how psychological aspects influence tourist behavior or preferences, but most of them only rely on Sensation Seeking, extraversion, and/or openness to experience scales (Bujisic et al., 2015; M. Jackson et al., 2001; C.-Y. Li et al., 2015; Nickerson & Ellis, 1991), which do not cover all Big Five's dimensions. Few studies try to correlate all Big Five dimensions with tourist behaviors or preferences. For example, Neidhardt, Schuster, Seyfang, and Werthner (2014); Neidhardt, Seyfang, Schuster, and Werthner (2015) performed a factor analysis on the 17 tourist roles proposed by Gibson and Yiannakis (2002) and the Big Five personality dimensions, obtaining seven factors that captured the tourists behavior, where some of them revealed to be correlated with personality di-

mensions: (1) *Sun loving and connected* – highly correlated to the sun lover tourist role and the neuroticism, openness and conscientiousness personality dimensions; (2) *Educational* – correlates organized mass tourist and educational tourist with agreeableness; (3) *Independent* – combines independent mass tourists I and II and seeker; (4) *Culture loving* – correlates archaeologist and high-class tourist with extraversion; (5) *Open minded and sportive* – combines anthropologist and sport tourist with extraversion; (6) *Risk seeking* – results from the correlation of action seeker, explorer and jetsetter; (7) *Nature and silence loving* – correlates escapist I and II.

Kvasova (2015) studied how personality influenced tourists' eco-friendly behavior, finding individuals with high agreeableness were strongly related to eco-friendly behavior, followed by conscientiousness and neuroticism, confirming several past studies on the same area of research (Hirsh, 2010; Markowitz et al., 2012; Milfont & Sibley, 2012). Regarding openness to experience, individuals with high imagination were negatively associated to eco-friendliness but individuals with high intellect were positively associated.

Jani (2014b) and Delic, Neidhardt, and Werthner (2016) studied how the Big Five correlated to a variety of tourist roles. Jani (2014b) explored that relationship using the Big Five and the 12 travel personalities (types) proposed by Gretzel et al. (2004). The author found significant personality differences between the travel types. Those who enjoy games of any type (Athlete type), historical sites, shopping, and water activities/attractions (Boater) are high in openness to experience, and those who like to lay around the beach (Beach bum) and spend time with family are low in that dimension. Shopping and Family travel types have a high conscientiousness, and Athlete and Gamer types are low in that factor. Trekker and All things travel types have higher extraversion, and Cultural, Beach bum, and Boater types are lower in extraversion. As for high agreeableness, it includes Boater and Family travel types, and low agreeableness the Gamer type. Low neuroticism was associated with Family and All things travel types. Delic, Neidhardt, and Werthner (2016) analyzed the relationship between the 17 tourist roles defined by Gibson and Yiannakis (2002) and the Big Five. For example, Sun Lover type was related to high neuroticism individuals, Archeologist to extraverts, and Drifter to less conscientious people. No significant correlations were found between the other tourist roles. As expected, they also found tourist roles varied with age, but that the Big Five personality dimensions were stable across ages.

All these studies show that the travel behavior and preferences are related to the tourists' personality. However, none, to the best of our knowledge, correlates the Big Five personality factors to the choice of raw categories of tourist attractions, but instead, to tourist typologies. With this work, we intend to fill that gap by proposing a model to predict the preference for a wide range of tourist attractions, adapted from the "Thesaurus on Tourism and Leisure Activities" of the World Tourism Organization (UNWTO, 2001), based on the tourists' five personality dimensions, aiming to help tourism (G)RS to provide recommendations for visiting attractions/destinations just by knowing the tourist's personality, and solve problems related to conflicting preferences in (occasional excursion) groups. We believe that creating subgroups with similar personalities, and therefore, similar tourist preferences, can help solve those conflicts.

This research is motivated by the evidence found in literature, from which it is possible to reason that the tourist typologies do not fully justify the tourists' preferences for tourist attractions, since many different combinations of intensity for the personality traits exist and therefore a single typology may not be enough for a certain tourist as well as not all the attractions present in a typology may be suitable for that tourist. This claim is supported by the results found by Gretzel et al. (2004) and Neidhardt et al. (2015). Although it is "easy" to recommend attractions based on a single personality dimension, individuals have a combination and different scores on the five personality dimensions. How do we aggregate all that to recommend the right tourist attractions? We cannot recommend an attraction classified for high extraversion and low neuroticism to someone low in both dimensions.

5.2.2.2 Tourism Motivation

Many studies on tourism motivation exist, some studying motives for travelling to specific sites (Collins-Kreiner & Kliot, 2000), tourism niches (Hassani & Moghavvemi, 2019; Heung & Leong, 2006; Otoo & Kim, 2020), senior tourists (Boksberger & Laesser, 2008; Otoo, Kim, Agrusa, & Lema, 2021; Patuelli & Nijkamp, 2016; Vigolo, 2017), or in general (Heitmann, 2011), others to propose scales or dimensions of motivations (Crompton, 1979; Pearce & Caltabiano, 1983), among others. These studies are particularly important to tourism marketing, and therefore to tourism (G)RS, so better and more tailored services and products can be delivered to tourists.

One of the first researchers to care for the tourists' motivations was Dann (1977), by trying to answer the question "What makes tourists travel?". Although some viewpoints could be found at the time, claiming the major reason for travelling was to escape from the daily routine, the ordinary, etc., there was no empirical evidence to demonstrate it (Dann, 1977; Lundberg, 1971). However, a general classification to explain tourist motivation with "push" and "pull" factors was widely accepted (Dann, 1977; Heitmann, 2011). "Push" factors refer to the tourist's physiological and psychological aspects (e.g., escape, relax, etc.) influencing his decision to travel, like needs and preferences. "Pull" factors pertain to the characteristics of the travel destination or external motivations that attract (pull) the tourist to visit it.

Later, Iso-Ahola (1982), suggested tourism motivation was mainly driven by escape and seeking, both having personal (psychological) and interpersonal (social) factors, and therefore he distinguished four dimensions: personal seeking, personal escape, interpersonal seeking, and interpersonal escape.

McIntosh and Goeldner (1985) proposed five types of motivations, reflecting the ideas of the Maslow's pyramid: Physical (the need for relaxation or other activities to reduce stress or refresh the body and mind), Emotional (to seek romance, adventure, spirituality, escapism or nostalgia), Cultural (to learn about the destination's culture and heritage), Interpersonal (the need to maintain or develop new relationships, by visiting relatives or friends, or meet new people), and Status and prestige (the need to enhance self-status and receive attention/valorization from others).

A very interesting travel motivation theory was developed by Pearce (1993), Pearce and Caltabiano (1983), and Moscardo and Pearce (1986): the Travel Career Ladder (TCL), latter modified to Travel Career Pattern (TCP) since tourists could be at more than one level at a time (Pearce & Lee, 2005). Also based on the Maslow's needs hierarchy (Maslow, 1970), the theory describes five different levels of tourist needs, from bottom to top: relaxation needs, safety/security needs, relationship needs, self-esteem and development needs, and finally, self-actualization/fulfillment needs. The theory argues that tourists' motivation changes according to their age and/or travel experience, resulting in a travel career. To understand pleasure travel motivation more broadly, Pearce and Lee (2005) identified a wide range of travel motive items and determined 14 underlying motivation factors: Novelty, Escape/relax, Relationship (strengthen), Autonomy, Nature seek-

ing, Self-development (host-site involvement), Stimulation, Self-development (personal development), Relationship (security), Self-actualize, Isolation, Nostalgia, Romance, and Recognition. They found escape/relax, novelty, relationship, and self-development were the most important motives for travelling. The more experienced travelers were more motivated by self-development through host-site involvement and nature seeking. The low experienced were more driven by stimulation, personal development, self-actualization, security, nostalgia, romance, and recognition.

Literature on travel motivation is very extensive and therefore only some works were presented, but one thing is clear, the main reasons for travelling have been very similar in the last decades and among different age echelons, being Exploration, to have Cultural/Nature experiences, and Relaxation/Escapism the most common motives.

Personality as Predictor of Tourism Motivation

By analyzing why someone chooses to travel to a specific site or tourist attraction can help find their travelling and behavioral patterns, which can greatly help improve the tourist's profile in a (G)RS and thus provide better recommendations. And, if, for instance, personality could be related to the motives behind travelling, it would be easier to propose certain attractions or destinations by just knowing the tourist's personality. As Heitmann (2011) points out, many factors can influence the tourists' behavior and choices, such as cultural and religious factors, demographics, and personal factors such as personality, lifestyle, occupation, income, among others. So, how does personality relate to the most common tourists' motivations?

As mentioned in Section 5.2.2, several tourist roles and typologies have been proposed to describe tourist behaviors (E. Cohen, 1972; Gray, 1970; S. C. Plog, 1974; V. L. Smith, 2012) but they do not explain the reasons behind those behaviors (Heitmann, 2011).

Not many works that study the relationship between (Big Five) personality and travelling motivations were found, and the ones existing, to the best of our knowledge, aim to relate personality and the motivations for specific tourism niches or destinations, such as religious tourism and cruise ship tourists (Abbate & Di Nuovo, 2013; Scaffidi Abbate, Di Nuovo, & Garro, 2017), travel curiosity (Jani, 2014a; Kashdan et al., 2009), volunteer tourism (Suhud, 2015), or just for the travel desire (Labbe, 2016), or relate other personality types to the travel intention (Kaewumpai, 2017; H. Kim,

Yilmaz, & Choe, 2019; Kwon & Park, 2015; Otoo et al., 2021), or only to one motive. Others use different scales of personality (not the Big Five).

A recent study of Scaffidi Abbate et al. (2017) compared the motivations (*Curiosity and discovery*, *Out-of-routine* and *Self and sociality*) and personality of religious travelers versus cruise ship tourists. Regarding religious travelers, the authors found openness to experience positively predicted *Curiosity and discovery* motivation and agreeableness negatively. Agreeableness and conscientiousness negatively predicted *Out-of-routine* motivation. *Self and sociality* was predicted by negative scores in openness to experience. A different pattern was found in cruise tourists, where openness to experience and agreeableness both positively influenced the curiosity motivation, and conscientiousness negatively. *Out-of-routine* motivation was negatively predicted by conscientiousness and neuroticism. Finally, openness to experience, extraversion (energy) and conscientiousness positively predicted *Self and sociality* motivation.

The findings in literature show that certain motivations for travelling in specific contexts can be predicted by personality dimensions. With this work, we intend to verify if that applies to a greater range of travel motivations, including the most common ones, abstracted from specific niches or destinations, and to propose a model to predict tourism motivations based on the tourists' Big Five personality dimensions.

5.2.2.3 Travel-Related Preferences and Concerns

To choose a travel destination is part of a process that starts with the need/desire for travelling (Mathieson & Wall, 1982), and the information that is collected is evaluated according to the traveler's needs and preferences as well as possible constraints. According to Hung et al. (2016), there are three types of travel constraints: intrapersonal (e.g., to feel guilty for travelling, to be afraid of travelling to a specific destination, limited knowledge of tourism), interpersonal (e.g., lack of travel partners), and structural (e.g., lack of time or money). For instance, many people would like to visit Ukraine, but due to the actual war it is not a choice. Also, someone might prefer to visit a country on summer instead of another season. Or someone may not be able to travel due to money or time constraints. In this study, we focused in the intrapersonal and interpersonal constraints and will consider them as concerns from now on.

Some concerns have shown to intensify with age (Fleischer & Pizam, 2002; Lindqvist & Björk, 2000; Vigolo, 2017; You & O'Leary, 1999), like the fear of becoming ill, lack of doctor availability, concerns for safety and personal security, sanitation, service and food quality (J. Kim, Wei, & Ruys, 2003; Lindqvist & Björk, 2000; Torres & Skillicorn, 2004). Health problems are more noticeable in older tourists (> 64 years old), reducing the length of vacations (Fleischer & Pizam, 2002), and increasing the concerns about travelling to long-haul or less developed destinations, flight durations, health insurance, or even humidity (Hunter-Jones & Blackburn, 2007). As pointed by Vigolo (2017), Huang and Tsai (2003) found senior Taiwanese travelers revealed preoccupation for leaving their house unattended, not having travel companions, dietary restrictions, or not having an enjoyable time and waste money. Chinese women were more concerned about "limited knowledge of tourism, health and safety, culture shock, lack of travel partners, low quality service facilities, limited availability of information, and negative reputation of tour guide" (Gao & Kerstetter, 2016; Vigolo, 2017). Emotional barriers like fear of the unknown, loss of freedom and loss of spontaneity were pointed as the highest barriers for family caregivers and their care-recipients by Gladwell and Bedini (2004).

Although safety and security have long been key concerns for many tourists (Larsen, Brun, & Øgaard, 2009; A. Poon & Adams, 2000), tourism in general is not seen as risky (Sönmez & Graefe, 1998a, 1998b). However, certain unexpected and tragical events can decrease the tourists' confidence and reduce the desire to travel. The attacks on the World Trade Center and the Pentagon, on September 11, 2001, were a sad example, which led to the mass cancelation of inbound and outbound flights (Floyd, Gibson, Pennington-Gray, & Thapa, 2004). The actual COVID-19 pandemic is another case, where to travel, either overseas or within the same country, is considered risky, and was even forbidden to many countries (Borkowski, Jażdżewska-Gutta, & Szmelter-Jarosz, 2021; Godovykh, Pizam, & Bahja, 2021; Morar et al., 2021; Neuburger & Egger, 2021; Tabak, Canik, & Guneren, 2021; Zenker, Braun, & Gyimóthy, 2021).

The study of the perceived risks in tourism has long been investigated (Dolnicar, 2005), being the concept first introduced by Bauer (1960). According to Dolnicar (2005), the study of perceived risks can be classified into two dimensions: negative perceived risks, which are not sought by the tourist, and positive perceived risks, which are actively sought by the tourist, such as sensation

seeking activities. In their investigation of the fears Australian tourists associate to leisure travel, in the context of domestic and overseas travel, Dolnicar (2005) found five categories of risk factors: (1) political risk, such as "terrorism, political instability, war/military conflict"; (2) environmental risk, like "natural disasters, landslides"; (3) health risk, like "lack of access to health care, life threatening diseases, lack of access to clean food and water"; (4) planning risk, such as "unreliable airline, inexperienced operator, not assured flight home"; and (5) property risk, such as "theft, loss of luggage". All the referred risks were more frequently associated to overseas travel. As for domestic travel, wildlife and the road's condition were the greatest concerns. The context may change everything. Negative events in association to fears and concerns can prevent the tourist from visiting certain places/attractions, from being involved in particular activities, or even from travelling.

As for travel-related preferences, someone might prefer to travel accompanied or alone, to a cold or hot weather destination, or to take a flight or travel by car, and so on. Travel preferences can also influence which destination to visit or even the decision to travel at all. For instance, Otoo, Kim, and Park (2020) studied eight travel-related features/preferences: travel duration (by flight), travel partners, accommodation type, travel arrangement type (own or package tour), information technology acceptance, tourism type (e.g., urban, eco, health), attractions type (e.g., historical, natural scenery), and activities type (outdoor, shopping, dining), and related them to the travel motivations they found. Ramires, Brandao, and Sousa (2018) studied what travel preferences and destination attributes tourists visiting Porto in Portugal preferred, namely: travel organizer, travel partners, transport to destination, type of accommodation, type of activities in the destination, transport in the destination, and how they were related to their travel motivations.

Many travel preferences and concerns can influence the travel plans, bringing limitations or even prevent tourists from travelling. To know them can improve (G)RS recommendations. But how does personality fits in these all? Is it an influencing factor for those preferences and/or concerns?

Personality as Predictor of Travel-Related Preferences and Concerns

Many studies that relate tourist typologies or personality to travel-related preferences and/or concerns, especially concerns, could be found.

Sandra Lee Basala (1997); Sandra L Basala and Klenosky (2001) found individuals with different travel styles (Familiarity Seekers, Average Travelers, and Novelty Seekers) had different travel-related preferences, namely regarding the type of accommodations, type of travel companions, and language of the host destination.

Beside relating demographics, M. Jackson and R. Inbakaran (2006) studied tourists visiting Australia and how their proposed personality types (Explorer: introvert+allocentric, Adventurer: extravert+allocentric, Guided: psychocentric+introvert, and Groupie: psychocentric+extravert) related to the preference for pre-planning a vacation, using internet to book travels, travelling alone, travel companions, intention to revisit a destination, length of stay, and destination's cultural similarity.

Considering three personality dimensions (extraversion, conscientiousness, and emotional sensitivity (neuroticism)), Maritz, Yeh, and Shieh (2013) studied how tourists' personality influenced the perceived travel risks (personal risk, property risk and liability risk), the travelling intention, and the perceived risk on travel intention. As for perceived travel risk, conscientiousness and emotional sensitivity positively influenced personal risk, emotional sensitivity positively predicted property risk, and finally, all three personality dimensions showed positive effects on liability risk. Extraversion did not appear to be affected by travel risks. Regarding travel intentions, all three personality dimensions positively influenced the travel intention. Perceived risk significantly affected travel intention in terms of personal and liability risks. Evidence suggested the perceived risk would reduce the influence of extraversion, conscientiousness, and emotional sensitivity on travel intention.

Using Plog's psychographic model (S. C. Plog, 2002), Morakabati and Kapuściński (2016) focused on the relationship between risk perception and the destinations' benefits, and if terrorism affected the willingness to travel according to the tourists' personality. Yazdanpanah and Hosseinlou (2016), studied the influence of the Big Five personality dimensions on the choice of transportation mode according to the weather conditions.

Carvalho, Pianowski, and Gonçalves (2020) studied if extraversion and conscientiousness were related to social distancing and handwashing COVID-19 containment measures in Brazil. They verified the less extraverted the more concerned with social distancing the participants were. Participants who considered neither of the two containment measures had lower conscientiousness

scores. Participants that adhered to both or one of the containment measures had higher conscientiousness.

Another study on COVID-19 pandemic (Aschwanden et al., 2021), focused on concerns related to the pandemic (e.g., become sick with coronavirus), precautions to avoid catching the disease (e.g., wear face mask), preparatory behaviors (e.g., stockpiling food), and duration estimates concerning the disease (e.g., time to return to normality), showed high neuroticism was related to more concerns but to fewer precautions, and unrelated to preparatory behaviors; high conscientiousness to more precautions; higher scores on extraversion were predictors of more optimistic duration estimates; and higher neuroticism of more pessimistic ones. Age showed to moderate the personality effect, revealing to be a great predictor of psychological and behavioral responses to the disease, especially in older adults (aged 65+): greater concerns were a result of higher openness scores, high openness and agreeableness values were predictors of more preparations and higher duration estimates, higher conscientiousness was positively associated with more preparatory behaviors, but had non-significance for middle-aged (40-64 years) and younger adults (18-39 years old), but was related to shorter duration estimates in middle-aged and younger adults and higher duration estimates on older adults. A similar study was also performed by Al-Omiri et al. (2021).

Faullant, Matzler, and Mooradian (2011) studied how extraversion and neuroticism influenced the joy and fear basic emotions in a mountaineering experience and in the satisfaction formation. They confirmed their proposed hypothesis that extraversion positively predicted joy, and neuroticism positively predicted fear, i.e., the more extraverted mountaineers experienced higher levels of joy while the more neurotic ones were more susceptible to experience fear.

It is undeniable that some leisure activities are more pleasant, or only possible, under certain weather conditions. For instance, to relax on the beach is more enjoyable in a sunny and warm weather than on cold or rainy conditions (Sabir, 2011; Shi, 2012), skiing is only possible on snowy conditions (not considering artificial snow). W.-Y. Liu, Yu, and Hsieh (2021) verified both tourists with low and high-place attachment greatly diminished their intentions to visit a National Forest in Taiwan when negative climate changes occurred. These is in line with the observation made by Shi (2012), that many tourists are motivated for travelling on particular weather conditions, selecting times of the year where the climate conditions are more favorable to them. The thermal comfort

"has a decisive influence on national and international tourist flows, and largely controls the duration of the tourist season, especially in mid- and high-latitude regions" (Mieczkowski, 1985). It is evident that the seasons and/or climatic conditions have a psychological effect on the tourists' motivation to travel (Becken, 2010; Scott & Lemieux, 2009), but is personality an influencing factor?

Besides the ones presented, many other variables can influence travel preferences and concerns, like the cases of certain phobias such as the fear of heights, dark, confined spaces, reptiles, among others. It would be very bad if a (G)RS recommended a tourist to visit the Eiffel Tower if she was afraid of heights, or to play an escape game with a dark and confined spaces theme. And where is personality in the middle of all those phobias? Mellstrom, Cicala, and Zuckerman (1976) argued individuals scoring high on thrill and adventure seeking were less prone to feel fear in anxiety-inducing situations, in fact, they might feel attracted to those situations. In their study, female students who were more anxious and neurotic revealed more fear of snakes, heights, and darkness.

As pointed by Morar et al. (2021),"It is well recognized that personality plays a special role in both perceptions of risks and preferences related to travel". However, most of the studies found were related to travel risks and perceptions of risk, and travel-related preferences. Studies correlating personality to other types of concerns, such as phobias, or climate preferences, were very hard to find. With this study, we hope to fill those gaps and provide a more thorough and complete study on how the Big Five personality dimensions impact travel-related preferences and concerns.

5.3 Methodology

This work continues the work presented in Alves et al. (2019); Alves et al. (2020). The same online questionnaire[22], created using Google Forms, was used to gather extra responses, since we wanted to increase the sample's heterogeneity and improve the "Personality vs Tourist Attractions Preference" model fit, as some of the limitations found were the sample's size and that most of the respondents had higher education, specially from Exact and Social Sciences. Using again the

22 Please consult http://www.gecad.isep.ipp.pt/grouplanner/dissemination.html. The questionnaire was anonymous and confidential, and approved by the Polytechnic of Porto Data Protection Office.

snowball sampling method, the questionnaire was sent, through a link using an especially elaborated email, to adolescents and adults (15+ years old) in Portugal with more diverse backgrounds and education/areas of formation, like the parents/sponsors of education of students and the educational community of two elementary and high-schools; scholars, professors and general employees of the Faculty of Fine Arts of the University of Porto and Lusófona University; to the Geek Girls Portugal group; and Herbalife® Group members. The link was also posted in two Facebook® groups (Association of Portuguese Research Fellows, and Travels Around the World Portuguese group). This resulted in 545 additional responses, in a total of n=1063 responses (summed up to the 518 responses obtained in the previous study), collected from January to September 2020.

The aggregated sample was then cleaned for inconsistent responses and several univariate outliers were removed (Pyle, 1999; Witten, Frank, Hall, & Pal, 2016), using both Microsoft® Excel® 365 and IBM® SPSS® Statistics 26. Namely, 16 responses were removed due to duplicated data, dubious, incoherent, or playful responses. Since responses in an extreme do not really mean an outlier behavior, the sample was searched for unengaged respondents, namely, respondents who entered repeating patterns in questionnaire sections with Likert scales, like entering only "7,7,7,7,7...", or "1,2,3,4,5,1,2..", etc. Respondents were also examined if they responded normal questions in the same direction as reverse-coded questions (BFI section), for example: "I am talkative" and "I am reserved". With these methods, 12 more outliers were removed, resulting in a final sample of n=1035. Boxplots were also drawn in SPSS for each variable, but as the sample was not very large, the outliers found by this method were not removed. Inconsistent open responses were uniformized (socio-demographic questions, section I), for example, some respondents answered in "country of birth" variants of "Portugal", like "Portuga" or "Portuguesa", and so, all inconsistent situations were converted to Portugal. There were no missing values in the questionnaire, except for the sensitive questions, which were not mandatory.

Using SPSS, several runs of Exploratory Factor Analysis (EFA) (Fabrigar, Wegener, MacCallum, & Strahan, 1999), an unsupervised machine learning technique, were performed on the BFI (questionnaire section II, 44 items) and on the Travelling Motivations items (section IV, 28 items), to check if the items aggregated as expected in the original scales, to ensure the unidimensionality and discriminant validity of the scales (Clark & Watson, 2016); and on the items of the Travel-

related Preferences and Concerns (section III, 34 items), and of the Tourist Attractions Preference (section V, 68 items), to discover latent factors underlying the dataset, and therefore unveil which items had the strongest correlation to a given factor (DiStefano, Zhu, & Mindrila, 2009). All four EFA were performed using the principal components extraction method with Varimax rotation and Keiser normalization (Eigenvalue > 1), suppressing coefficients with a saturation below 0.40 in the factors. Items scoring in more than one factor, with a difference less than 0.10, were removed, as well as items with a communality below 0.50 that weren't contributing to the models adequacy (Bryman & Cramer, 1992; Marôco, 2010). Factors with low reliability (Cronbach's Alpha $\alpha < 0.60$) were also removed (Hair, Anderson, Tatham, & Black, 2009). Except for the BFI scale, the resulting factors were then renamed to more meaningful names, to better represent the concepts they were measuring (see Table 5.7, Table 5.9, and Table 5.11).

After performing the EFA, the Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA) methodologies (Byrne, 2016; Marôco, 2010) were conducted on each extracted scale, using IBM® SPSS® AMOS version 26. For each scale, a first order model was drawn to confirm if the observed variables (questionnaire items) saturated the latent variables, i.e., the extracted factors, and what correlations existed between them. For the estimations, the maximum likelihood method was applied. Several adjustments were needed to reach an acceptable/good goodness-of-fit of the models, such as eliminating items with a regression weight lower than 0.50 (Marôco, 2010), and covarying errors within the same factors as suggested by the largest modification indexes (maintaining only the ones with statistically significant covariances with values ≥ 0.10 (Marôco, 2010)), resulting in the proposed final scales, shown in Table 5.6, Figure 5.3, Figure 5.5, and Figure 5.7.

The resulting BFI scale was then used to predict the preference for the (I) proposed tourist attractions, (II) travel-related preferences and concerns, and (III) travel motivations, again using Structural Equation Modeling and CFA, applying the maximum likelihood method for estimation. To improve the models' fit, the same adjustment process used in the previous CFA was applied. This resulted in the final proposed models: "Personality vs Tourist Attractions Preference" (Figure 5.4), "Personality vs Travel Motivations" (Figure 5.6), and "Personality vs Travel-related preferences and concerns" (Figure 5.8).

All the obtained results are detailed in Section 5.4.

5.4 Results and Analysis

During the questionnaire dissemination, it was very hard to find the needed respondents, and we can say it was not related to the questionnaire's size, as we performed other type of questionnaires in other works, much smaller, and the same difficulty was found. Persons are not so available to help and probably they find boring to fill questionnaires, independently of their size.

We noticed respondents had some difficulties in filling the formation area question, as it was an open question due to the heterogeneity inherent to the possible responses. Many respondents did not know what to answer and responded areas that did not correspond to the intended. Extra work was needed to clean the data and make the right correspondence.

5.4.1 Sample Characterization

5.4.1.1 Demographics

As can be seen in Table 5.2 and Figure 5.1, the sample is composed mostly by Portuguese citizens (94%) of a varied age range, being the majority females (74%), adults and young adults (≤ 55 years old, 94%), with 70% between 23 and 55, and a mean of 35 years old. 60% of the respondents are in some sort of a relationship and 42% have children. Most of them live with their partners and/or children (53%), and 36% with their parents and/or other relatives (as 24% of the sample has less than 23 years old and many are still studying). As for the formation area, 31% are from "Engineering & Technology", 26% from "Social Sciences", followed by 13% from "Humanities", 11% from "Exact" and "Natural Sciences", and 10% from "Medical & Health Sciences", but only 69% have higher education. Regarding the professional situation, most of the sample represents employed workers (61%, where 8% are self-employed as employer or as isolated), 28% students, 7% working students, and the remaining 4% are unemployed, domestic, or retired. 25% of the respondents had already lived in other countries and 97% visited other countries, where 66% travelled to 4 or more countries in their life, and 56% to other continents besides Europe, within the last 2 years (79%, 6 months (41%)), meaning they have a richer experience of different cultures. Most of the sample travelled abroad 3 times or less per year (78%), meaning the contact with other

cultures, although diverse and recent, is not routinely experienced. When in leisure, most of the respondents (96%) travel accompanied, of which 79% are family.

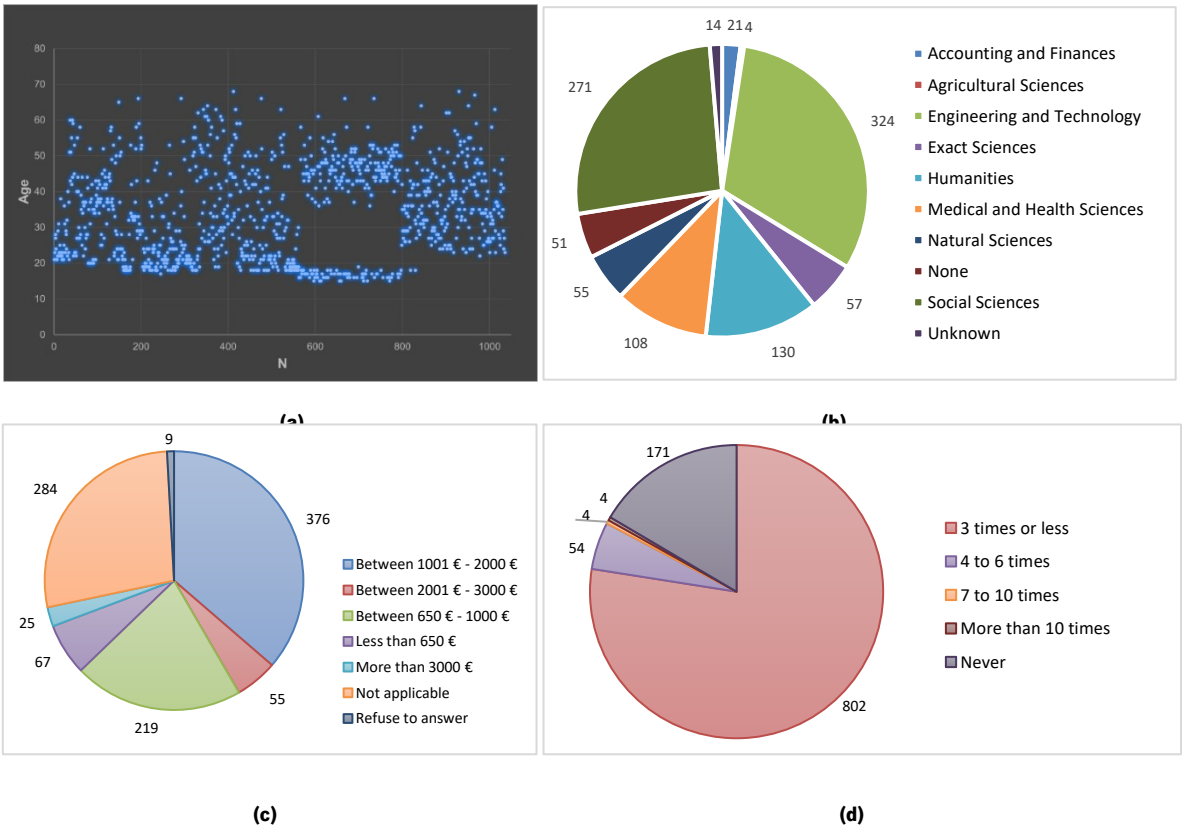
Table 5.2. Sample descriptive statistics (n=1035)

		n	%			n	%
Age	< 23	253	24.4	**Marital status**	Single	365	35.3
	23-35	303	29.3		In a relationship	185	17.9
	36-45	238	23.0		Non-marital partnership	71	6.9
	46-55	188	18.2		Married	360	34.8
	>55	53	5.1		Divorced/Separated	47	4.5
	Min = 15	Max = 68			Widow(er)	7	0.7
Sex	Female	769	74.3	**Has children**	No	604	58.4
	Male	266	25.7		Yes	431	41.6
Citizenship	Portuguese	970	93.7	**Lived in other Countries**	Yes	262	25.3
	Other	65	6.3		No	773	74.7
Higher education				**Health problems**	None	654	63.2
					Allergies/Intolerances	182	17.6
	No	325	31.4		Chronic disease	99	9.6
	Yes	710	68.6		Disability	16	1.5
					Combination	64	6.2
					Refused to answer	20	1.9
Formation area	Engineering & Technology	324	31.3	**Lives with**	Alone	87	8.4
	Exact Sciences	57	5.5		Partner and/or Children	546	52.8
	Humanities	130	12.6		Parents/Other relatives	374	36.1
	Medical & Health Sciences	108	10.4		Friends/Colleagues	28	2.7
	Natural Sciences	55	5.3	**Professional situation**	Employed	627	60.6
	Social Sciences	271	26.2		Student	293	28.3
	None/Unknown	65	6.3		Working student	70	6.8
	Other	25	2.4		Other	45	4.3
Liquid income (after taxes)	Less than 650€	67	6.5	**Professes a religion**	Yes	493	47.7
	Between 650-1000€	219	21.2		No, but believes in a God/Superior Being	230	22.2
	Between 1001-2000€	376	36.3		No, is agnostic	128	12.4
	Between 2001-3000€	55	5.3		No, is atheist	173	16.7
	More than 3000€	25	2.4		Refused to answer	10	1,0
	Not applicable	284	27.4	**Different countries visited**	3 or less	320	30.9
	Refused to answer	9	0.9		4 to 10	443	42.8
Continents visited	Europe	437	42.2		11 or more	237	22.9
	Europe, Africa	103	10.0		Never visited other countries	29	2.8
	Europe, Africa, America	128	12.4		Refused to answer	6	0.6

		n	%			n	%
	Europe, America	142	13.7	**Last time visited another country**	Last 6 months	425	41.1
	Europe, Asia, Africa, America	87	8.4		Last 2 years	389	37.6
	Other combinations	109	11,0		More than 2 years ago	188	18.2
	Never visited other continents	29	2.8		Never	33	3,1
Travel companions	Friends/Colleagues	158	15.3	**Travels abroad per year**	Never	171	16.5
	Partner	231	22.3		3 times or less	802	77.5
	Partner and children	277	26.8		4 to 6 times	54	5.2
	Relatives	312	30.1		7 to 10 times	4	0.4
	Nobody	41	4.0		More than 10 times	4	0.4
	Other	16	1.5				

Some statistics are not shown as they are related to another ongoing study.

Compared to the previous study (Alves et al., 2020), there are more adults between 23 and 55 years old (56% before, now 70%), and the number of respondents with children increased from 31% to 42%, meaning there are more participants supposedly with different responsibility/concerns. The formation areas are also more varied. The other sample characteristics remain similar.



(c) **(d)**

Figure 5.1. Respondents' (a) age range, (b) formation areas, (c) liquid income, (d) leisure travels abroad per year; n=1035

5.4.1.2 Personality

To assess the respondents' personality, the Big Five Inventory (44 items) was used, which is one of the most widely used personality inventories. The BFI assesses an individual on the Goldberg's Big Five dimension of personality (Lewis R Goldberg, 1990), using a 5-point Likert scale. To facilitate interpretation, instead of calculating the scores for each participant, the mean value for each personality dimension is presented. Figure 5.2 shows the responses distribution for each dimension.

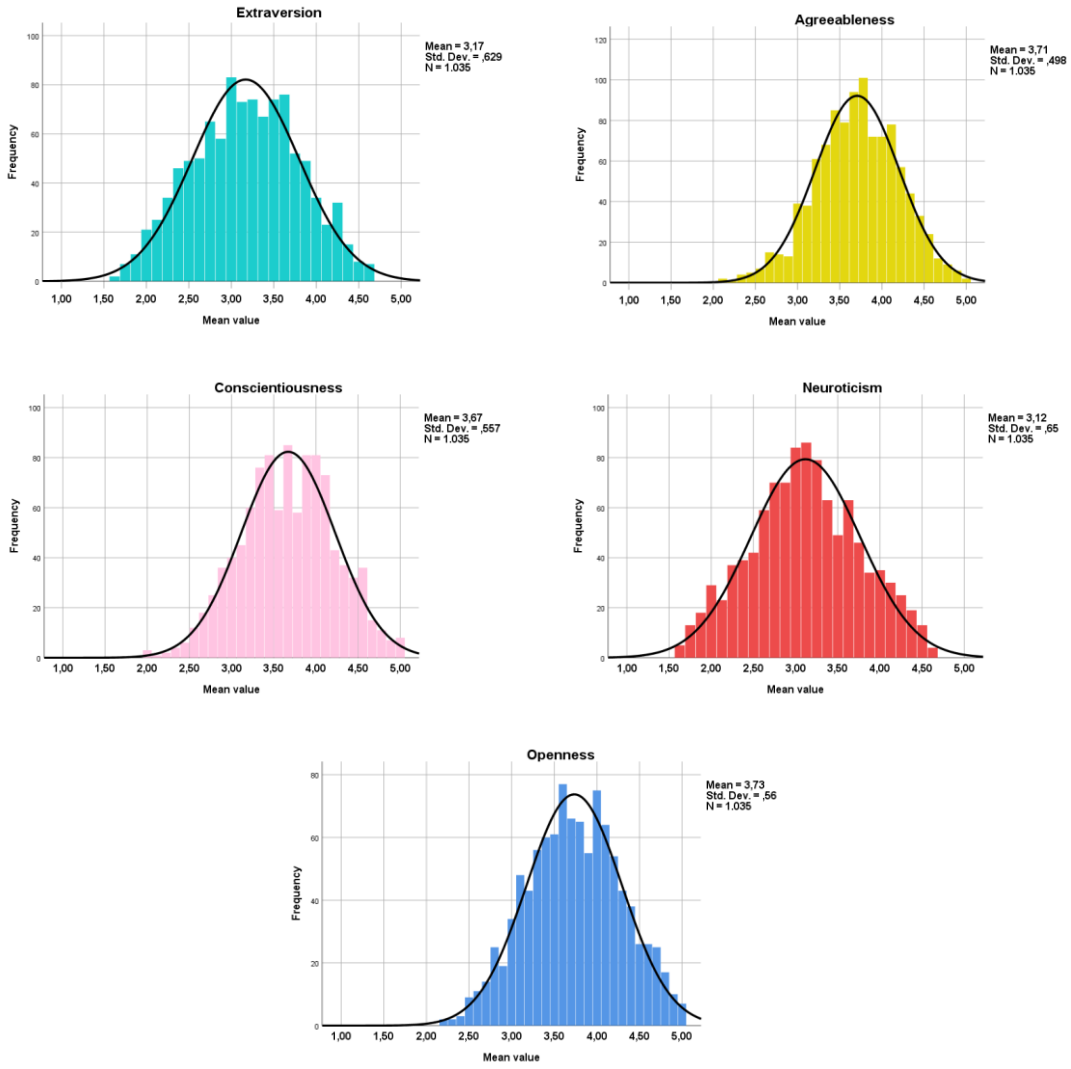


Figure 5.2. Distribution of the five personality dimensions responses (participants' mean value)

Clearly, there are 3 dimensions with responses above the mid-point, revealing a slight negative skewness, i.e., participants situated themselves more between "3-Neither agree nor disagree" and

"5-Agree strongly": agreeableness, conscientiousness and openness, confirming the results found in our previous study (Alves et al., 2020), reflecting the same social desirability bias, which usually happens more in self-reporting questionnaires (Pedregon et al., 2012), like the desire of being kind and moral in the case of agreeableness; truthful, self-effective and effortful in the case of conscientiousness; and more intellectual in the case of openness to experience. The other two dimensions, extraversion and neuroticism, have the mean value near the scale mid-point.

All five distributions follow the shape of a normal curve, and according to the values of skewness and kurtosis obtained, and respective standard errors, although having a slight skew and kurtosis, they are in acceptable ranges and the data is considered not significantly different from a normal distribution[23] (Field, 2013; Gravetter, Wallnau, Forzano, & Witnauer, 2020; Sposito, Hand, & Skarpness, 1983).

5.4.1.3 Tourist attractions preference

A total of 68 items representing a wide range of different tourist attractions, following the most significant terms from the United Nations World Tourism UNWTO (2001), were presented to the respondents in the questionnaire. Table 5.3 summarizes the aggregated results.

Table 5.3. Participants' preferences for tourist attractions, in percentage of agreement.

		Totally Disagree						Totally Agree
		1	2	3	4	5	6	7
A1	Go to a Gastronomy Festival (food and/or drinks)	5.7	6.6	7.0	14.1	*24.5*	*22.2*	*19.9*
A2	Watch a natural phenomenon (e.g., volcanic eruption or northern lights)	2.6	2.0	3.5	7.6	*12.7*	*25.9*	***45.7***
A3	Watch a religious celebration	*21.1*	*13.6*	*13.6*	*18.3*	15.9	9.9	7.6
A4	Visit the historic cities/villages of the destination	0.5	1.3	1.7	5.6	*13.1*	*30.6*	***47.1***
A5	Visit an oceanarium	7.6	5.8	8.2	*17.9*	*23.4*	*20.6*	*16.5*
A6	Visit caves/caverns/volcanoes	4.3	3.1	3.4	10.8	*19.1*	*27.5*	*31.8*
A7	Visit archaeological sites / ruins	1.4	2.4	3.1	12.0	*20.3*	*26.3*	*34.6*
A8	Attend cultural activities / artistic performances	1.4	1.7	4.3	11.1	*23.3*	*30.6*	*27.5*
A9	Go to the disco/nightclub	*28.3*	*16.0*	*12.9*	*16.0*	13.6	8.3	4.7
A10	Appreciate natural landscapes	0.2	0.3	0.8	3.0	*8.7*	*27.7*	***59.3***
A11	Do hiking / mountaineering	2.7	3.1	5.8	10.0	*24.9*	*24.4*	*29.0*
A12	Practice aquatic sports (e.g., sailing, canoeing, diving, jet skiing)	12.6	10.1	10.6	*17.8*	*16.0*	*15.5*	*17.4*
A13	Go to a theme park (e.g., Disneyland Paris)	6.4	6.8	6.4	10.7	*19.3*	*22.7*	*27.7*
A14	Undergo health and wellness treatments (e.g., hydrotherapy centers, mineral water resorts)	10.6	8.1	9.6	*18.1*	*21.1*	*15.0*	*17.6*

23 The statistics for the BFI responses can be found in Appendix B at http://www.gecad.isep.ipp.pt/grouplanner/dissemination.html (UMUAI Appendix).

		Totally Disagree						Totally Agree
		1	2	3	4	5	6	7
A15	Go to a Zoo	15.6	11.1	7.9	*18.1*	*18.7*	*14.9*	*13.7*
A16	Attend a typical celebration of the destination (e.g., popular celebrations, carnivals, fireworks)	2.4	1.5	3.3	8.9	*19.8*	*31.5*	*32.6*
A17	Go to a film festival	10.3	9.4	12.2	*21.0*	*21.0*	*14.8*	*11.4*
A18	Taste typical local dishes	0.7	1.0	1.6	5.6	*14.0*	*25.7*	***51.4***
A19	Visit a botanical garden	4.5	4.3	5.2	16.4	*24.4*	*23.9*	*21.3*
A20	Visit monuments (e.g. churches, cathedrals, castles, fortresses, monasteries, palaces, etc.)	1.0	1.5	3.4	5.7	*15.1*	*26.9*	***46.5***
A21	Visit a beach for its natural beauty	1.4	0.3	0.8	4.2	*11.0*	*27.0*	***55.5***
A22	Go to the beach (sunbathing/ swimming)	5.4	3.6	4.6	7.9	*17.7*	*21.3*	*39.5*
A23	To enjoy / buy local handicrafts	2.4	2.5	4.2	14.7	*27.0*	*23.8*	*25.5*
A24	Ride a bike	11.3	7.5	8.9	*19.8*	*22.4*	*16.5*	*13.5*
A25	Go to a funfair (e.g., amusements such as Ferris wheel, bumper cars, etc.)	14.0	10.0	9.9	*18.6*	*19.0*	*14.8*	*13.7*
A26	Attend gyms / fitness centers	*44.2*	*17.6*	*13.6*	11.1	7.1	3.9	2.6
A27	Go to a water park	16.9	10.0	11.2	15.9	16.2	13.5	16.2
A28	Go to a SPA / beauty center	*22.1*	*11.6*	*11.6*	*15.7*	14.7	12.0	12.4
A29	Do motorsports (e.g., karting, motocross)	*30.5*	*14.0*	*11.4*	14.8	12.2	8.9	8.2
A30	Have a picnic	6.7	5.6	6.3	17.3	*24.9*	*21.3*	*18.0*
A31	To go shopping / see storefronts (window shopping)	*18.4*	*13.6*	*11.5*	*18.6*	18.7	10.5	8.7
A32	Visit museums of historical themes	3.8	7.3	10.5	9.5	*19.1*	*22.5*	*27.2*
A33	Visit museums of scientific themes (e.g., planetarium, paleontology)	3.8	6.3	10.8	11.2	*19.3*	*24.0*	*24.6*
A34	Visit viewpoints of natural landscape	0.5	2.4	7.0	6.9	*11.5*	*24.7*	***47.1***
A35	Visit viewpoints of urban landscape	3.7	7.5	10.3	14.7	*20.4*	*21.3*	*22.1*
A36	Visit nature or wildlife reserves	1.8	1.3	2.8	7.4	*15.5*	*28.8*	*42.4*
A37	Observe sub-aquatic environments / marine life (e.g., snorkeling, submarine)	10.3	6.2	8.4	14.1	*15.3*	*20.2*	*25.5*
A38	Visit large man-made constructions (e.g., bridges, tunnels, mines)	6.3	6.1	11.3	16.4	*22.1*	*19.5*	*18.3*
A39	Go to a thematic parade (e.g., military, electronic music)	*19.0*	*13.8*	*16.1*	*20.3*	16.3	8.4	6.0
A40	Participate in a gastronomy tour (typical and/or gourmet dishes, wine tasting)	5.9	6.7	8.5	14.0	*24.4*	*20.9*	*19.6*
A41	Walk in the forest / woods	3.3	3.1	3.2	11.2	*24.3*	*28.1*	*26.8*
A42	Take a walk along the river / sea coast	1.1	1.2	2.2	6.3	*20.4*	*32.1*	*36.8*
A43	Go to a music festival/concert	8.5	6.6	9.8	15.3	*21.2*	*21.5*	*17.2*
A44	Go to a dance/ballet festival	15.0	11.4	12.9	18.4	17.6	14.0	10.8
A45	Go to balls (dancing)	*24.6*	*14.3*	*15.7*	*16.7*	12.8	8.2	7.7
A46	Practice climbing or bungee jumping	*30.2*	*13.3*	*13.2*	13.8	13.7	6.5	9.2
A47	Visit mountain areas / gorges	7.4	7.1	10.0	14.1	*21.7*	*20.0*	*19.5*
A48	Go to a live music bar/place	7.7	5.6	9.2	17.4	*23.6*	*21.2*	*15.4*
A49	Take boat trips to know the destination's coast	4.1	5.0	7.4	11.5	*20.4*	*25.0*	*26.6*
A50	Take boat trips for the historical value of the route	5.2	6.5	8.2	13.3	*20.7*	*24.0*	*22.1*
A51	Take boat trips for the pleasure of boating	12.9	10.0	10.8	*14.7*	*15.7*	*18.2*	*17.8*
A52	Take a walk in a city park	1.0	2.0	2.5	11.4	*25.1*	*33.1*	*24.8*
A53	Play ball sports (e.g., football, handball, volleyball, tennis)	*33.6*	*16.4*	*11.6*	13.5	11.3	6.4	7.1
A54	Do a safari	10.0	6.4	7.0	11.5	*20.4*	*19.2*	*25.6*
A55	Play at the casino	***52.2***	*15.1*	*10.8*	9.7	6.4	3.6	2.3

		Totally Disagree						Totally Agree
		1	2	3	4	5	6	7
A56	Assist to a sporting competition (e.g., watch a football game from a club of that country)	*34.8*	*12.0*	*10.3*	13.5	13.2	8.7	7.4
A57	Ride a horse	*25.3*	*11.9*	*10.7*	*15.3*	15.7	10.8	10.2
A58	Hunt / fish	***61.4***	*13.2*	*7.5*	7.8	4.3	2.9	2.8
A59	Participate in an escape game	*40.4*	*13.6*	*9.9*	13.7	9.6	6.0	6.9
A60	Watch a bullfight	***82.0***	*6.3*	*3.6*	4.0	2.1	0.8	1.3
A61	Go to the circus	***53.8***	*12.6*	*9.0*	10.4	7.1	3.7	3.5
A62	Go on a cruise	14.4	7.3	6.7	14.6	*17.2*	*17.6*	*22.2*
A63	Do air sports (e.g., parachute jump, skydiving, gliding)	*33.9*	*11.2*	*9.2*	11.8	11.6	10.0	12.4
A64	Go to the swimming pool to swim/dive	11.6	5.4	7.3	13.2	*18.6*	*19.4*	*24.4*
A65	Go to the swimming pool to relax	5.3	4.9	5.6	10.5	*18.8*	*23.1*	*31.7*
A66	Have vacation on an island	3.2	2.3	2.9	8.1	*18.5*	*27.2*	*37.8*
A67	Assist an opera/theater	13.3	7.5	8.4	15.3	*20.1*	*19.2*	*16.1*
A68	Ski	*28.9*	*9.5*	*10.2*	*16.0*	13.6	8.8	12.9

The highest values that contribute to most of the responses are italics, and the values that are similarly distributed are underlined. Values >45% are in bold.

Everyone seems to like almost all sort of tourist attractions when travelling on vacations, with a clear significant majority on attractions like watching a natural phenomenon, visit historic cities/villages, appreciate natural landscapes (including beautiful beaches), taste typical local dishes, and visit monuments. The opposite can also be said for attending gyms, playing at the casino, hunting/fishing, (decidedly) watching bullfights, and going to the circus, which are definitely not a choice when on vacation. What relationship exist between those preferences and the participants' personality? Section 5.4.2.2 shows the results.

5.4.1.4 Travelling motivations

The participants' travelling motivations were measured using Pearce and Lee (2005) proposed items, using the two items with highest loading for each motive. The items were then mixed up in the questionnaire's respective section so items from the same motive ended separated. The aggregated results can be found in Table 5.4.

Clearly, except for questions M8 and M22, participants are on the same side regarding motivations for travelling in leisure, confirming most motives proposed by Pearce and Lee (2005). To be close to nature, meet the locals, have adventuresome experiences, develop personal interests and skills, understand more about self & work on personal values, be with respectful persons, get isolated, feel the destination's atmosphere, experience something different, get away from everyday stress/demands, interact with family/friends & strengthen those relationships, have no obligations

& be independent, are all possible motives for travelling in leisure. The great majority also agreed that to meet new amorous partners and get recognized by others were not motives to go on vacation. It is obvious that not all motives are suitable for the same type of vacations and need to be contextualized. And is there a similar personality between similar travelling motives? In Section 5.4.2.3 we analyze how personality relates to those motives.

As previously mentioned, the participants responded quite differently to two questions measuring Pearce and Lee (2005) Nostalgia dimension, M8 and M22. Most of them agreed they want to think about good times spent in the past but are equally divided in reflecting on past memories (37% for agree and disagree). Although scoring in the same Nostalgia dimension, according to the results obtained, M8 is related to thinking about good memories, and M22 relates to past memories, either good or bad, possibly suggesting reflections akin to learning from experience (Table 5.4).

5.4.1.5 Travel-related preferences and concerns

One section of the questionnaire was related to travel-related preferences and concerns (Alves et al., 2020), where we asked the participants questions related to their preferences and concerns when travelling. The questions and aggregated results are shown in Table 5.5.

Much information can be obtained from the responses collected, but only the relevant for this study is presented. Most respondents: prefer outdoor activities but are not willing to take physical risks; like to study the destination's history prior to travelling but consider it is not important to plan the vacation days in advance and that there should be no time schedules; want the destination to include cultural/learning components and try to include as many attractions as possible; are not worried if there is no mobile phone network available; like destinations where few people have been to, considering important to see exotic attractions or different from their culture, but would never visit an important city without seeing its iconic monuments, not feeling more keen to visit a destination for being "in vogue" or mediatized; would not travel to a highly polluted or high criminality/armed conflicts destination; consider important the accommodation's comfort; always buy souvenirs; would accept a travel package from a travel agency but would like to be involved in the choice process; are not incommoded if they have to spend vacations with strangers or travel in a group organized by a travel agency, but would prefer to travel with tourists similar to them, all corresponding to a data distribution with positive or negative skewness. It is important to notice that

although these results represent the median tourist, they do not mean that for each tourist the preferences cluster this way.

Table 5.4. Participants' travelling motivations, in percentage of agreement (questions adapted from Pearce and Lee (2005)).

		Totally Disagree						Totally Agree
		1	2	3	4	5	6	7
M1	Being close to nature	1.1	1.1	3.1	9.3	*19.5*	*29.5*	*36.5*
M2	Meeting the locals	1.7	2.4	4.8	12.9	*23.7*	*28.8*	*25.6*
M3	Having daring/adventuresome experience	3.4	3.5	7.6	16.9	*24.3*	*24.7*	*19.6*
M4	Develop my personal interests	0.1	0.3	0.8	5.9	*17.9*	*36.3*	*38.7*
M5	Being with respectful people	0.4	0.3	0.9	8.4	*12.4*	*29.7*	***48.0***
M6	Understanding more about myself	1.4	1.8	2.6	16.3	*18.1*	*26.2*	*33.6*
M7	Being away from the crowds of people	3.3	5.9	9.2	*26.8*	*20.7*	*16.5*	*17.7*
M8	Thinking about good times I've had in the past	4.5	6.6	7.4	*23.3*	*18.2*	*19.1*	*20.9*
M9	Having romantic relationships	*25.4*	*13.2*	*7.0*	*20.6*	11.8	11.5	10.5
M10	Showing others I can do it	*22.3*	*13.4*	*11.2*	*23.8*	11.5	9.6	8.2
M11	Feeling the special atmosphere of the vacation destination	0.5	0.6	1.0	6.6	*17.4*	*32.6*	*41.4*
M12	Getting away from everyday psychological stress/pressure	0.5	0.7	1.5	4.3	*9.8*	*25.5*	***57.8***
M13	Doing something with my family/friend(s)	0.3	0.1	0.3	4.8	*11.0*	*27.7*	***55.7***
M14	Being obligated to no one	3.5	3.4	4.0	13.3	*13.9*	*20.6*	*41.4*
M15	Getting a better appreciation of nature	0.7	1.6	1.4	7.6	*16.9*	*28.1*	*43.6*
M16	Observing other people in the area	3.2	3.8	4.7	17.1	*21.2*	*23.5*	*26.6*
M17	Experiencing thrills	3.9	3.9	7.7	*18.6*	*25.6*	*18.3*	*22.0*
M18	Developing my skills and abilities	1.7	1.3	4.0	*14.5*	*21.6*	*26.4*	*30.5*
M19	Being near considerate people	1.3	1.7	2.4	*13.4*	*20.8*	*28.1*	*32.3*
M20	Working on my personal/spiritual values	2.8	2.7	5.0	*20.6*	*19.7*	*24.0*	*25.2*
M21	Enjoying isolation	7.4	10.0	10.5	*23.6*	*20.8*	*14.4*	*13.3*
M22	Reflecting on past memories	11.6	12.4	13.0	26.0	14.6	10.8	11.6
M23	Meeting amorous partners	***53.8***	*15.5*	*5.7*	*13.7*	4.8	3.8	2.7
M24	Being recognized by other people	*23.9*	*11.7*	*11.6*	*21.7*	14.4	8.7	8.0
M25	Experiencing something different	0.9	1.2	1.3	8.6	*20.9*	*28.8*	*38.5*
M26	Getting away from the usual demands of life	0.9	1.1	1.6	6.5	*11.2*	*26.1*	***52.7***
M27	Strengthening relationships with my family/friend(s)	1.4	0.4	1.2	6.7	*14.1*	*28.5*	***47.7***
M28	Being independent	3.8	2.8	3.8	*17.7*	*17.4*	*22.8*	*31.8*

The highest values that contribute to most of the responses are italics, and the values that are similarly distributed are underlined. Values >45% are in bold

Curiously, there is a clear "balanced" division in some responses: 40% of the respondents would prefer to dine with at most 5 people and 43% would not; 41% is not afraid of getting ill or accidents while on vacations and 46% is; 33% care about the money spent on vacation and 31% do not care; 41% agree it is always better to travel in group, regardless of the destination, and 40% do not; 41% are not afraid of getting lost in a distant country, but 45% are; 32% prefer to have a good surprise while 28% prefer to fulfill expectations; 30% are indifferent if they contribute to the destination's local economy but 34% like to feel they contribute. Regarding the destination's weather conditions,

35% prefer hot weather, but also 35% do not have a preference, and 28% like warm weather. Cold weather is not a choice for the respondents. Most participants have some sort of phobias/fears (e.g., fear of heights, confined spaces, etc.).

Probably not all preferences and concerns were chosen by the same type of participants. Do personality dimensions predict travel-related preferences and concerns? If so, which ones? In Section 5.4.2.4, we answer those questions.

Table 5.5. Participants' travel-related preferences and concerns, in percentage of agreement.

		Totally Disagree						Totally Agree
		1	2	3	4	5	6	7
P1	When travelling on leisure, I prefer outdoor activities	1.1	2.1	4.0	11.0	*22.4*	*30.5*	*28.9*
P2	Under no circumstances I like to take risks related to my physical integrity	3.8	9.3	13.6	*14.4*	*15.8*	*18.4*	*24.7*
P3	A dinner with friends ideally should have a maximum of 6 people	16.3	13.8	12.4	17.5	15.6	13.1	11.3
P4	When going on vacations I take into account the destination's cultural offer	1.5	3.0	5.4	12.5	*16.2*	*29.8*	*31.6*
P5	I am afraid of getting ill or having accidents whilst away on vacations	11.8	17.6	11.4	13.6	17.2	14.8	13.6
P6	I would never travel to a place where there was no mobile phone network	*21.4*	*18.5*	*14.7*	*14.9*	10.4	10.5	9.6
P7	When planning vacations, I try to include as many places/attractions as possible	2.0	4.9	7.1	13.8	*18.4*	*24.3*	*29.5*
P8	To be perfect, a vacation needs that every day is planned in advance	*14.5*	*16.3*	*17.5*	*15.7*	16.3	12.1	7.5
P9	Within my possibilities, when on a vacation I don't look at expenses	10.8	14.8	18.6	16.4	17.1	13.5	8.8
P10	Before travelling I like to know/study the history of the destination	3.1	5.2	9.6	14.1	*22.9*	*24.2*	*21.0*
P11	Regardless of the destination, it is always better to travel in group	10.9	14.3	14.8	*19.5*	15.6	12.7	12.3
P12	In a distant country, one of my worst fears would be to get lost	12.8	14.6	13.7	13.7	15.0	15.6	14.7
P13	I like to go where few people have been to before	7.7	9.6	11.6	*23.6*	*16.7*	*17.1*	*13.7*

		Totally Disagree						Totally Agree
		1	2	3	4	5	6	7
P14	For me, to feel comfort is always the most important (quality of facilities/products)	3.3	7.0	11.7	*17.3*	*29.4*	*19.4*	12.0
P15	For me, to fulfill expectations is more important than a good surprise	8.7	14.1	17.6	25.7	15.2	12.7	6.1
P16	When on vacations abroad, I like to feel that I am contributing to the local economy	8.2	8.2	10.1	30.3	19.2	15.1	8.8
P17	For me, while on vacations there should be no time schedules	3.2	7.1	11.9	14.9	*18.4*	*20.3*	*24.3*
P18	For me, a good vacation has to include a cultural/learning component	1.9	3.9	5.1	14.0	*24.3*	*25.8*	*25.0*
P19	I would never visit a great city without seeing its iconic monuments	3.9	4.3	7.0	10.2	*18.9*	*23.8*	*31.9*
P20	I would never travel to a destination with high pollution levels	4.6	10.3	*18.3*	*19.8*	*15.9*	*17.4*	*13.6*
P21	For me, it's important to see exotic things or that are very different from my culture	1.5	4.9	6.7	16.5	*20.8*	*26.0*	*23.6*
P22	When I return from a vacation, I always bring souvenirs for me, family or friends	4.2	6.8	4.4	10.0	*16.5*	*22.3*	*35.7*
P23	If a destination is "in vogue" or appears in the media, I feel more like visiting it	*14.6*	*14.7*	*17.0*	*22.1*	*16.4*	9.4	5.8
P24	I would be willing to travel in a group organized by a travel agency	8.4	10.2	11.5	*15.8*	*17.6*	*18.2*	*18.3*
P25	I would never go on vacation with strangers (making common trips and meals)	*16.3*	*17.4*	*17.9*	*16.5*	11.7	10.7	9.5
P26	If I were to travel in a group, I would rather do it with people similar to me	3.0	3.9	7.3	*20.1*	*23.9*	*23.6*	*18.3*
P27	I would never travel in a group due to privacy reasons	*34.2*	*21.4*	*15.4*	14.1	6.6	4.0	4.4
P28	I would be incapable of travelling to a high criminality rate / armed conflict destination	2.9	6.9	7.6	9.7	*13.7*	*21.5*	*37.7*

		Totally Disagree						Totally Agree
		1	2	3	4	5	6	7
P29	I like to visit uncommon places or observe peculiar things (e.g., world records, pop icons, historical items, etc.)	2.2	4.6	8.2	*17.9*	*24.9*	*23.7*	*18.5*
P30	I'm afraid of:			P31	When planning vacations, I generally prefer to go a place with:			
	Heights	*30.9*			Cold weather	2.5		
	Travelling on water	3.4			Warm weather	*27.6*		
	Flying	3.6			Hot weather	*35.0*		
	Being under water	*11.6*			I don't have a preference	*34.9*		
	Confined spaces	*14.1*						
	Other	5.4						
	I have no fears	*31.0*						
P34	Considering an itinerary / vacation plan presented by a travel agency, I would prefer:	To have a complete proposal, with everything defined, 'ready to use'		24.3	To be involved in the choice process, have more control and monitor all stages of the process			*75.7*

The highest values that contribute to most of the responses are italics, and the values that are similarly distributed are underlined
Some questions are not shown as they are related to another ongoing study.

5.4.2 How does Personality predict Preferences for Tourist Attractions, Travel Motivations, Preferences and Concerns?

In this section, we present the results of the EFA and CFA performed on the questionnaire items for each studied travel aspect, except for personality, where we present only the CFA results.

5.4.2.1 Personality

The EFA of the BFI responses confirmed the Big Five personality dimensions, aggregating the items into the expected personality dimensions. CFA confirmed the EFA results (Table 5.6), but some items were removed due to a regression weight < 0.45 (we considered items above this threshold as the scale consistency increased), resulting in 21 items from the 44 in the original scale, as the items used in the proposed models had to represent the sample used for the study. This probably means the sample needed to be larger to maintain all the 44 items.

All the dimensions' Cronbach's Alpha crossed the 0.60 threshold for psychological variables (John & Benet-Martínez, 2000), having an acceptable to good reliability (George & Mallery, 2019). The

full scale α is acceptable (α = 0.685), confirming the items in the scale were related to the same concepts, as expected. The model fit has a χ^2/df value of 3.590 (acceptable), a CFI of 0.928, GFI of 0.945, PCFI of 0.769 and PGFI of 0.712, revealing a good goodness-of-fit, and the RMSEA = 0.050 and p(RMSEA<=0.05) = 0.485 a very good adjustment (Marôco, 2010). The scale is therefore suitable for the study.

5.4.2.2 Personality vs Tourist Attractions Preference

As a result of performing the EFA on the 68 items representing the tourist attractions, several items were eliminated[24] according to the criteria previously referred (Section 5.3), resulting in a final scale with 50 items, and 11 factors extracted that explained 64% of the total variance. The 11 factors aggregated items measuring the same concepts, as shown in Table 5.7 and by their high Cronbach's Alpha reliability values[25]. The sampling adequacy (Kaiser-Meyer-Olkin, KMO = 0.886) is good (Pestana & Gageiro, 2008), and the correlation between the variables is significative (Bartlett's Test of Sphericity Sig. = 0,000, < 0,05). The reliability for the full scale is excellent (α = 0.914), confirming the items in the scale are all related to the same concept, and can therefore be used as a reference. The obtained factors were then named to meaningful descriptions representing the concepts we believe they symbolized.

The CFA of the extracted factors showed the observed variables (attractions items) saturated the latent variables (factors, i.e., tourism categories), confirming the items were correctly related to the proposed tourism categories (Figure 5.3). The items A3, A5, A18, A38, A56, A59, and A60 had to be removed from the model, as they had a regression weight < 0.50 (see Section 5.3). All factors' regression weights were statistically significant in the prediction of their respective items for p < 0.001*** (two-tailed). The model revealed an overall acceptable goodness-of-fit (χ^2/df=5.649, CFI=0.823, GFI=0.815, PCFI=0.732, PGFI=0.693, RMSEA=0.067, p(RMSEA ≤ 0.05)=0.000), meaning the model is valid and that the items provide an acceptable fit for the proposed model, confirming the proposed "Tourism Categories" model.

24 Although aggregating in factors that seemed to measure the same concepts, the items with coefficients < 0.40, communalities < 0.50, that belonged to factors with a low reliability (α < 0.60), that were scoring alone, or that were scoring in more than one factor, with a difference less than 0.10, were eliminated from the sample: A7, A8, A16, A19, A21, A23, A24, A26, A30, A31, A51, A52, A53, A54, A57, A61, A62, A67.
25 Being an exploratory analysis, it is acceptable to consider factors with Cronbach's Alpha values ≥ 0.60 (Hair et al., 2009).

By calculating the mean value each participant scored for the Tourism Categories (factor scores), it was possible to find that there are kinds of tourist attractions that participants always like to include in their vacations, independently of their personality, as is the case of Wild Nature Activities (F2), Sun, Water & Sand (F4), Museums, Boat trips & Viewpoints (F5), Cultural heritage (F7), Gastronomy events (F9), and Natural phenomena (F11). The opposite can be said for Sports & Games (F8), where most of the respondents did not consider important to include them in their leisure vacations. This is in line with the results found in Section 5.4.1.3[26].

Table 5.6. Confirmatory Factor Analysis of the Big Five Inventory responses, confirming the 5 personality factors extracted using EFA and their respective items, the standardized regression weights between the items and factors (all items are statistically significant at ***p<0.001 level (2-tailed)), and each factor's Cronbach's Alpha reliability (α).

Factor	Item	Description	Regression Weight	α
Openness	5	Is original, comes up with new ideas	0.784	0.810
	15	Is ingenious, a deep thinker	0.594	
	20	Has an active imagination	0.669	
	25	Is inventive	0.796	
	40	Likes to reflect, play with ideas	0.475	
Conscientiousness	13	Is a reliable worker	0.591	0.697
	28	Perseveres until the task is finished	0.561	
	33	Does things efficiently	0.628	
	38	Makes plans and follows through with them	0.543	
Extraversion	1	Is talkative	0.462	0.761
	11	Is full of energy	0.686	
	16	Generates a lot of enthusiasm	0.738	
	36	Is outgoing, sociable	0.579	
Agreeableness	7	Is helpful and unselfish with others	0.574	0.671
	32	Is considerate and kind to almost everyone	0.534	
	42	Likes to cooperate with others	0.689	
Neuroticism	4	Is depressed, blue	0.513	0.766
	9R	Is relaxed, handles stress well	0.733	
	24R	Is emotionally stable, not easily upset	0.640	
	34R	Remains calm in tense situations	0.681	
	39	Gets nervous easily	0.608	
			Full scale α	0.685

The full scale α is also presented at the end of the table

Table 5.7. Varimax rotated component matrix for the proposed Tourism Categories, showing the 11 factors extracted using EFA and their respective items, the estimated correlations between the items and factors, and each factor's Cronbach's Alpha reliability (α).

Factor	Item	Description	Estimated correlation	α
Adrenaline	A46	Practice climbing or bungee jumping	0.799	0.862
Activities	A63	Do air sports (e.g., parachute jump, skydiving, gliding)	0.774	
F1	A68	Ski	0.734	
	A12	Practice aquatic sports (e.g., sailing, canoeing, diving, jet skiing)	0.711	

26 The corresponding graphics can be found in Appendix C at http://www.gecad.isep.ipp.pt/grouplanner/dissemination.html (UMUAI Appendix)

Factor	Item	Description	Estimated correlation	α
	A29	Do motorsports (e.g., karting, motocross)	0.658	
	A37	Observe sub-aquatic environments / marine life (e.g., snorkeling, submarine)	0.521	
	A59	Participate in an escape game	0.436	
Wild Nature Activities F2	A41	Walk in the forest / woods	0.843	0.836
	A11	Do hiking / mountaineering	0.760	
	A42	Take a walk along the river / seacoast	0.667	
	A10	Appreciate natural landscapes	0.655	
	A47	Visit mountain areas / gorges	0.618	
	A36	Visit nature or wildlife reserves	0.546	
Party, Music & Nightlife F3	A43	Go to a music festival/concert	0.796	0.850
	A44	Go to a dance/ballet festival	0.790	
	A45	Go to balls (dancing)	0.743	
	A48	Go to a live music bar/place	0.677	
	A17	Go to a film festival	0.596	
	A9	Go to the disco/nightclub	0.581	
	A39	Go to a thematic parade (e.g., military, electronic music)	0.472	
Sun, Water & Sand F4	A65	Go to the swimming pool to relax	0.803	0.815
	A64	Go to the swimming pool to swim/dive	0.745	
	A22	Go to the beach (sunbathing/ swimming)	0.707	
	A66	Have vacation on an island	0.694	
Museums, Boat trips & Viewpoints F5	A34	Visit viewpoints of natural landscape	0.786	0.857
	A32	Visit museums of historical themes	0.780	
	A33	Visit museums of scientific themes (e.g., planetarium, paleontology)	0.742	
	A50	Take boat trips for the historical value of the route	0.729	
	A49	Take boat trips to know the destination's coast	0.714	
	A35	Visit viewpoints of urban landscape	0.707	
Theme & Animal Parks F6	A15	Go to a Zoo	0.774	0.803
	A13	Go to a theme park (e.g., Disneyland Paris)	0.670	
	A5	Visit an oceanarium	0.667	
	A27	Go to a water park	0.619	
	A25	Go to a funfair (e.g., amusements such as Ferris wheel, bumper cars, etc.)	0.563	
Cultural Heritage F7	A20	Visit monuments (e.g. churches, cathedrals, castles, fortresses, monasteries, palaces, etc.)	0.775	0.632
	A4	Visit the historic cities/villages of the destination	0.690	
	A38	Visit large man-made constructions (e.g., bridges, tunnels, mines)	0.539	
	A3	Watch a religious celebration	0.531	
Sports & Games F8	A58	Hunt / fish	0.713	0.668
	A60	Watch a bullfight	0.698	
	A55	Play at the casino	0.561	
	A56	Assist to a sporting competition (e.g., watch a football game from a club of that country)	0.499	
Gastronomy Events F9	A1	Go to a Gastronomy Festival (food and/or drinks)	0.798	0.735
	A40	Participate in a gastronomy tour (typical and/or gourmet dishes, wine tasting)	0.770	
	A18	Taste typical local dishes	0.693	
Health & Well-being F10	A14	Undergo health and wellness treatments (e.g., hydrotherapy centers, mineral water resorts)	0.724	0.801
	A28	Go to a SPA / beauty center	0.626	

Factor	Item	Description	Estimated correlation	α
Natural Phenomena F11	A2	Watch a natural phenomenon (e.g., volcanic eruption or northern lights)	0.686	0.639
	A6	Visit caves/caverns/volcanoes	0.626	
			Full scale α	0.914

The full scale α is also presented at the end of the table

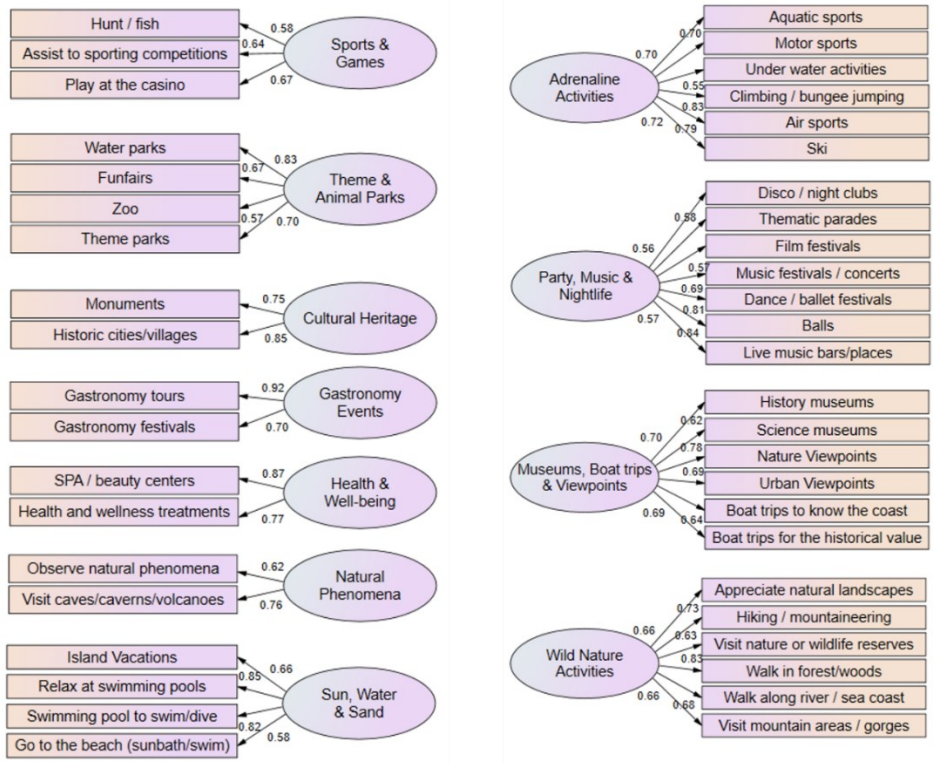


Figure 5.3. Simplified Structural Equation Model for the proposed "Tourism Categories" model, obtained using CFA. For readability, only the regression weights (standardized) are presented ($\lambda \geq 0.5$).

In order to answer one of this study's research questions, the Personality dimensions were related to the Tourism Categories obtained, using CFA. As shown in Figure 5.4 and Table 5.8, there is a clear relationship between the Big Five personality dimensions and the preference for tourist attractions.

The model's fit indicators show an overall acceptable goodness-of-fit (χ^2/df=4.409, CFI=0.771, GFI=0.767, PCFI=0.721, PGFI=0.696, RMSEA=0.057, p(RMSEA ≤ 0.05)=0.000), suggesting the items provide a satisfactory fit, confirming the proposed "Personality vs Tourist Attractions Preference" model.

By analyzing the model, interesting relationships were found, confirming most results in our previous study (Alves et al., 2020). Individuals with a high preference for Adrenaline Activities show a

high extraversion and low conscientiousness. This is in line with the findings reported in literature by Jani (2014b) and Delic, Neidhardt, and Werthner (2016), and with the dimensions themselves, since a positive extraversion is related to individuals who are adventurous, daring, and that seek excitement, taking unnecessary risks for adrenaline, and a negative conscientiousness to persons who are more spontaneous, less thoughtful and cautious (Costa Jr et al., 1995). The other personality dimensions did not present statistically significant values to be considered.

Wild Nature Activities are associated to the Nature category extracted in the previous study, but the item related to caves/volcanoes went to a new category representing natural phenomena, better refining the proposed model, which was accomplished by the sample improvement. Wild Nature Activities are preferred by extraverted and agreeable persons with low conscientiousness, which is in line with the dimensions' definition, since extraverted individuals are more energetic, have a high level of activity and seek excitement and adventures, which can be accomplished by performing the wild nature activities proposed in our model. The same can be said for agreeableness, where we can easily relate traits like being generous, empathetic, unable to manipulate others, and to put the interests of others first, to concerns for nature. Regarding the low conscientiousness, if we look at type of activities that can be performed in wild nature, such as mountaineering, visit gorges, do safaris, and so on, we can find that it requires some stomach and less caution, which are characteristics of a low conscientious person. These results confirm the findings related to extraversion by Schneider and Vogt (2012), S. C. Plog (2002), Bujisic et al. (2015), Jani (2014b), Neidhardt et al. (2015), and Delic, Neidhardt, and Werthner (2016); to agreeableness by Hirsh (2010) and Kvasova (2015); and to conscientiousness by Jani (2014b) and Delic, Neidhardt, and Werthner (2016).

All five personality dimensions were found to predict preferences for Party, Music & Nightlife activities/attractions, with negative values for openness to experience, conscientiousness, and agreeableness, and positive for neuroticism with a very strong influence from extraversion. First, we can see that the duplication of respondents in this study brought a more refined model, dropping the items related to attending opera/theater and other cultural events, which were contributing to a positive agreeableness and openness to experience in the previous study where we were forced to name the tourism category with a different name. The remaining items explain the negative values

of those two dimensions. Although the agreeableness weight is close to zero, and not considered relevant for the tourism category, nightlife is associated with "violent" behaviors. A negative openness may reveal not so intellectually oriented or interested in art or educative programs persons. Less thoughtful and cautious, who are willing to spend large amounts of money for momentaneous pleasure, and more spontaneous persons can explain the negative conscientiousness. The strong influence of extraversion is related to very sociable, energetic, excitement-seeking, and high-spirited individuals, characteristics commonly associated to nightlife activities and events with large groups of people. To the best of our knowledge, we were the first to study this type of activities and relate them to the Big Five.



Figure 5.4. Simplified Structural Equation Model for the proposed "Personality vs Tourist Attractions Preference" model, obtained using CFA. For readability, only the regression weights (standardized) for the Tourism Categories items are presented ($\lambda \geq 0.5$). The regression weights for the relationship between the Personality Dimensions and Tourism Categories can be found in Table 5.8

To swim or relax at the beach/swimming pool, or spend vacations on an island, are activities strongly related to high extraversion, negative openness, and slightly neurotic persons (in line with the Sun Lover type (Delic, Neidhardt, & Werthner, 2016; Gibson & Yiannakis, 2002)). These results support the ones found in the previous study, except openness, which now is negative, supporting the outcomes found by Jani (2014b) for that dimension, which are related to spend time

with family and lay at the beach. Neuroticism can be related to the need for predictable vacations, which can be found in typical beach/hotel-related vacations.

Table 5.8. Standardized regression weights for the relationship between the BFI dimensions and the preference for Tourist Attractions, obtained using CFA.

Tourism Category	BFI Dimension	Regression Weight	p
Adrenaline Activities	**Extraversion**	**0.715**	***
F1	**Conscientiousness**	**-0.320**	***
	Agreeableness	0.024	0.524
	Neuroticism	0.012	0.706
	Openness	-0.039	0.224
Wild Nature Activities	**Extraversion**	**0.404**	***
F2	**Agreeableness**	**0.573**	***
	Conscientiousness	**-0.223**	***
	Neuroticism	0.053	0.120
	Openness	0.017	0.608
Party, Music & Nightlife	**Extraversion**	**0.751**	***
F3	**Agreeableness**	**-0.050**	***
	Neuroticism	**0.129**	***
	Openness	**-0.115**	***
	Conscientiousness	**-0.108**	**0.003**
Sun, Water & Sand	**Extraversion**	**0.617**	***
F4	**Neuroticism**	**0.076**	**0.026***
	Openness	**-0.232**	***
	Agreeableness	0.008	0.827
	Conscientiousness	0.016	0.648
Museums, Boat trips & Viewpoints	Extraversion	0.063	0.097
F5	**Agreeableness**	**0.525**	***
	Neuroticism	**0.078**	**0.033***
	Openness	**0.078**	**0.029***
	Conscientiousness	**-0.182**	***
Theme & Animal Parks	**Extraversion**	**0.790**	***
F6	**Agreeableness**	**-0.123**	**0.003**
	Neuroticism	**0.128**	***
	Openness	**-0.204**	***
	Conscientiousness	**-0.077**	**0.026***
Cultural Heritage	**Agreeableness**	**0.625**	***
F7	Openness	-0.006	0.085
	Extraversion	-0.019	0.612
	Neuroticism	0.044	0.213
	Conscientiousness	-0.006	0.864
Sports & Games	**Extraversion**	**0.717**	***
F8	**Agreeableness**	**-0.309**	***
	Openness	**-0.152**	***
	Conscientiousness	**-0.150**	***
	Neuroticism	0.010	0.796
Gastronomy Events	**Extraversion**	**0.459**	***
F9	**Agreeableness**	**0.187**	***
	Openness	**-0.116**	**0.002**
	Conscientiousness	**-0.089**	**0.023***
	Neuroticism	-0.010	0.784

Tourism Category	BFI Dimension	Regression Weight	p
Health & Well-being	**Extraversion**	**0.649**	***
F10	**Agreeableness**	**-0.168**	***
	Neuroticism	**0.144**	***
	Openness	**-0.143**	***
	Conscientiousness	**0.079**	**0.029***
Natural Phenomena	**Extraversion**	**0.336**	***
F11	**Agreeableness**	**0.605**	***
	Conscientiousness	**-0.365**	***
	Neuroticism	0.045	0.246
	Openness	0.020	0.598

Statistically significant values are in bold and shaded in green (* p < 0.05 (2-tailed), ** p < 0.01 (2-tailed), *** p < 0.001 (2-tailed))

The categories Museums & Landscapes and Boat Tours from the previous study merged into the new category Museums, Boat trips & Viewpoints, dropping the item related to boating just for the pleasure of it. The EFA in the increased sample allowed to find similarities between the two factors, proposing they should belong to the same factor. They all have in common to view/appreciate some natural or historical scenery, which was not the case of boating for pleasure. These preferences were found to be predicted by four personality dimensions, with a stronger influence from a positive agreeableness and negative conscientiousness, probably because less cautious people are more willing to take boat trips, and since viewpoints are generally located in high places, high conscientious persons may not be willing to go as they might be more susceptible to heights. The other two dimensions slightly positively influenced the preference, having a small relevance in the prediction.

Going to a water park, funfairs, zoo or theme parks are activities preferred by highly extraverted persons (energetic and excitement-seeking), slightly neurotic (individuals that feel more comfortable with friends and family), with negative agreeableness, openness (individuals who prefer familiarity, standard and not so intellectually challenging activities), and conscientiousness (revealing persons that are willing to take minor risks). With the new data, we observed a twist in the impact of agreeableness, which now is negative.

Monuments and historic cities/villages are the type of attractions preferred by highly agreeable persons, probably the ones that easily accompany family and friends just to make them happy, confirming the results found by Neidhardt et al. (2015) and Jani (2014b). Contrary to our previous study, we could not find relationship between the other four personality dimensions.

Sports & Games, like to enjoy sporting competitions, play at the casino, and hunt/fish, are preferences predicted by high extraversion values, which can derive from the energy, excitement and gregariousness inherent to this type of activities, but also to the need of competitiveness and dominating/be the best, confirming the findings of Schneider and Vogt (2012) and Neidhardt et al. (2015); but negative agreeableness, openness and conscientiousness, verifying the findings of Jani (2014b), who reported the Gamer type was related to low agreeableness and conscientiousness individuals. The difference in agreeableness from the previous study can be due to the items removed related to practicing ball sports and escape rooms, which are activities that involve cooperativeness and more open individuals. Negative openness and conscientiousness might by related to individuals who are willing to break rules and act without thinking.

Gastronomy tours/festivals are positively sought by extraverted and agreeable individuals with some negative openness and conscientiousness. This is in line with the results we previously found that who enjoys wine and food are generally high-spirited and cheerful persons. A low conscientiousness and openness can be due to less awareness or not caring for health issues persons, generally having a great pleasure in food/wine tasting and/or "addicted" in consuming more than needed allied to a low intellect, as this category is not directed for fine dining activities.

All personality dimensions are related to Health & Wellbeing (attending SPA/beauty centers and health and wellness treatments), with a clear prediction by highly extraverted (are not worried about exhibiting their body/intimacy), slightly conscientious (care for their health/wellbeing) and neurotic individuals (again worried for their health, or that stress out easily, being this sort of activities a way of relaxing), with low openness and agreeableness (more conservative, preferring routine and more interested in their own problems).

Finally, a new tourism category related to observing Natural Phenomena (like visiting caves/volcanoes or assisting to northern lights, volcanic eruptions) arose. A positive agreeableness is the most weighting dimension, followed by extraversion, and a negative conscientiousness, which is the same profile as for Wild Nature Activities.

Although some personality dimensions did not have a significant correlation to the choice of certain tourist attractions, it does not mean those correlations do not exist, but that a greater and more representative sample for each type of profile is needed. Also, it is important to note that the re-

sults found show that only some characteristics from each personality dimension explain the preferences for tourist attractions, indicating that the preferences could be finer predicted by using a questionnaire to evaluate each dimension's six traits more precisely, supporting the issues reported by Yee et al. (2011). For example, a person considered extraverted may not be a risk taker or like adrenaline activities. It wouldn't be very good if the RS suggested bungee jumping to the tourist.

All the different tourism categorizations and personality dimensions fall short when compared to the individual experience that a specific destination/attraction can offer, for example, the medieval fair in Sines, Portugal, is one of the greatest fairs, recreating historical moments, but there are others that are simple and are more commercially oriented.

5.4.2.3 Personality vs Travelling Motivations

As a result of performing the EFA on the 28 items representing the travelling motivations, four items were eliminated[27] according to the criteria previously referred (Section 5.3), resulting in a final scale with 24 items, and 6 factors extracted that explained 62% of the total variance. The 6 factors aggregated items measuring the same concepts or somehow related, as shown in Table 5.9 and by their high Cronbach's Alpha reliability values. The sampling adequacy (Kaiser-Meyer-Olkin, KMO = 0.853) is good (Pestana & Gageiro, 2008), and the correlation between the variables is significative (Bartlett's Test of Sphericity Sig. = 0,000, < 0,05). The reliability for the full scale is good (α = 0.875), confirming the items in the scale are all related to travelling motivations, and can therefore be used as a reference. The obtained factors were named to meaningful descriptions representing the concepts we believe they symbolized.

As can be seen in Table 5.9, except the four items that add to be removed and M12 and M26, all pairs of items that were measuring the same concepts in Pearce and Lee (2005) scale aggregated together after the EFA. We can also see that the pairs of items belonging to different dimensions in Pearce and Lee (2005) aggregated together in this study to constitute a new dimension, reducing the sample dimension, meaning the EFA considered they were measuring similar concepts, which

27 Although aggregating in factors that seemed to measure the same concepts, the items with coefficients < 0.40, that were scoring alone, or that were scoring in more than one factor, with a difference less than 0.10, were eliminated from the sample: M2, M7, M16, M21. More details can be found at http://www.gecad.isep.ipp.pt/grouplanner/dissemination.html

is enforced by the obtained high reliability values, except for the Escape Obligations factor, which was on the limit of acceptance.

Table 5.9. Varimax rotated component matrix for the proposed Travelling Motivations, showing the 6 factors extracted using EFA and their respective items, the estimated correlations between the items and factors, and each factor's Cronbach's Alpha reliability (α).

Factor	Item	Description	Estimated correlation	α
Self-development &	M20	Working on my personal/spiritual values	0.723	0.828
Reliance	M6	Understanding more about myself	0.715	
FM1	M18	Developing my skills and abilities	0.685	
	M19	Being near considerate people	0.628	
	M5	Being with respectful people	0.599	
	M4	Develop my personal interests	0.523	
Connectedness &	M9	Having romantic relationships	0.717	0.784
Recognition	M10	Showing others I can do it	0.712	
FM2	M24	Being recognized by other people	0.688	
	M23	Meeting amorous partners	0.676	
	M22	Reflecting on past memories	0.622	
	M8	Thinking about good times I've had in the past	0.536	
Novelty & Excitement	M25	Experiencing something different	0.762	0.745
FM3	M17	Experiencing thrills	0.699	
	M3	Having daring/adventuresome experiences	0.691	
	M11	Feeling the special atmosphere of the vacation destination	0.557	
Bond & Relax	M13	Doing something with my family/friend(s)	0.834	0.713
FM4	M27	Strengthening relationships with my family/friend(s)	0.733	
	M12	Getting away from everyday psychological stress/pressure	0.601	
Nature enjoyment	M1	Being close to nature	0.858	0.845
FM5	M15	Getting a better appreciation of nature	0.824	
Escape obligations	M14	Being obligated to no one	0.756	0.599
FM6	M26	Getting away from the usual demands of life	0.609	
	M28	Being independent	0.567	
			Full scale α	0.875

The full scale α is also presented at the end of the table

When performing the CFA, items M9 and M23, both related to romance, were removed from the Connectedness & Recognition factor due to a regression weight < 0.50. We also decided to remove the Escape Obligations factor, not only for having a low reliability, but because it had two items with a regression weight < 0.50, resulting in the model presented in Figure 5.5. The five factors' regression weights were statistically significant in the prediction of their respective items for $p < 0.001^{***}$ (two-tailed). The model revealed an overall good goodness-of-fit ($\chi^2/df=5.999$, CFI=0.912, GFI=0.921, PCFI=0.709, PGFI=0.645, RMSEA=0.070, p(RMSEA ≤ 0.05)=0.000), meaning the model is valid for the study and the items provide a good fit, confirming the proposed "Travelling Motivations" model. We can also observe the model includes the most common travel-

ling motives found in literature: Novelty & Excitement (Exploration), Nature enjoyment (Nature experiences), and Bond & Relax (Relaxation/Escapism).

The SEM to confirm what personality dimensions were predicting which travel motivations (Figure 5.6) revealed an overall acceptable fit (χ^2/df=6.379, CFI=0.822, GFI=0.849, PCFI=0.721, PGFI=0.695, RMSEA=0.072, p(RMSEA ≤ 0.05)=0.000), confirming the model is valid for the study and the items provide an acceptable fit, confirming the proposed "Personality vs Travelling Motivations" model.

At a first impression, it might seem difficult to explain the observed correlations. We believe the statistically significant positive influence of neuroticism on Self-development & Reliance, Connectedness & Recognition, and Novelty & Excitement motivations (Table 5.10) is related to individuals who are self-conscient (internal control locus) of the need to work on those characteristics/capacities from an emotional intelligence perspective, having the capability of looking at themselves, recognizing the need to contact with others and themselves, which can be good to open horizons and have different perspectives.

We can say openness to experience is somehow related to all tourism motivations, being associated to experiencing different things, curiosity, having a greater weight on Self-development & Reliance and Bond & Relax, motivations strongly related to individuals with a higher intellect, that need to be stimulated, prone to wander the mind off, and empathetic to self and others' feelings. The motivations related to openness are supported by Abbate and Di Nuovo (2013); Scaffidi Abbate et al. (2017) and Kashdan et al. (2009) studies.

Curiously, the agreeableness, extraversion, and conscientiousness personality dimensions could not predict the proposed travelling motivations, actually they had to be removed from the model due to very low regression weights in the corresponding items. As motivations to travel depend on many factors, such as the context, destination, traveler's mood, time of year, companions, etc., it can explain why not all dimensions could be related to the motivations for travelling (Table 5.10).

5.4.2.4 Personality vs Travel-related Preferences and Concerns

As a result of performing the EFA on the 29 items representing the relevant travelled-related preferences and concerns for this study, several items were eliminated[28] according to the criteria previously referred (Section 5.3), resulting in a final scale with 18 items, and 4 factors extracted that explained 50% of the total variance. The 4 factors aggregated items measuring the same concepts, as shown in Table 5.11 and by acceptable Cronbach's Alpha reliability values29. The sampling adequacy (Kaiser-Meyer-Olkin, KMO = 0.805) is good (Pestana & Gageiro, 2008), and the correlation between the variables is significative (Bartlett's Test of Sphericity Sig. = 0,000, < 0,05). The reliability for the full scale is acceptable (α = 0.682), confirming the items in the scale are all related to the same concept, and can therefore be used as a reference. The obtained factors were then named to meaningful descriptions representing the concepts we believe they symbolized.

The EFA on the items for the Travel-related Preferences and Concerns revealed interesting and not so obvious aggregations, showing many items were measuring the same concepts or somehow related. Regarding concerns, the participants consider important to feel safe and comfortable, are not willing to take risks regarding the physical integrity, and want to have some sort of previsibility to avoid uncomfortable or risky events, preferring the familiar to the unknown, which is easier when travelling with familiars or friends, instead of strangers in a group. As for travel-related preferences, to have cultural experiences, like visiting the most famous monuments, learn about the destination's history, see things different from their culture, and visit unusual/exotic places, are the most important for the respondents. All these outcomes support the results found in literature, previously detailed in Section 5.2.2.3.

The CFA on the proposed factors led to the removal of the items P13, P15, P24R, and P28, as they had a regression weight < 0.50, resulting in the model presented in Figure 5.7. The four factors' regression weights were statistically significant in the prediction of their respective items for $p < 0.001^{***}$ (two-tailed). The model revealed an overall very good goodness-of-fit ($\chi 2/df=2.754$, CFI=0.958, GFI=0.974, PCFI=0.737, PGFI=0.649, RMSEA=0.041, p(RMSEA ≤ 0.05)=0.982),

28 Although aggregating in factors that seemed to measure the same concepts, the items with coefficients < 0.40, communalities < 0.50, that belonged to factors with a low reliability (α < 0.60), that were scoring alone, or that were scoring in more than one factor, with a difference less than 0.10, were eliminated from the sample: P1, P3, P8, P9, P11, P16, P17, P20, P22, P23, P26. Please consult http://www.gecad.isep.ipp.pt/grouplanner/dissemination.html for further details.

29 Being an exploratory analysis, it is acceptable to consider factors with Cronbach's Alpha values ≥ 0.60 (Hair et al., 2009).

meaning the model is valid for the study and the items provide a very good fit, confirming the proposed "Travel-related Preferences and Concerns" model.

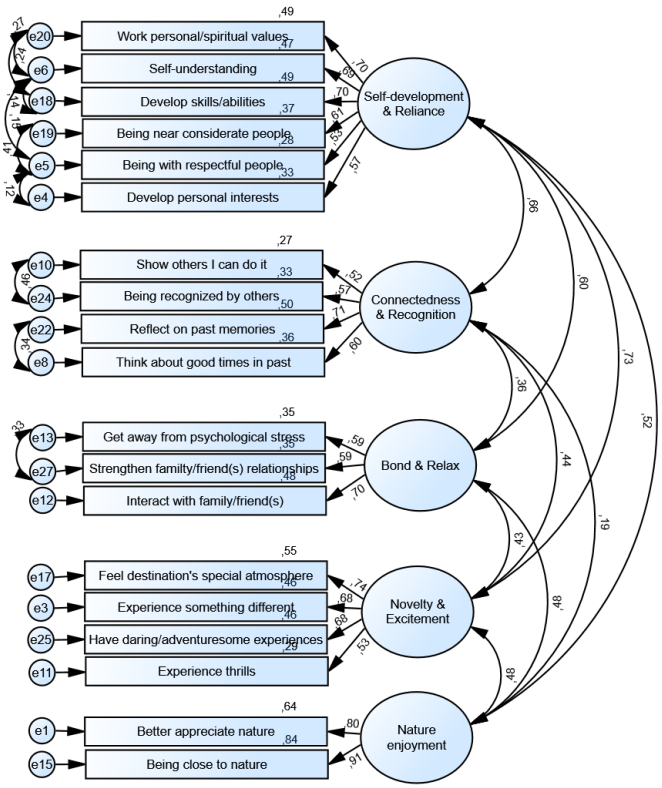


Figure 5.5. Simplified Structural Equation Model for the proposed "Travelling Motivations" model, obtained using CFA. The five factors' regression weights were statistically significant in the prediction of their respective items for $p < 0.001$*** (two-tailed)

Table 5.10. Standardized regression weights for the relationship between the BFI dimensions and Travelling Motivations, obtained using CFA.

Factor	BFI Dimension	Regression Weight	p
Self-development & Reliance FM1	***Neuroticism***	***0.125***	***0.001****
	Openness	***0.429***	*****
Connectedness & Recognition FM2	***Neuroticism***	***0.169***	*****
	Openness	***0.226***	*****
Novelty & Excitement FM3	***Neuroticism***	***0.156***	*****
	Openness	***0.189***	*****
Bond & Relax FM4	Neuroticism	0.049	0.205
	Openness	***0.372***	*****
Nature enjoyment FM5	Neuroticism	0.028	0.450
	Openness	***0.285***	*****

Statistically significant values are in bold and italics (** $p < 0.01$ (2-tailed), *** $p < 0.001$ (2-tailed))

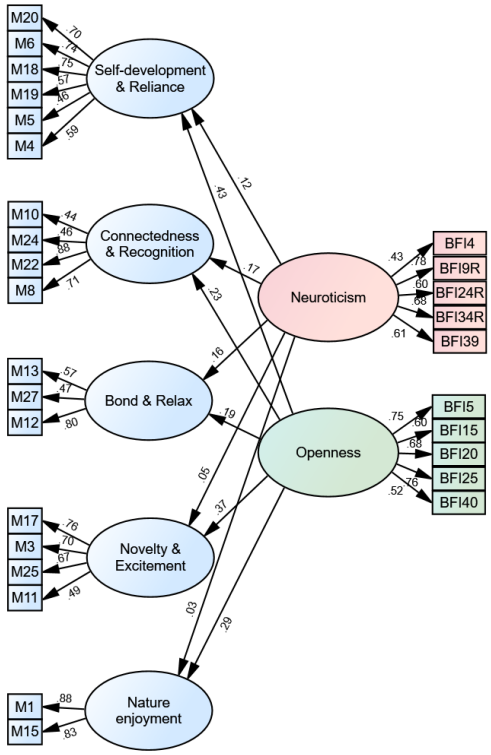


Figure 5.6. Simplified Structural Equation Model for the proposed "Personality vs Travelling Motivations" model, obtained using CFA. For readability, the error variables have been removed. The items label can be found at Table 5.6 and Table 5.9

The SEM to confirm what personality dimensions were predicting which travel-related preferences an concerns (Figure 5.8) revealed an overall acceptable fit ($\chi 2/df=4.488$, CFI=0.809, GFI=0.877, PCFI=0.716, PGFI=0.733, RMSEA=0.058, p(RMSEA ≤ 0.05)=0.000), confirming the model is valid for the study and the items provide an acceptable fit, confirming the proposed "Personality vs Travel-related Preferences and Concerns" model.

All personality dimensions are related to travel-related preferences and concerns, although with lower regression weights compared to the tourism categories and travelling motivations (Table 5.12). Individuals with a low extraversion and neuroticism, with some degree of agreeableness and openness, are more preoccupied with comfort, safety and health concerns (Previsibility & Safety), which can be confirmed by the findings of Maritz et al. (2013), Tan (2020), Carvalho et al. (2020), and Al-Omiri et al. (2021). The conscientiousness regression weight was not statistically significant to be considered.

Table 5.11. Varimax rotated component matrix for the proposed Travel-related Preferences and Concerns, showing the 4 factors extracted using EFA and their respective items, the estimated correlations between the items and factors, and each factor's Cronbach's Alpha reliability (α).

Factor	Item	Description	Estimated correlation	α
Previsibility & Safety	P14	For me, to feel comfort is always the most important (quality of facilities / products)	0.700	0.731
FP1	P6	I would never travel to a place where there was no mobile phone network	0.690	
	P12	In a distant country, one of my worst fears would be to get lost	0.682	
	P15	For me, to fulfill expectations is more important than a good surprise	0.564	
	P5	I am afraid of getting ill or having accidents whilst away on vacations	0.551	
	P2	Under no circumstances I like to take risks related to my physical integrity	0.531	
	P28	I would be incapable of travelling to a high criminality rate / armed conflict destination	0.504	
Cultural & Learning Experiences FP2	P18	For me, a good vacation must include a cultural / learning component	0.793	0.782
	P4	When going on vacations I take into account the destination's cultural offer	0.783	
	P10	Before travelling I like to know/study the history of the destination	0.703	
	P19	I would never visit a great city without seeing its iconic monuments	0.671	
	P7	When planning vacations, I try to include as many places/attractions as possible	0.607	
Uniqueness & Exoticness FP3	P21	For me, it is important to see exotic things or that are very different from my culture	0.729	0.615
	P29	I like to visit uncommon places or observe peculiar things (e.g., world records, pop icons, historical items, etc.)	0.688	
	P13	I like to go where few people have been to before	0.679	
Familiarity FP4	P27	I would never travel in a group due to privacy reasons	0.777	0.608
	P24R	I would be willing to travel in a group organized by a travel agency	0.772	
	P25	I would never go on vacation with strangers (making common trips and meals)	0.659	
			Full scale α	0.682

The full scale α is also presented at the end of the table. R denotes reversed questions.

The concern for travelling in groups of strangers (Familiarity) is predicted by a negative agreeableness (revealing individuals more concerned about themselves), neurotic (who are more comfortable with family/friends having difficulty in socializing with strangers) and conscientious persons (careful and less spontaneous). To the best of our knowledge, we could not find works relating the Big Five to this type of concerns. The other dimensions were not statistically significant.

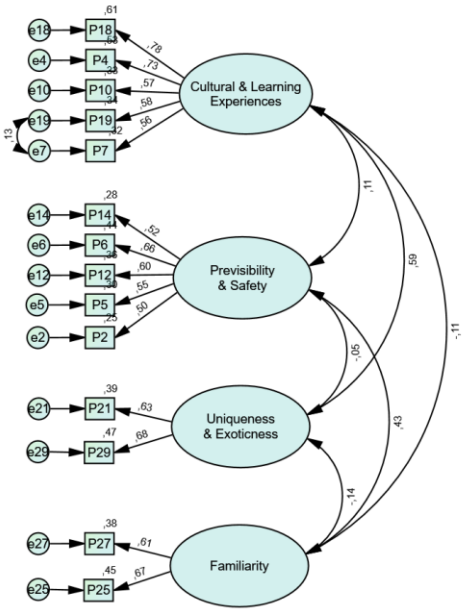


Figure 5.7. Simplified Structural Equation Model for the proposed "Travel-related Preferences and Concerns" model, obtained using CFA. The items label can be found at Table 5.11

Cultural & Learning Experiences are preferences positively sought by neurotic and conscientious persons, with a negative openness to experience. These predictions are easily explained, as neurotic are more anxious and therefore study the destination before travelling, conscientious persons are more organized and inclined to plan their vacations in advance, which is in line with the negative openness.

Uniqueness & Exoticness is pursued by extraverted (seeking adventure, new things), agreeable (get along with others) and open to experience (sensible to beauty and patterns, curious, needing variety and novelty) persons.

The last two type of preferences can be corresponded to the choice of certain attractions, namely from the Museums, Boat trips & Viewpoints, Cultural Heritage, and Wild Nature Activities tourism categories, having several personality dimensions in common (Table 5.12).

5.4.2.5 Personality vs Fears and Weather Preferences

The questionnaire allowed to obtain very interesting and useful information. In this section, we correlated personality to fears and the type of weather preferred when on vacations, to explore if and how they were related.

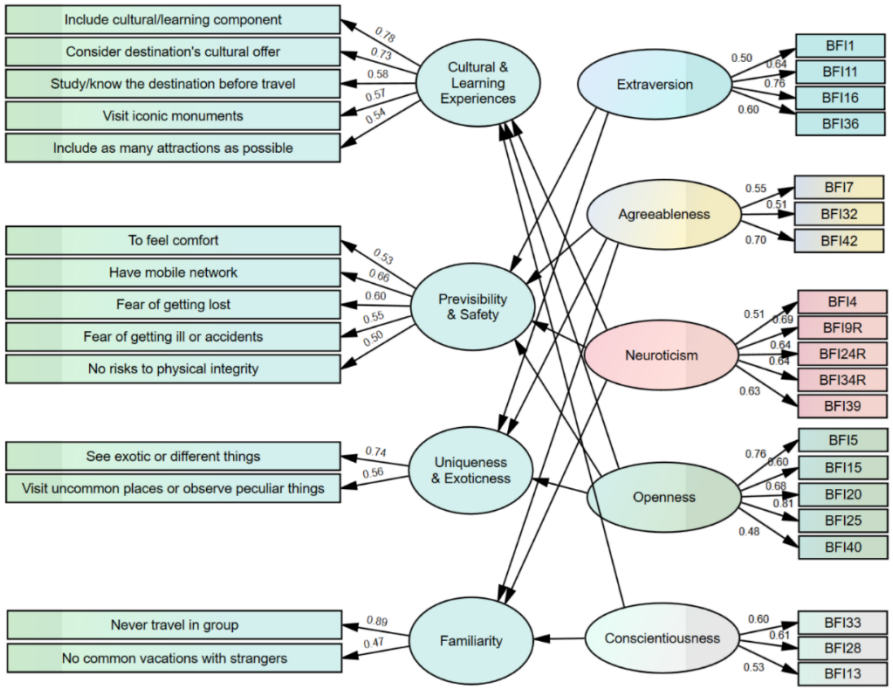


Figure 5.8. Simplified Structural Equation Model for the proposed "Personality vs Travel-related Preferences and Concerns" model, obtained using CFA. For readability, only the regression weights (standardized) for the Travelling Concerns and BFI items are presented (λ ≥ 0.5). The standardized regression weights for the relationship between the Personality Dimensions and Travelling Concerns can be found in Table 5.12. The BFI items label can be found at Table 5.6.

Table 5.12. Standardized regression weights for the relationship between the BFI dimensions and Travel-related preferences and Concerns, obtained using CFA.

Factor	BFI Dimension	Regression Weight	p
Previsibility & Safety (FP1)	***Extraversion***	***0.086***	***0.033****
	Agreeableness	***0.241***	*****
	Neuroticism	***0.080***	***0.043****
	Openness	***0.148***	*****
	Conscientiousness	0.049	0.274
Cultural & Learning Experiences (FP2)	***Neuroticism***	***0.296***	*****
	Openness	***-0.128***	***0.001****
	Conscientiousness	***0.277***	*****
	Extraversion	-0.001	0.979
	Agreeableness	-0.051	0.249
Uniqueness & Exoticness (FP3)	***Extraversion***	***0.254***	*****
	Agreeableness	***0.193***	*****
	Openness	***0.142***	***0.002****
	Neuroticism	0.049	0.266
	Conscientiousness	-0.041	0.412
Familiarity (FP4)	***Agreeableness***	***-0.303***	*****
	Neuroticism	***0.123***	***0.006****
	Conscientiousness	***0.221***	***0.004****
	Extraversion	0.019	0.627
	Openness	-0.033	0.372

The statistically significant values are bold and italics (* p < 0.05 (2-tailed), ** p < 0.01 (2-tailed), *** p < 0.001 (2-tailed))

As can be observed in Table 5.13, neuroticism is clearly associated with persons who have some sort of fear. The more neurotic a person is, the most susceptible to having fears is. Low values of extraversion and openness are also predictors of persons with more fears. This confirms the results found by Mellstrom et al. (1976), Faullant et al. (2011), and Al-Omiri et al. (2021). Although negative, agreeableness and conscientiousness were not statistically significant to be considered.

Weather conditions revealed to be correlated with personality, answering to another research question: yes, personality is an influencing factor in the preference for weather conditions and consequently, in the choice of the destination. The preference for hot weather conditions at the vacation destination is positively predicted by extraverted, agreeable and conscientious individuals. Slightly neurotic, with low extraversion and openness individuals prefer to go to destinations where the weather is warm. All personality dimensions seem to influence the choice of cold weather conditions, being sought by low extraversion, agreeableness and conscientiousness persons, but with positive neuroticism and openness values. However, it is important to notice that only 2.5% of the respondents preferred cold weather, meaning it is not a relevant choice for vacations. Open to experience individuals with low conscientiousness and neuroticism seem to not care about the weather conditions at the vacation destination.

Table 5.13. Correlations between personality, fears, and climate conditions preference at the destination.

	Fears	Hot weather	Warm weather	Cold weather	No weather preference
Extraversion (E)	***-.068****	***.143****	***-.100****	**-.076***	-0.024
Agreeableness (A)	-0.020	***.071****	-0.047	**-.139****	0.019
Conscientiousness (C)	-0.007	***.122****	-0.031	**-.066***	***-.071****
Neuroticism (N)	***.202****	-0.034	***.078****	**.115****	***-.078****
Openness (O)	***-.061****	-0.058	***-.094****	**.071***	***.123****

The statistically significant values are bold and italics (** correlation is significant at the 0.01 level (2-tailed), * correlation is significant at the 0.05 level (2-tailed))

As can be seen, all different types of weather conditions revealed different combinations of personality dimensions, with different weights, meaning they can be used to model tourists in the (G)RS to predict what destinations can be recommended in what time of the year.

We believe, to the best of our knowledge, to be the firsts to present those relationships, as no studies related to the prediction of personality in the choice of weather conditions for vacations were found.

5.5 Automatic Group Recommendations Just by Knowing the Tourists' Personality

In this study, one of the problems we propose to mitigate is the cold-start problem in (G)RS by automatically modeling the tourists profile based on their personality, namely their tourist attractions preference, traveling motivations, and travel-related preferences and concerns. The proposed models showed the referred travel aspects are related to the tourists' personality and that the five personality dimensions have different impacts on the choice of tourist attractions, travel motivations, preferences and concerns.

To automatically model the tourists' travel preferences, the global score[30] for each tourist's travel aspect, according to the analyzed sample, is calculated according to the expressions presented next. This simple mapping is intended to suppress the need for gathering large amounts of information from the users interaction to give the first recommendations, which most (G)RS depend on.

5.5.1 Model 1: Tourist Attractions Preference

Let the personality of a Tourist T_i be represented by $P_{T_i} = \{O_{T_i}, C_{T_i}, E_{T_i}, A_{T_i}, N_{T_i}\}, i \in \{1, 2, \ldots, n\}$, where O_{T_i} represents the Tourist's Openness to Experience score, C_{T_i} the Conscientiousness score, E_{T_i} the Extraversion score, A_{T_i} the Agreeableness score, and N_{T_i} the Neuroticism score.

The following expressions represent the personality dimensions that significantly contribute for a tourist T_i tourist attraction preference $AP_{T_i} \in [0, 1]$, $i \in \{1, 2, \ldots, n\}$, for a certain tourism category F_j, $j \in \{1, 2, \ldots, 11\}$. For instance, in Equation 1, the preference for the tourism category F_1 (Adrenaline activities) by tourist T_i is predicted by the Extraversion regression weight for that category multiplied by the Tourist's Extraversion score plus the Conscientiousness regression weight multiplied by the Tourist's Conscientiousness score.

$$AP_{T_iF_1} = 0.715 \times E_{T_i} - 0.320 \times C_{T_i} \quad (1)$$

$$AP_{T_iF_2} = 0.404 \times E_{T_i} + 0.573 \times A_{T_i} - 0.223 \times C_{T_i} \quad (2)$$

$$AP_{T_iF_3} = 0.751 \times E_{T_i} - 0.050 \times A_{T_i} + 0.129 \times N_{T_i} - 0.115 \times O_{T_i} - 0.108 \times C_{T_i} \quad (3)$$

$$AP_{T_iF_4} = 0.617 \times E_{T_i} + 0.076 \times N_{T_i} - 0.232 \times O_{T_i} \quad (4)$$

$$AP_{T_iF_5} = 0.525 \times A_{T_i} + 0.078 \times N_{T_i} + 0.078 \times O_{T_i} - 0.182 \times C_{T_i} \quad (5)$$

30 Based on the factor score weights calculated by Amos (regression weights for predicting the unobserved variables from the observed variables).

$$AP_{T_iF_6} = 0.790 \times E_{T_i} - 0.123 \times A_{T_i} + 0.128 \times N_{T_i} - 0.204 \times O_{T_i} - 0.077 \times C_{T_i} \quad (6)$$

$$AP_{T_iF_7} = 0.625 \times A_{T_i} \quad (7)$$

$$AP_{T_iF_8} = 0.717 \times E_{T_i} - 0.309 \times A_{T_i} - 0.152 \times O_{T_i} - 0.150 \times C_{T_i} \quad (8)$$

$$AP_{T_iF_9} = 0.459 \times E_{T_i} + 0.187 \times A_{T_i} - 0.116 \times O_{T_i} - 0.089 \times C_{T_i} \quad (9)$$

$$AP_{T_iF_{10}} = 0.649 \times E_{T_i} - 0.168 \times A_{T_i} + 0.144 \times N_{T_i} - 0.143 \times O_{T_i} + 0.079 \times C_{T_i} \quad (10)$$

$$AP_{T_iF_{11}} = 0.336 \times E_{T_i} + 0.605 \times A_{T_i} - 0.365 \times C_{T_i} \quad (11)$$

5.5.2 Model 2: Travelling Motivations

The tourist T_i predicted travelling motivation $TM_{T_i} \in [0,1]$, $i \in \{1,2,\ldots,n\}$, for a certain motivation factor FM_j, $j \in \{1,2,\ldots,5\}$ is calculated as follows:

$$TM_{T_iFM_1} = 0.125 \times N_{T_i} + 0.429 \times O_{T_i} \quad (12)$$

$$TM_{T_iFM_2} = 0.169 \times N_{T_i} + 0.226 \times O_{T_i} \quad (13)$$

$$TM_{T_iFM_3} = 0.156 \times N_{T_i} + 0.189 \times O_{T_i} \quad (14)$$

$$TM_{T_iFM_4} = 0.372 \times O_{T_i} \quad (15)$$

$$TM_{T_iFM_5} = 0.285 \times O_{T_i} \quad (16)$$

5.5.3 Model 3: Travel-Related Preferences and Concerns

The tourist T_i predicted travel-related preference $TP_{T_i} \in [0,1]$, $i \in \{1,2,\ldots,n\}$, for a certain travel-related preference factor FP_j, $j \in \{2,3\}$ is calculated as follows:

$$TP_{T_iFP_2} = 0.296 \times N_{T_i} - 0.128 \times O_{T_i} + 0.277 \times C_{T_i} \quad (17)$$

$$TP_{T_iFP_3} = 0.254 \times E_{T_i} + 0.193 \times A_{T_i} + 0.142 \times O_{T_i} \quad (18)$$

The tourist T_i predicted travel-related concern $TC_{T_i} \in [0,1]$, $i \in \{1,2,\ldots,n\}$, for a certain travel-related concern factor FP_j, $j \in \{1,4\}$ is calculated as follows:

$$TC_{T_iFP_1} = 0.086 \times E_{T_i} + 0.241 \times A_{T_i} + 0.080 \times N_{T_i} + 0.148 \times O_{T_i} \quad (19)$$

$$TC_{T_iFP_4} = -0.303 \times A_{T_i} + 0.123 \times N_{T_i} + 0.221 \times C_{T_i} \quad (20)$$

5.5.4 Model 4: Creating Subgroups with Similar Interests

The other problem we propose to mitigate is the conflicting preferences in groups of tourists. As the probability of heterogeneity is greater with larger groups of tourists, if we use the proposed models to create subgroups of tourists with similar interests, we can minimize the group's heterogeneity and conflicts of interest, which in turn facilitates reaching a consensus in the recommenda-

tion process and the generation of more precise recommendations to the subgroups. This type of aggregation can be advantageous in promoting more socialization and the creation of bounds between the group members (Alves et al., 2019), especially in occasional groups of tourists (e.g., promoted by travel agencies, companies, or other organized groups).

Considering it only makes sense to have (sub)groups of 3 or more elements, let $G_e = \{T_i, \dots, T_n\}$ be a group of Tourists for a certain excursion e, where $e,\ i \in \{1, 2, \dots, n\}$ and $\langle G_e \rangle \geq 3$; $AP_{T_i} = \{AP_{T_iF_1}, \dots, AP_{T_iF_{11}}\}$ the set of tourist attractions preference of Tourist T_i, $TM_{T_i} = \{TM_{T_iFM_1}, \dots, TM_{T_iFM_5}\}$ the set of travelling motivations of Tourist T_i, $TP_{T_i} = \{TP_{T_iFP_2}, TP_{T_iFP_3}\}$ the set of travel-related preferences of Tourist T_i, and $TC_{T_i} = \{TC_{T_iFP_1}, TC_{T_iFP_4}\}$ the set of travel-related concerns of Tourist T_i. The Tourist's simplified profile can be represented by $profile_{T_i} = \{AP_{T_i},\ TM_{T_i},\ TP_{T_i},\ TC_{T_i}\}$.

Let poi_k, k ∈ $\{1, 2, \dots, n\}$, be a point of interest representing a certain tourist attraction. Considering a point of interest has a certain personality, and therefore, according to the proposed models, it scores a certain value on each tourism category, travel motivation, travel-related preference, and travel-related concern, we can represent poi_k using the same Tourist's profile parameters: $profile_{poi_k} = \{AP_{poi_k},\ TM_{poi_k},\ TP_{poi_k},\ TC_{poi_k}\}$.

To find out how much a certain poi_k in the excursion destination is similar to a certain tourist T_i, we calculate the Euclidean distance between them:

$$d(T_i, poi_k) = \sqrt{\begin{array}{c}\left(AP_{T_iF_1} - AP_{poi_kF_1}\right)^2 + \left(AP_{T_iF_2} - AP_{poi_kF_2}\right)^2 + \cdots + \left(AP_{T_iF_{11}} - AP_{poi_kF_{11}}\right)^2 + \\ \left(TM_{T_iFM_1} - TM_{poi_kFM_1}\right)^2 + \cdots + \left(TM_{T_iFM_5} - TM_{poi_kFM_5}\right)^2 + \left(TP_{T_iFP_2} - TP_{poi_kFP_2}\right)^2 + \\ \left(TP_{T_iFP_3} - TP_{poi_kFP_3}\right)^2 + \left(TC_{T_iFP_1} - TC_{poi_kFP_1}\right)^2 + \left(TC_{T_iFP_4} - TC_{poi_kFP_4}\right)^2\end{array}} \quad (21)$$

Following the same logic in a previous study (João Carneiro, Martinho, et al., 2020), we propose the algorithms presented next to create the subgroups, where $difScoresT_iT_j$ represents the difference between the maximum and minimum scores T_i gives to the list of N preferred POI of the other tourist T_j (see Equation 22). The resulting $difScoresT_iT_j$ can be classified into one of five possible weight levels (Table 5.14).

$$difScoresT_iT_j = \max\left(T_i(poiScoreSum)\right) - \min\left(T_i(poiScoreSum)\right),\ if\ \max\left(T_i(poiScoreSum)\right) \neq \min\left(T_i(poiScoreSum)\right)\ else\ \max\left(T_i(poiScoreSum)\right) \quad (22)$$

Table 5.14. $difScoresT_iT_j$ weight levels

Weight level	$\boldsymbol{difScoresT_iT_j}$
5	$difScoresT_iT_j \geq 0.80$
4	$0.60 \leq difScoresT_iT_j < 0.80$
3	$0.40 \leq difScoresT_iT_j < 0.60$
2	$0.20 \leq difScoresT_iT_j < 0.40$
1	$difScoresT_iT_j < 0.20$

Algorithm 1. Calculation of the similarity between a poi_k and a Tourist T_i

1 For each T_i in G_e do
2 For each poi in the excursion destination do
3 Using the Euclidean distance, calculate how much poi is similar to T_i (Equation 21)
4 Add poi and respective similarity to T_i list of poi
5 Order T_i list of poi by descending similarity

Table 5.15. Possible degrees of compatibility between Tourists

Compatibility Degree	Definition
5	Very Compatible (VC)
4	Compatible (C)
3	Medium Compatible (MC)
2	Few Compatible (FC)
1	Least Compatible (LC)

After applying Algorithm 3, the created subgroups already have the best POI recommendations.

The proposed algorithms are currently being tested for accuracy, and we are developing a model to determine how many POI should be recommended according to the weight the Tourist gives to each travel aspect. For example, if the Tourist considers "Sun, Water & Sand" as the preferred category, more POI from that category should be recommended opposed to the other categories.

Algorithm 2. Determining how much a Tourist is compatible with the other Tourists in G_e

1 For each T_i in G_e do
2 $poiScoreSum \leftarrow 0,\ n \leftarrow 0$
3 For each T_j in Ge do
4 If ($T_i \neq T_j$)
5 While $n < N$ (we only want to compare to T_j the N preferred poi)
6 For each poi in T_j list of poi (obtained in step 5 of Algorithm 1)
7 Get respective T_i poi similarity value and add to $poiScoreSum$
8 Add T_j and $poiScoreSum$ (normalized) to $T_i.compatibilityList$ (list containing the other members in group and how much T_i is compatible with them)
9 Increment n by 1

10 Calculate the difference between the maximum and minimum scores T_i gave to list of N preferred POI of the other tourists, $difScores T_i T_j$ (see Equation 22)
11 Calculate $weightLevel$ for $difScores T_i T_j$ according to Table 5.14
12 For each T_j in T_i $compatibilityList$ do
13 $compatibility \leftarrow 1$
14 While $T_j.poiScoreSum \leq (\max(T_i.poiScoreSum) - compatibility \times \left(\frac{difScores T_i T_j}{weightLevel}\right))$ and $compatibility < 5$
15 $compatibility \leftarrow compatibility + 1$
16 $T_j.compatibility \leftarrow 6 - compatibility$
17 Order $T_i.compatibilityList$ in descending order of $compatibility$

Algorithm 3. Creating subgroups of Tourists according to the degree of Compatibility (Table 5.15)

1 While G_e is not empty
2 While there are Very Compatible (VC) tourists on G_e
3 $mostCompatibleTourist \leftarrow null,\ count \leftarrow 0$
4 For each T_i in G_e do
5 $countVC \leftarrow 0$
6 For each T_j in G_e
7 If ($T_i \neq T_j$)
8 If T_j considers T_i Very Compatible based on $T_j.compatibilityList$
9 $countVC++$
10 If ($countVC > count$ and $count > 1$) //at least 2 more VC tourists needed to form subgroup
11 $count \leftarrow countVC$
12 $mostCompatibleTourist \leftarrow T_i$
13 Create subgroup with $mostCompatibleTourist$ and all the Tourists in G_e that consider $mostCompatibleTourist$ Very Compatible
14 Remove $mostCompatibleTourist$ from G_e and all other added Tourists

15 Repeat steps 2 to 14 but now for Compatible tourists (value 4)

16 For each T_i in G_e do //Try to assign a subgroup for the remaining Tourists
17 If number of subgroups > 1
18 Check which subgroup brings more satisfaction to T_i (under development)
19 Add T_i to the most satisfying subgroup
20 Remove T_i from G_e
21 Else create subgroup with all tourists
22 Remove all tourists from G_e

5.6 Reflections and Future Work

The travel and tourism domain is very vast and complex, and is profoundly related to the tourists' psychological aspects. The evolution of internet and mobile devices led to more demanding tourist

consumers, eager to obtain better and emotional experiences, and consequently to the proliferation of recommender systems (RS) for tourism, aiming to provide personalized suggestions of places and attractions to visit. Personality computing came to leverage those systems by taking advantage of the psychology of tourism, leading to the creation of personality-aware RS, as it is evidenced that personality is related to the users' preferences and solves the cold-start problem inherent to the classic RS.

Many RS for tourism can be found in literature, but few use the raw dimensions of personality to predict the tourists' preferences, especially if we talk of GRS. We believe GRS can be greatly improved by using raw psychological aspects, such as personality, to form groups of tourists with similar preferences, providing more personalized recommendations and solving conflicting preferences. Another advantage is that this logic can be extrapolated to other domains. Although several studies on the relationship between personality and travel aspects exist, most of them are based on tourist typologies/roles, which do not disclose the kind of personality traits the tourists have, and therefore it is hard to predict how they influence those preferences and behaviors, and consequently, are not so accurate, as not all attractions in a typology are suitable for the same tourist and a combination of typologies might be needed. In this work, we proposed to solve those limitations by finding the relationships between the Big Five personality dimensions, and the preference for a wide range of tourism categories, travelling motives and travel-related preferences and concerns, aiming to provide a solid ground for tourism GRS researchers to automatically model more accurate tourist's profiles and create groups with similar preferences, providing more accurate and pleasing recommendations, and consequently increase the tourists' experience and satisfaction.

Regarding the sample, this time we gathered the double of responses, with participants from more heterogenous ages and areas of formation, representing a "young" market (adults and young adults, ≤ 55 years old). However, most respondents are females (74%), meaning there can be a bias towards female preferences. The sample represents the Portuguese culture, but it can be concluded that they have many similarities with the results found in literature for other cultures. The same social desirability bias from our previous work was observed in the BFI responses to the items of the same personality dimensions (agreeableness, neuroticism, and conscientiousness),

confirming the typical phenomenon of self-reporting questionnaires, although the respondents had more diverse profiles.

The “Tourism Categories” and “Personality vs Tourist Attraction Preferences” models improved their goodness-of-fit, but not as much as expected (more responses for each type of personality and gender would be needed to considerably improve the models’ fit), and certain tourism categories were finer grained as we managed to obtain a more heterogenous sample, successfully predicting the tourists' preferences based on their personality.

Relevant relationships between personality and travelling motivations were found, especially regarding high values of openness to experience, meaning personality can be a differentiating factor in predicting motivations, although needing more profound research, as motivations are highly dependent on the type of destination and context, which could be confirmed by relating motivations to tourism categories, which was not the scope of this study. Also, the “Personality vs Travelling Motivations” model needs to be improved, so all personality dimensions can be considered.

The proposed travel-related preferences aggregated into two factors that could be easily corresponded to some tourism categories. On one hand it was a good outcome, as it could confirm the relationship found between personality and the corresponding tourism categories, on the other hand, it might mean the items used needed to be improved to better capture other type of travel-related preferences. The travel-related concerns also aggregated into two factors, representing the participants’ fears and preoccupations, successfully predicted by their personality.

Although being predicted by personality, the proposed models need to be better tested, to determine if the personality dimensions are enough to make accurate predictions, or if other characteristics of the tourists need to be considered for better recommendations, being an ongoing study, where we are developing a mobile GRS prototype for tourism to test the models in real use-case scenarios (Alves et al., 2022). For example, during the study, we noticed that younger participants were more prone to adrenaline activities than older ones, and the results clearly showed it would be possible to obtain finer grained predictions, i.e., if we had used a personality questionnaire to obtain the 30 personality traits, instead of the 5 personality dimensions, and correlate them to the proposed travel aspects, we could have obtained more accurate predictions. This finding is supported in literature by Yee et al. (2011) and Aschwanden et al. (2021). For instance, we cannot

recommend a crowded medieval fair to a high extraversion scorer who is low on the gregariousness trait. This means not only the personality information available needs to be more granular, but the context and particularities related to the attractions need to be known in advance, which we are addressing by developing an ontology of tourist attractions that will be used in the algorithm for calculating the tourist's preference for each attraction, including the tourist's four travel aspects preference.

With this work, we managed to provide objective relationships between the Big Five personality dimensions, and some respective traits, and the preference for a wide range of tourism categories, travelling motives and travel-related preferences and concerns, contributing with a formalization that can be used by researchers of (G)RS for tourism to automatically model the tourists' profile based on their raw personality, being, to the best of our knowledge, the firsts to do so, mitigating the cold-start problem. Especially in the case of occasional groups (promoted or not by a tourism agency), the tourists' profile can then be used to match the group members and create subgroups of tourists with similar interests, minimizing the groups' heterogeneity and conflicts of interest.

To solve the problem related to filling tedious and long questionnaires on personality, we are also implementing gamification components in the GRS prototype as a proof of concept to test if we can implicitly acquire the tourists' personality, which can then be adapted to any kind of system.

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Availability of data and material

The questionnaire used and the aggregated results are available at Appendix A in the following url: http://www.gecad.isep.ipp.pt/grouplanner/dissemination.html.

6

GROUPLANNER: A GROUP RECOMMENDER SYSTEM FOR TOURISM WITH MULTI-AGENT MICROSERVICES



A photograph showing one of the experiments' participant logging in to the GRS prototype (reproduced with permission).

Paper Details	Grouplanner: A Group Recommender System for Tourism with Multi-Agent Microservices
Authors	Patrícia Alves, Domingos Gomes, Catarina Rodrigues, João Carneiro, Paulo Novais, Goreti Marreiros
Paper Type	Conference Article
Conference Name	PAAMS'22: 20th International Conference on Practical Applications of Agents and Multi-Agent Systems
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Place	L'Aquila, Italy
DOI	https://doi.org/10.1007/978-3-031-18192-4_37
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Published	13 October 2022
Publisher	Springer
URL	https://link.springer.com/chapter/10.1007/978-3-031-18192-4_37
CORE2021	Rank B

Abstract

To provide recommendations to groups of tourists is a very complex task, especially due to conflicting preferences and the group's heterogeneity. The introduction of Multi-Agent Systems (MAS) can be the leverage we are looking for. Their autonomy, isolated state, distribution, and loose coupling make them suitable for the development of distributed systems, being the concept similar to a Microservices architecture. This connection brought a new approach, the Multi-Agent Microservices (MAMS) architecture, which exposes agents as resources through REST endpoints, changing the way MAS are seen and implemented, facilitating the user ↔ agent interaction, with a more efficient interoperability, bringing faster and more intelligent systems. In this demonstration, we propose the use of a MAMS architecture to represent the tourists in a mobile Group Recommender System for Tourism prototype, Grouplanner, exposing their agents and knowledge as resources that can be consumed by HTTP clients by directly communicating with the tourists' agents using REST endpoints, in order to provide faster and better recommendations.

Keywords: Group Recommender Systems, Multi-Agent Microservices, Tourism.

6.1 Introduction

Recommender Systems (RS) are an increasingly important tool to help users obtain personalized recommendations in a variety of domains. The travel and tourism domain are a good example, however, when groups of tourists are involved, conflicts related to the users' preferences and the group's heterogeneity arise. Several authors proposed the use of Multi-Agent Systems (MAS) to help with those limitations, and proactively make recommendations based on the tourists' profile and context, enriching the tourists' experience (Borràs et al., 2014; Ravi et al., 2021).

It can be seen in literature that the use of MAS is becoming more frequent and applied to a variety of different domains (João Carneiro, Andrade, et al., 2020; Joaquim Neto, A Jorge Morais, Ramiro Gonçalves, & António Leça Coelho, 2022b; Zouad & Boufaida, 2020). One of the greatest advantages of using MAS is that their autonomy, isolated state, distribution, and loose coupling (W. Collier et al., 2019) allows the development of distributed systems (Batet et al., 2012), being the concept similar to Microservices (MS), as argued by W. Collier et al. (2019), who believe that "an agent can be viewed as a type of Microservice that can be deployed seamlessly within any Micro-

service ecosystem". According to the authors, there are many similarities between MAS and MS, such as the isolated state, distribution, elasticity, automated management, and loose coupling, as well as how easy it is for MS to meet the social ability, autonomy, and reactivity of agents, with the advantage that agents can be proactive. These similarities led to the Multi-Agent MicroServices (MAMS) architecture, that consists on Agent-Oriented MS exposed through REpresentational State Transfer (REST) endpoints (W. Collier et al., 2019), where requests can be responded asynchronously by the agents. This type of architecture can change the way MAS are seen and implemented, facilitating the implementation of agile development methods (W. Collier et al., 2019), and the way agents are accessed and used, bringing faster and more intelligent systems.

This paper presents an improvement and demonstration of part of our work, on modeling a mobile Group Recommender System (GRS) for tourism using the tourists' personality to predict their preference for tourist attractions (Alves et al., 2020) and intelligent agents with Microservices (Alves et al., 2019; João Carneiro, Andrade, et al., 2020), where we propose the use of a MAMS architecture to expose the agents and their capabilities as resources, facilitating the user ↔ agent interaction, the access to the agents' knowledge and capabilities, and a more efficient interoperability, to provide faster and more personalized recommendations.

6.2 Main Purpose

This demonstration intends to show how we managed to implement a MAS using MAMS in a mobile GRS for tourism prototype, Grouplanner, allowing direct communication with the tourists' agents using REST endpoints, and how the agents use their social abilities to interact with each other and provide individual and group recommendations.

Each tourist is represented by an agent in the MAMS (Tourist Agent), modelled with the tourist's profile (demographic data, personality, travel-related preferences and concerns, and motivations for traveling), which is accessible through a REST endpoint from the MAMS REST Application Programming Interface (API) (see Figure 6.1). The objective is to expose Tourist Agents as resources through a REST API (W. Collier et al., 2019), so the information on the tourists can be shared easily and faster. The agents can share their knowledge and interaction data, either internally and externally, and collaborate to provide more accurate and satisfying recommendations to the tourists,

reducing the group conflicts, without the need of a broker agent in the environment to communicate with the other agents.

.NET is one of the most used object-oriented programming frameworks for implementing web services and interoperable cross-platform applications, and it was therefore used to implement the Grouplanner prototype. As for the development of the MAMS, many multi-agent platforms can be found in literature (Pal et al., 2020). We chose ActressMAS (Leon, 2022) for its simplicity and ease of use, and because it was one of the few agent frameworks that uses C# programming language, being more suitable for integrating with the .NET framework.

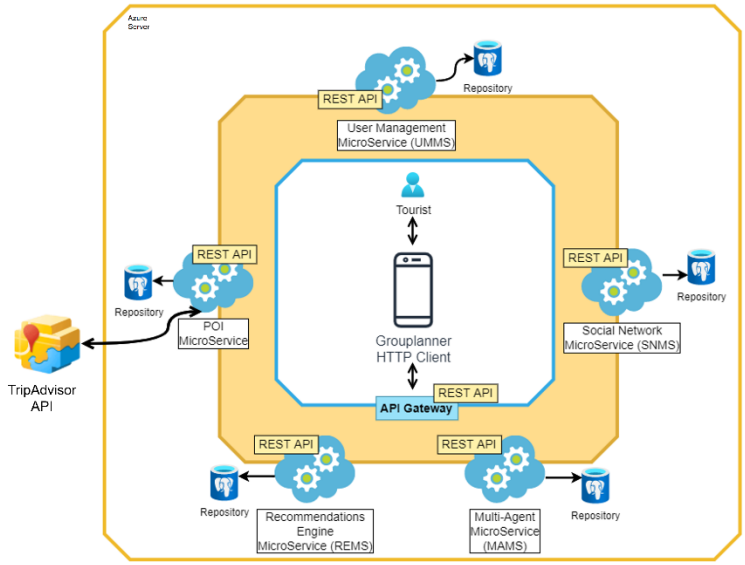


Figure 6.1. Grouplanner Microservices architecture.

6.3 Demonstration

When a tourist user registers in the Client App, he is first registered and authenticated/authorized in the system, using the ASP.NET Core Identity and JSON Web Tokens (JWT), through the API Gateway, which was developed using the ASP.NET Core framework, that acts as a single-entry point into the system, having all the HTTP Clients requests to pass through it.

After the registration, a JSON with the tourist's profile is built and sent at the same time to the User Management MS (UMMS) and the MAMS, via an HTTPS POST request. The MAMS parses the JSON file and brings life to a Tourist Agent (TourAg) in the environment, modelled with the tourist's profile, registering it in the environment's concurrent dictionary (Leon, 2022). The UMMS

stores the tourist's data in the corresponding repository, necessary for consults and updates in the app.

When a tourist requests individual recommendations of Points-Of-Interest (POI), a JSON message is sent, via HTTPS, directly to her TourAg in the MAMS, using the URL: "https://<domain>/mams/agents/tourists/<TourAg-name>/requestRecommendation". Having access to the tourist's knowledge base, the respective TourAg compiles the tourist's profile into a JSON and asks the Recommendations Engine MS (REMS) for the 10 best POI that match her personality[31], as predicted in the "Personality vs Tourist Attractions Preference" model proposed in our previous work (Alves et al., 2020), and according to a POI Ontology. The REMS responds to the TourAg with a JSON containing the suggested POI, after which the TourAg uses her social ability to ask the other TourAg if there are better suggestions based on their current knowledge, updating them accordingly. The final recommendations are then sent to the requesting user.

When a tourist creates an excursion group (e.g.: "One Adventure"), becoming the group owner, a JSON containing the group's information is sent to the MAMS (URL: "https://<domain>/mams/groups/registerGroup"), which immediately creates a Travel Agent (TrvAg) with the group's data, responsible for that group (see next dialogue).

(12/05/2022 10:20:20) Travel Agent 1 has been added
(12/05/2022 10:20:20) [TrvAg-1]: Greetings, I am the Travel Agent for the "One Adventure" excursion group.

When the group owner requests recommendations for the group, an HTTPS request is sent to the group's TrvAg (URL: "https://<domain>/mams/agents/groups/OneAdventure/requestRecommendation"), which divides the group into subgroups with similar personalities, meaning a group can be divided into two or more subgroups, depending on the tourists' personality (if all the tourists have similar personalities the main group will not be divided). In the example (Figure 6.2, left image), the group was divided into three subgroups, where one has more interest in Adrenaline activities, another in Gastronomy events, and the other in Museums, Boat trips & Viewpoints[32].

31 To facilitate the demonstration, we are not considering the tourists' demographic data, motivations, nor travel-related preferences and concerns.
32 This division is also based on the "Personality vs Tourist Attractions Preference" model proposed in our previous work (Alves et al., 2020).

After creating the subgroups, they are sent via HTTPS in a JSON message to the REMS, which proceeds as in the individual recommendations previously mentioned.

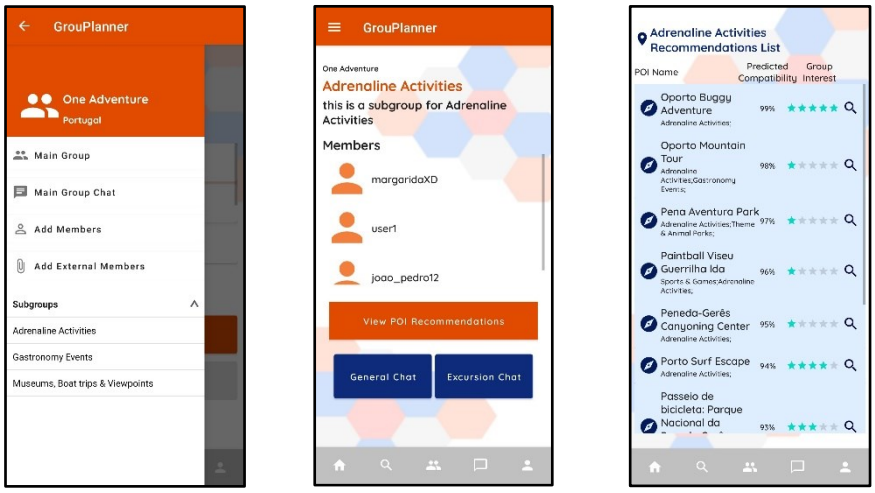


Figure 6.2. (Left) Grouplanner user interface showing the 3 subgroups formed; Center: Detail of the members in the "Adrenaline Activities" subgroup formed. (Right) List of POI recommended to the "Adrenaline Activities" subgroup.

After assigning the 10 best POI to each subgroup, the service responds with a JSON message to the requesting TrvAg with the recommended POI list. The TrvAg then communicates with the Tourist Agents to learn what should, or should not, be recommended using the same strategy mentioned for the individual recommendations (as can be seen in the next dialogues).

The final POI list is then sent by the TrvAg to the Grouplanner HTTP Client, which creates the proposed subgroups and assigns their respective tourists, and at the same time to the group's Social Network MS (SNMS), responsible for persisting all the (sub)groups data, necessary for future consults within the app. Each subgroup can then consult its respective recommended POI list (see Figure 6.2, right side image).

6.4 Conclusions

In this paper, we briefly demonstrated how we implemented a MAMS in a mobile GRS prototype using a Microservices architecture, and how the agents were exposed as resources and exchanged information between them.

Just by using HTTP requests, the Tourist Agents knowledge and capabilities can be accessed by any HTTP client, meaning the proposed MAMS can be used by recommender systems exposing a

REST API, to obtain knowledge on tourists' preferences according to their personality, demographic data, etc. The ability to make individual recommendations is a plus, as the respective Tourist Agent can learn with the feedback/evaluation given by the tourist to the suggested/visited POI, and therefore gain knowledge to help provide better group recommendations.

Due to space limitations, the remaining implementation details, the Recommendations Engine algorithms and the POI Ontology will be presented in future works.

(12/05/2022 10:20:30) [TrvAg-1]: margaridaXD, please tell me your score for each personality dimension.
(12/05/2022 10:20:30) [TrvAg-1]: user1, please tell me your score for each personality dimension.
…
(12/05/2022 10:20:31) [TourAg-margaridaXD]: Hi TrvAg-1, here are my personality scores: …
(12/05/2022 10:20:31) [TourAg-user1]: Hi TrvAg-1, here are my personality scores: ...
…
(12/05/2022 10:20:32) [TrvAg-1]: margaridaXD, you have a personality very similar to user1, joao_pedro12 and antonio, so I will put you together.
(12/05/2022 10:20:32) [TrvAg-1]: user1, you have a personality very similar to margaridaXD, joao_pedro12 and antonio, so I will put you together.
…
(12/05/2022 10:20:33) [TrvAg-1]: I finished analyzing the group members and decided to create 3 subgroups, one more motivated by "Adrenaline activities", other by "Gastronomy events", and another by "Museums", "Boat trips & Viewpoints".
(12/05/2022 10:20:33) [TrvAg-1]: margaridaXD, user1, joao_pedro12 and antonio, you were assigned to subgroup "Adrenaline activities".
… //After receiving the POI list for each subgroup from REMS:
(12/05/2022 10:40:10) [TrvAg-1]: I have the following POI recommendation for these subgroups, does anyone has something against the recommendations?
(12/05/2022 10:40:12) [TAg-margaridaXD]: I am afraid of water activities, can you please recommend other POI?
(12/05/2022 10:40:14) [TAg- Joana]: I went to Nómadas Adventure Tours, but it's a 1 star to me.
…
(12/05/2022 10:40:10) [TrvAg-1]: According to the feedback received, I have changed the POI list recommendation and will send it to the group.
(12/05/2022 10:40:10) [TrvAg-1]: POI recommendations sent to "One Adventure" group.

7

ARE HETEROGEINITY AND CONFLICTING PREFERENCES NO LONGER A PROBLEM? PERSONALITY-BASED DYNAMIC CLUSTERING FOR GROUP RECOMMENDER SYSTEMS



An image showing tourists with conflicting tourist preferences trying to choose a destination and tourist attractions to visit. Generated with AI, Image Creator in Bing, October 2024

Paper Details	**Are Heterogeinity and Conflicting Preferences No Longer a Problem? Personality-Based Dynamic Clustering for Group Recommender Systems**
Authors	Patrícia Alves, André Martins, Francisco Negrão, Paulo Novais, Ana Almeida, Goreti Marreiros
Paper Type	Journal Article
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Year	2024
DOI	https://doi.org/10.1016/j.eswa.2024.124812
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URL	https://doi.org/10.1016/j.eswa.2024.124812
JCR 2023	IF 7.5. Ranked in: Computer Science, Artificial Intelligence #26/197 Q1; Engineering, Electrical & Electronic #25/352 Q1; Operations Research & Management Science #6/106 Q1

Abstract

The complexity associated with groups of tourists led to the emergence of Group Recommender Systems (GRS) for tourism. But if generating recommendations for small groups is a complex task, to provide them to large and occasional groups is even more. This complexity is especially due to the group's heterogeinity, conflicting preferences, the information overload found on the internet and the tourists' different ways of coping with the information, hindering the recommendation process from the users' profile construction to the final recommendation of a list of points of interest (POI) to visit. In this work, we show how we tackled the identified issues in a GRS prototype, Grouplanner, including the cold-start problem, by predicting the tourists' preferences based only on their personality and dividing the main group into subgroups of similar personality; by using a Multi-Agent Microservice; a novel dynamic clustering algorithm, d-means, adapted from the k-means algorithm, that does not need to know the number of clusters a priori; and association rules. Using a personality dataset of n=100k users, the proposed d-means algorithm was tested against two baselines (k-means and k-means++), showing better results in the clustering quality and scalability. We were also able to determine a large set of association rules to refine the recommendations, although further improvements are needed. To test the Grouplanner prototype, a simulation with real users (n=35) was conducted. The results showed the subgroups formed were very compact, revealing a very good clustering quality, with an average silhouette of s = 0.91. 11 of the 15 proposed tourist preferences were successfully predicted and used for the preliminary recommendation lists, being 92% of the participants satisfied with the individual recommendations and 96% with the group recommendations.

Keywords: Group Recommender System; Personality; Dynamic Clustering; Multi-Agent Microservice; Cold-Start; Leisure Tourism

7.1 Introduction

Leisure tourism is a very complex area (Alves et al., 2019; Delić et al., 2020; Garcia et al., 2011; Neidhardt et al., 2014; Sertkan et al., 2019) as it involves sensorial experiences and emotions, being subject to many variables. This complexity aggravates when groups of tourists, like excursions of casual groups of tourists, are involved, increasing the heterogeinity and conflicting prefer-

ences (Boratto & Carta, 2010), which is not made easier with the excessive information found on the internet. Where to go? Which tourist attractions are more compelling for a certain group of tourists? Group Recommender Systems (GRS) for tourism came to tackle that complexity and information overload, helping in the choice of a destination, accommodations, points of interest (POI) to visit, etc. However, the GRS for tourism found in literature are limited, either having time-consuming and intrusive configurations, a great amount of data to build the tourists' initial profile, complex preference aggregation strategies, or are not concerned about how the tourists feel during the excursion and in the group, like reducing the sense of misplacement, increase the group members socialization and the sense of companionship and belonging to the group, or how their limitations like fears/phobias or disabilities impact the group satisfaction. How can these limitations be overcome?

As first identified by Jameson (2004), and as well known in literature, the four main challenges of GRS are: (i) how to obtain the group members' individual preferences and if they should be known and analyzed by the other members; (ii) how the users' preferences should be combined, in a nonmanipulable manner, to generate recommendations that satisfy all the group members; (iii) how to effectively present suitable and explainable recommendations for each group member; (iv) how to support the group members in deciding and negotiating the final recommendation.

As evidenced in our previous work (Alves, Martins, Saraiva, et al., 2023; Alves et al., 2020) and in the existing literature, personality has a strong influence on the users' preferences in a variety of domains (Cantador & Fernández-Tobías, 2014; Ferwerda et al., 2015; Martijn et al., 2022; Rawlings & Ciancarelli, 1997; Yee et al., 2011) and is demonstrating to provide better results than standard approaches (Nunes et al., 2008; Tondello et al., 2017). This can be the leverage needed to improve group recommendations, as the correlation between the users' personality and preferences can match up users with similar interests helping to minimize the group's heterogeinity and conflicting preferences, mitigating the cold-start problem. As human personality is considered stable over time (McCrae & Costa Jr, 1997), the users' personality only needs to be assessed once, being an advantage that can be seized and reused across different domains.

This work aims to help solve the identified limitations by automatically providing recommendations of tourist attractions/activities to visit/perform at a certain destination, along with a justification,

while caring for the tourists' needs, without the need for previous data to build the tourists' initial profile and the first recommendations, solving at the same time the cold-start problem, the groups' heterogeinity and conflicting preferences. That is, the aim is to provide initial recommendations that satisfy the majority of group members with the minimum necessary information, just by knowing the tourists' personality, and avoid the emotional contagion phenomenon usually associated to groups (Delic & Masthoff, 2018; Delić et al., 2020), being, to the best of our knowledge, the firsts to do so (Sharma, Banwala, Elouaghzani, & Katarya, 2023).

This paper unfolds how we implemented the personality vs tourist preferences models in a mobile GRS prototype, Grouplanner, and modified the algorithms proposed in our previous work (Alves, Martins, Saraiva, et al., 2023), to solve the identified issues. This new approach dynamically creates (in real time) personality-based clusters when the tourists register in the app, eliminating the need for users to rate POI to create the initial clusters as previously proposed (Alves, Martins, Saraiva, et al., 2023), leading to an alternative algorithm and solving the cold-start problem. This paper materializes a comprehensive study of the work done so far, so it can be understood as a whole, being the prototype functioning briefly demonstrated in Alves, Martins, Novais, and Marreiros (2023)[33].To validate the proposed d-means algorithm it was compared with two baselines: k-means and k-means++. To validate the prototype, it was tested in a simulation with real users and the results analyzed.

In short, this paper has the following new contributions:

- A personality-based dynamic clustering algorithm, d-means, is proposed, being a novel strategy for aggregating preferences, that aggregates tourists with high similar personalities (≥ 0.80) using an adaptation of the k-means algorithm, automatically creating the best clusters in real-time as the users register in the application, being to the best of our knowledge, a novelty in GRS;
- As the clustering is based on the tourists' personality high similarity, we eliminated the need to know the number of initial clusters as well as the need for previous interaction data and ratings from users. This strategy solves the cold-start problem, as the clusters' members are automatically assigned with a predicted preliminary preference score in

33 More details can also be found at http://www.gecad.isep.ipp.pt/grouplanner/dissemination.html

categories of tourism and travel-related preferences & concerns immediately after registering, allowing a preliminary recommendation list. The clusters are used to form subgroups of tourists with similar interests when requesting a recommendation for large/occasional groups of tourists, as we believe it will be more beneficial to them than to stay in the main (heterogeneous) group;

- Use of the Apriori algorithm to find rules in the existing clusters, according to the tourists' profile and travel history. The rules are used to create lists of POI to include or exclude in the recommendation lists. This information is very useful for the recommendation engine at the time of assigning the points of interest, so that and other similar POI are included or not in the recommendation list for a subgroup, ameliorating the initial recommendations;
- Consideration of weather conditions using data retrieved from an external weather API. This means when a recommendation is requested, the recommendation engine will check for suitable POI according to the weather conditions on the excursion dates, updating the recommended list from 5 days before the excursion begins until it ends.

Beside the referred contributions, we are also working on a proof of concept to gamify the GRS prototype to remove time-consuming and intrusive configurations, such as the personality questionnaire used to assess the users' personality, by using short duration minigames to implicitly acquire the tourists' personality (Alves, Trindade, et al., 2024). With this, we intend to show that the users' personality traits can be acquired unobtrusively just by using minigames and without the need for large amounts of data, and therefore machine-learning algorithms, to gather it.

The remainder of the paper is structured as follows: Section 7.2 describes the background and some related work on GRS for Tourism, Agent-based RS, and clustering techniques used in GRS, along with some reflections; Section 7.3 presents the methodology used; Section 4 describes the conducted experiments to validate the proposed d-means algorithm and the performed simulation to test the GRS prototype. Section 7.5 shows the obtained results and respective analysis; and finally, Section 7.6 reflects on the contents addressed in the paper and describes what will be done as future work.

7.2 Background and Related Work

Although many RS for tourism exist in literature, implementing and comparing different types of Machine-Learning and Decision-Making algorithms for different stages of the recommendation process, ranging from a single type of tourist activity to a broader range, not many are for groups (Amato, 2023; Blanco, Ge, & Pitner, 2023; Djebali, Gabot, & Guerard, 2023; El Majjodi, Elahi, El Ioini, & Trattner, 2020; Gavalas et al., 2014; Kuo & Li, 2023; Nadeem et al., 2022; Vathis, Konstantopoulos, Pantziou, & Gavalas, 2023; Yalcin, Ismailoglu, & Bilge, 2021). In the Section 7.2.1, we present some relevant works.

7.2.1 Group Recommender Systems for Tourism

Some of the first GRS used simpler techniques at the time, like INTRIGUE (Ardissono et al., 2003), which was one of the first GRS, that helps find sightseeing destinations and itineraries in Italy based on manual configurations made by a responsible tourist to characterize the members representing the excursion group. The configurations are then used to divide the group into subgroups of similar preferences, being the recommendations given to each subgroup along with some explanations. Some authors use preference aggregation and incompatible preferences management like Travel Decision Forum (Jameson, 2004), e-Tourism (Garcia et al., 2009), and MyFoodGRS (Emamgholizadeh, Delić, & Ricci, 2024), or average ratings and/or critiques like CATS (McCarthy, McGinty, et al., 2006; McCarthy, Salamó, et al., 2006a), Where2eat (Guzzi, Ricci, & Burke, 2011) or the chat-based mobile GRS STSGroup (T. N. Nguyen & Ricci, 2018). Abolghasemi, Engelstad, et al. (2022) proposed a GRS based on pairwise preferences and on the Thomas-Kilmann conflict resolution styles (Thomas, 2008) that can be used in large groups and in different domains. The TKI styles and pairwise preferences are used to simulate the negotiation between the group members, where the members influence each other to reach a consensus on the ratings according to their weights on the TKI styles.

The GRS proposed by M.-H. Park, Park, and Cho (2008) uses a Bayesian network to model the user's individual preferences based on the user's context and profile. The Analytic Hierarchy Process from multi-criteria decision-making is then used to provide the most suitable recommendations of restaurants considering the modeled individual preferences. Hootle+ (Álvarez Márquez & Ziegler, 2016) is a hotel GRS prototype where each group member chooses the features they want

the hotels to have, and how much important a feature is. The chosen features are then presented to the group, which decides to accept them as a filter or not, creating the group's preference model. Using content-based filtering, the preference model is compared to the hotel's attributes in the database, recommending the hotels with the highest scores. The final recommendation is reached upon the group members negotiation and voting. A similar approach was made by Marques et al. (2016) for a mobile GRS for choosing a restaurant.

New approaches are being considered, like using location-based social networks (LBSN), like Sojahrood et al. (2023) who developed a POI GRS based on LBSN, with a dataset retrieved from the Foursquare Swarm, that uses a switching hybrid group recommendation algorithm for different types of groups: for ephemeral groups, they use a group-based approach; for persistent and homogeneous groups, they use a simple aggregation-based method; and for persistent and heterogeneous groups, they execute the improved-based method; outperforming the baselines in the three types of groups. Other examples of GRS that use LBSN to recommend the most suitable POI are the works of Ayala-Gómez, Daróczy, Mathioudakis, Benczúr, and Gionis (2017) and Khazaei and Alimohammadi (2019). A very recent approach is the one of Delic et al. (2024), who use a chatbot to support the group discussions, preference elicitations, and item rankings, to provide a fair recommendation using the average without misery preference aggregation strategy.

As can be seen from the existing literature, the GRS authors are attempting to find better strategies to provide more accurate and satisfying group recommendations, trying to involve the user in the recommendation process, and find better preference aggregation and negotiation strategies. However, the research in the area is slowly evolving, still having important open issues (Álvarez Márquez & Ziegler, 2016; Alves et al., 2019; Delić et al., 2020; Masthoff, 2015; Ricci, 2022), such as the best approach (a) to know the users' preferences (implicitly or explicitly), (b) to provide the first recommendation without the need for the users interaction, negotiation or feedback (lack of ground-truth data), (c) to combine the individual preferences to provide more accurate and satisfactory group recommendations, or if instead of aggregating preferences, the group members interactions should be mediated, (d) to satisfy the needs of the group according to the context, (e) to increase the sense of companionship and belonging to the group, (f) diminish the sense of

fear/being lost or (g) to support the group members in reaching a faster and more satisfactory final choice without the social contagion phenomenon.

One of the RS main purposes is to provide automatic recommendations, but, to the best of our knowledge, none, except one (M.-H. Park et al., 2008), provides a preliminary automatic recommendation for the group, depending exclusively on the users interaction and feedback on the existing features or POI to provide the first recommendations. Also, according to Sertkan et al. (2019), few studies focus on the tourists' personality. These are two of the open issues, (a) and (b), we propose to solve, by automatically providing initial recommendations without the users explicit desired preferences or feedback on the existing POI, using only the tourists' personality, which also solves the cold-start problem.

The works of Sertkan et al. (2020) and Neidhardt et al. (2015) are examples of an interesting way of implicitly acquiring the tourists' profile, the former by uploading up to 7 pictures the user considers to represent his preferences which can then be re-ranked to build the touristic profile, that can also be adjusted, to obtain destination recommendations. This strategy implies some work from the user to find the best pictures to upload. The latter work presents a set of fixed pictures the user needs to choose to automatically build her profile (a faster strategy), presenting a combination of travel profiles she is most compatible with. The user then needs to indicate various attribute preferences to obtain POI recommendations. Although the profile elicitation is easier, it does not explicitly indicate the type of preferred tourist attractions and therefore is not so detailed as a profile that uses the users' personality to predict more refined tourist preferences, as we propose. Instead, it proposes a combination of tourist typologies, which has a broader range of preferences which do not apply to all kinds of tourists. In this work, we propose a solution to obtain a more detailed profile with distinction on the preferred tourism categories using the users' personality, that uses the personality models previously suggested (Alves, Martins, Saraiva, et al., 2023), instead of a broader tourist typology.

The existing GRS try to find a satisfactory recommendation to fit all the group members, but most of them are more suitable for small groups, need a great amount of data to build the first recommendations or need many interactions and negotiation between the users to obtain the final recommendation. To use the tourists opinions and negotiation is a very complex task in large and

casual groups (e.g., 20+ members), like excursion groups organized by travel agencies, ending up with unsatisfied members when the groups are large and heterogeneous, because, as evidenced by Jameson et al. (2003), they were persuaded to choose an item they did not want or because they felt the need to satisfy the other group members choosing unwanted items. We propose to solve those problems (open issues (c), (e), (f) and (g)) by, instead of trying to find a list of POI to satisfy all the group members at once, divide the main group into subgroups of similar personalities, and therefore preferences, automatically assigning to each subgroup a preliminary list of POI to visit based on the members' personality, alleviating or even eliminating the posterior negotiation phase, as the group was divided into smaller subgroups and can use ratings to accept or discard POI in the recommendation list without the influence of the other subgroup's members (more details in Sections 7.2.3 and 7.3.4).

7.2.2 Agent-based Recommender Systems

To help with limitations found in Recommender Systems, some authors are also proposing the use of Multi-Agent Systems (MAS) to automatically learn the user's profile and proactively make recommendations (Alves et al., 2022; Batet et al., 2012; Borràs et al., 2014). The autonomy, elasticity, distribution, isolated state, and loose coupling of MAS (W. Collier et al., 2019; Wooldridge & Jennings, 1995) allow the creation of distributed systems (Batet et al., 2012), characteristics similar to the ones of Microservices, permitting the deployment of intelligent agents as microservices, the Multi-Agent Microservices (MAMS) architecture (W. Collier et al., 2019). This architecture can take us further if implemented in a GRS, by creating easily accessible agents and a faster system.

The use of MAS in Recommender Systems is expanding in the most varied domains (João Carneiro, Andrade, et al., 2020; Neto et al., 2022b), but only few, and complex approaches, related to tourism can be found. Bekkerman, Kraus, and Ricci (2006) used an individual and self-learning case-based recommender system for tourism assets, Trip@dvice, to develop a GRS. The GRS uses automated negotiation agents, that represent the group members, which cooperatively negotiate and use the individual recommendations and user preference models to provide group recommendations. Lorenzi et al. (2011); Lorenzi, Loh, and Abel (2012) designed a Multi-Agent RS for travel agencies to help users find personalized travel packages. Using the Distributed Artificial Intelligence paradigm, different agents can be used simultaneously to respond to requests asyn-

chronously. The requests are divided into partial tasks and handled by distinct agents, who search information in their local knowledge base following the Case-based Reasoning approach, or if the needed information is not found, in the community by cooperating with other agents. The final recommendation is then presented to the user, who evaluates it, contributing to the agents' confidence degree.

The RS proposed by Batet et al. (2012) provides personalized recommendations of cultural and leisure activities, to the tourists visiting a city, also using a MAS. The architecture consists of different types of agents, where each tourist is represented by a User Agent, the tourism activities by Activity Agents, a Broker Agent that allows the communication between the User and Activity Agents, and the Recommender Agent, which keeps a repository with all the user profiles, with context-aware dynamic updates, providing recommendations based on collaborative and content-based recommendation techniques.

Ravi et al. (2021) proposed a Multi-Agent cloud-based framework for recommending personalized POI. The framework implicitly gathers the user's travel behavior and activity from social networks, and six agents are responsible for detecting the changes in the user's behavior and preferences, to dynamically update the user's profile, aided by a reference ontology. The recommendations list is generated by using a multi-level collaborative filtering algorithm and the ontology created by the MAS. Although an interesting work, there are no details on how the MAS actually works.

Joaquim Neto, António Jorge Morais, Ramiro Gonçalves, and António Leça Coelho (2022a) proposed a context-based Multi-Agent RS to help evacuate the occupants of buildings in case of fire, by providing real-time information on the faster evacuation paths using the users' context data obtained from the surrounding Internet of Things objects. The use of Agent-based Modeling is also a technique based in MAS that can be useful in the tourism context to simulate different complex scenarios and determine changes caused by the tourists' actions or choices by using different machine-learning techniques (Wallinger, Grundner, Majic, & Lampoltshammer, 2023).

In this work, we use a MAMS to facilitate the recommendation process and the access to the agents' knowledge through REST endpoints. We tried to simplify the implementation and communication process by only modeling two types of agents, one to represent the tourists, and another to represent the (sub)groups.

7.2.3 Solving Conflicting Preferences by Clustering Tourists with Similar Personalities

The interaction and relationship between group members with different personalities, and consequently, different tourist preferences are susceptible to conflicts, as the members exchange their divergent opinions and to negotiate and reach a consensus might be a very difficult task, especially in large occasional groups of tourists. This is aggravated by the well-known contagion phenomenon, which can easily spread within the group and negatively or positively "contaminate" the other members (Delic & Masthoff, 2018; Delić et al., 2020), leading to recommendations that can falsely satisfy the group members. Also, the social influence and contagion phenomenon in choice processes can lead to more unsatisfactory recommendations than recommendations based on well-defined facts and rules. For instance, considering the Thomas-Kilmann conflict resolution styles (Thomas, 2008), a very dominating tourist can convince other tourists to visit a POI he likes more than the other tourists. He becomes satisfied but the other tourists don't. This result was demonstrated on a study conducted by Delic et al. (2017), who found passive participants were the most unsatisfied individuals and that mixed types led to more satisfactory results. They also found that more open to experience, less neurotic and agreeable persons were the most satisfied with the recommendations. Pei, Gao, Yan, Zhou, and Wu (2024) proposed to solve conflicting preferences by using opinion dynamics, trust dynamics, and scorings. It is well evidenced that how an individual copes with a conflicting situation can influence the group decisions (Joao Carneiro et al., 2018; Thomas, 2008), as well as the emotions, social relationships, and social identity (Delić et al., 2020). However, we believe this is not the main focus of intelligent systems, i.e., one of the advantages of using intelligent systems is to overcome certain human limitations and improve their quality of life. Considering all that, we believe dividing the main excursion group into subgroups of similar interests, and providing preliminary recommendations based on the users' profile and ratings given to POI visited in the past, can provide a more accurate, fair and satisfactory recommendation list of POI, than a list that was constructed based on the opinions exchanged by the tourists during the process with the social influence aforementioned, i.e., we believe the social influence can negatively affect the (sub)groups satisfaction and travel experience. Although it is demonstrated that decisions are better made in groups (Michaelsen, Watson, & Black, 1989; Shaw, 1932), in

the case of choosing a tourist attraction to visit, the influence of others can mislead a tourist to visit places she will not like.

Although many preference aggregation strategies exist (Delić et al., 2020; Ismailoglu, 2022; Massimo & Ricci, 2021; Masthoff, 2015; Najafian et al., 2020), we believe that clustering tourists based in their raw personality instead of different types of preferences/ratings can lead to faster recommendations, a consensus without much or any negotiations, and more satisfied tourists. As well pointed by Forsyth (2018), group decisions seldom aggregate the opinion of the majority, and certain aggregation strategies can be more suitable for certain groups than others (Masthoff, 2015; Najafian et al., 2020), like the case of occasional large tourist groups. Hence, if a tourist is assigned to a cluster with tourists of similar personalities, the tourist attractions preference will also be similar, which reduces the main group heterogeinity and can avoid conflicts and biased opinions in the choice process, leading to more precise and personalized group recommendations. With this clustering strategy we propose to solve open issues (c) and (e), and (f) by providing recommendations considering each (sub)group's needs (disabilities and fears/phobias). More details can be found in Section 7.3.2.

Several models that use clustering to improve group recommendations can be found in literature. Ntoutsi, Stefanidis, Nørvåg, and Kriegel (2012) propose gRecs, that pre-partitions users into clusters of users with similar preferences using hierarchical agglomerative clustering. Using collaborative filtering, they predict the individual ratings (preferences) for the unrated items for each user in the respective cluster and use them to calculate the aggregated ratings for the group. The recommendations for a user are then based on the respective cluster members' preferences, eliminating the need for searching similar users in the database, suggesting the top-k items along with explanations, as explanations are important to help the users understand the recommendations (Barkan, Bogina, Gurevitch, Asher, & Koenigstein, 2024; De Campos, Fernández-Luna, & Huete, 2024; Najafian et al., 2020).

Boratto and Carta (2015) explored group recommendation approaches that use clustering to automatically detect groups of users with similar preferences. They argue the best approach to predict group preferences for an item is to use an average of the individual preferences, and that using all the predictions generated for individuals is more accurate than other approaches. They also

give some advice to help in the development of GRS that automatically detect groups. Using the MovieLens 1M and 10M datasets, Bi, Qu, Wang, and Shen (2017) propose a group-specific singular value decomposition method that extends the singular value decomposition (SVD) model by incorporating between-subject dependency, taking advantage of missing information from users or items (movies) to cluster users according to the quantiles of the ratings they have provided, and the items according to the release dates, assuming users or items from the same cluster share the same group effects. They evaluate the efficacy of the proposed approach by comparing its performance against four competing matrix factorization models under the regularized SVD, finding their approach demonstrates superior performance across all configurations.

Nozari and Koohi (2020) present Influence-Based Group Recommendation (IBGR), that uses Fuzzy C-means and the Pearson Correlation Coefficient to cluster users of compatible interests. Their main focus is how the group members influence each other by using trust and similarity to estimate new ratings. IBGR modifies the ratings of its members by taking into account their influence, i.e., the adjustment of a member's rating for an item is determined by subtracting their rating from the ratings of other members, multiplied by the respective influence weight assigned to each member. The average aggregation strategy is then used to calculate the group's rating for each item, considering the influenced-based ratings. The top-k items are then recommended. Although interesting, this proposal is complex and goes against our objective of avoiding the contagion phenomenon associated with groups.

An online learning algorithm, cluster-based bandits, is proposed by Shams, Anderson, and Leith (2021) to help with the cold-start problem. The algorithm is capable of rapidly learning the other users' preferences using only 10 to 12 rated items to reliably distinguish between 16 and 32 user groups, respectively. To cluster the users into groups, they use training data to predict the ratings' mean and variance for a certain item for each group, which is tested with different numbers of clusters.

The increased demand for recommendations and the items available has caught the attention of researchers, which are developing algorithms capable of dealing with high-throughput data streams and perform streaming recommendations, dynamically evolve with their content and/or generating online the used models (Chandramouli, Levandoski, Eldawy, & Mokbel, 2011; He et al.,

2023; H. Liu, Zhao, Wang, Liu, & Tang, 2020; Lourenço, Meira, & Marreiros, 2023; J. A. Silva et al., 2013). Although interesting and useful approaches, Grouplanner is targeted for tourists and not for high-throughput data stream services, as the number of users will not increase indefinitely, and it was not programmed to handle transient large volume data (J. A. Silva et al., 2013). That is not the purpose of the proposed GRS. However, the proposed algorithm is dynamic, by assigning a new user and eventually updating existing ones in real time, i.e., it processes the information as soon as it is received. Also, due to impositions of the Grouplanner application, the users' profile is saved in the database, which is not suitable for a streaming algorithm that uses fixed memory and single scan, as it implies forgetting part of past data, data that is crucial to perform the clustering and apply the association rules.

Although various clustering algorithms exist and some are being used in recommender systems (Ackermann et al., 2012; Aggarwal, Philip, Han, & Wang, 2003; Bengali & Veldt, 2023; Ezugwu et al., 2022; Mai, Assent, & Storgaard, 2016; Massimo & Ricci, 2021; Saxena et al., 2017), they need previous interaction data and/or ratings given by other users to provide the first recommendations. Also, the number of clusters needs to be known a priori. We believe this is not the best approach, as it forces us to know all the referred information in advance, not actually solving the cold-start problem. Besides, the fact that someone gives the same rating as another user does not mean they rated it for having the same reason. The underlying reason is crucial to understand if the ratings given are similar, so the clusters are the most accurate and representative of the whole group as possible. For example, a user might have rated a beach with 5 stars because she appreciates its natural beauty and another user because he just likes to swim in the sea and the water of that beach is perfect for that. Also, it is common to find users in the same cluster with different ratings for the same item, which adds noise to the ratings (Shams et al., 2021). Therefore, if instead we aggregate users based on their personality similarity, they will have similar preferences and ratings for the same reasons, increasing the clustering quality.

To accomplish that and solve the cold-start problem, we modified the k-means algorithm, creating d-means, an algorithm that incrementally creates/modifies clusters in real-time as the users register in the application, taking advantage of the users' personality, without needing to define the number of clusters a priori, previous interaction data and ratings (see Section 7.3.2).

7.3 Methodology

7.3.1 The Prototype Architecture

The Grouplanner prototype is a mobile application developed for Android platforms using Android Studio, Visual Studio, Java and the .NET framework (Alves, Martins, Novais, et al., 2023).

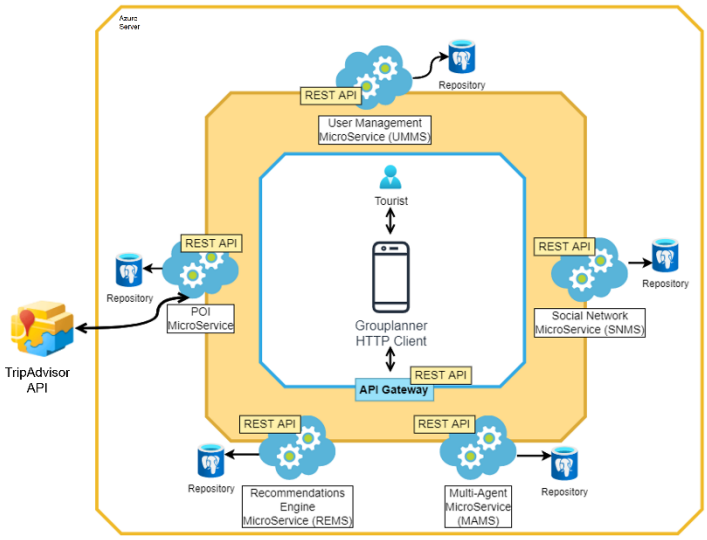


Figure 7.1. Grouplanner Microservices Architecture (first published in Alves et al. (2022)).

As can be observed in Figure 7.1, Grouplanner is composed of five MS, deployed in a free Microsoft Azure server, and the communication between them is performed by sending requests to HTTP REST endpoints. The MS have the following features:

User Management MS (UMMS) – responsible for managing and persisting the registered users' data (demographic data, personality, disabilities (physical impairments, deafness, blindness, heart conditions), fears/phobias (heights (acrophobia), claustrophobia, crowded spaces (agoraphobia)), tourist attractions preference, travel-related preferences & concerns, (un)visited POI, rated POI and other profile related information);

Multi-Agent MS (MAMS) – composed of agents created in the MAMS environment every time a new tourist user registers in the application or a new excursion group is created. Every user is represented by an intelligent agent modeled with the respective profile. The MAMS is responsible for creating dynamic clusters of similar personality tourists and in the case of excursion groups, dividing the main group into subgroups based on those clusters and on the excursion's tourists' personality;

Recommendation Engine MS (REMS) – responsible for finding the best POI to recommend to the tourists in a POI ontology (D. L. C. d. Silva, 2023), according to their tourist attractions' preference, travel-related preferences & concerns, disabilities, fears/phobias, and the restrictions found by the MAMS;

POI MS (POIMS) – Contains all the POI to be suggested, persisted in a repository, obtained from the TripAdvisor API (at the moment only POI from the north of Portugal are available in the app).

The POI microservice is responsible for managing all the POI. Communicates with the Google Places API to retrieve the information needed for a user to register a newly visited POI or to show updated information on the POI presented in the recommendation lists.

Social Network MS (SNMS) – manages the groups and subgroups' information and chats, essential for future consultations within the app and presentation of their information in the user interface.

All microservices repositories use a PostgreSQL database.

At the moment, the Grouplanner prototype allows the registration of tourist users; their profile update and incremental improvement; to register POI visited in the past, rate them from 1 to 5 stars, and define if they want to visit them again; search for other registered users and view their visited POI history; create excursion groups, define excursion dates, add users to the excursion (registered and/or external users, like accompanying relatives), force pairing with other group members, and chat with the group members; request individual and group recommendations for specific dates.

Although they are not used to provide the initial recommendations, the tourists' POI history and respective ratings combined with the tourists' profile are used to improve the recommendation process, i.e., the agents in the MAMS can learn from the tourists' travel experience and profile to reason on rules for the existing clusters, and consequently, to the corresponding tourists. The capability of providing individual recommendations is crucial, as the agents responsible for the subgroups (or main group if no subgroups are formed) can learn with the evaluation given to the suggested POI by the respective tourist, and therefore gain knowledge to help provide better individual

and group recommendations. Also, if the tourists are satisfied with the individual recommendations, it means a more solid base can be provided for the groups' recommendations.

7.3.2 Registration of Tourists with Dynamic Clustering

When a tourist user registers in the application, she needs to fill some basic profile information (*name*, *username*, *email*, *gender*, *birthdate*, *country*, *city*, *nationality, fears/phobias, and disabilities*) and the personality questionnaire (Big Five Inventory (BFI), 44 items, which assesses in a 5-point Likert scale the respondent's score on the Goldberg's five dimensions of personality (Lewis R Goldberg, 1990)), as can be seen in Figure 7.2(a), Figure 7.2(b) and Figure 7.2(c). It is important to consider that, if the tourist does not respond truthfully to the BFI, the recommendations can be less accurate. In the BFI screen, the users are warned to respond honestly so they can receive relevant recommendations. It is therefore up to the user to respond honestly or not to the personality questions.

The user's profile is then sent via HTTPS POST to the UMMS and MAMS, being the communication protocol detailed in Alves, Martins, Novais, et al. (2023).

As is evidenced in literature, completing personality questionnaires can be a tedious task and is subject to the social desirability bias usually associated to self-reporting questionnaires (Pedregon et al., 2012). Although the prototype uses the BFI to determine the tourists' personality, as previously mentioned, we are working on ways of gamifying the application by developing minigames to implicitly detect their personality (Alves, Trindade, et al., 2024), namely the 30 personality traits of the Five Factor Model of personality (Costa & MacCrae, 1992; Digman, 1990). With this approach, we will not only avoid intrusive questionnaires, but also the social desirability bias and untruthful answers, and the need for great amounts of data to determine personality by other implicit methods (Finnerty et al., 2016; Tkalcic & Chen, 2015), improving at the same time the tourists' involvement and motivation while using the application (Xu et al., 2016).

The normalized personality scores are used by the MAMS to predict the tourist's preference in 11 categories of tourism and in 4 travel-related preferences & concerns (see Figure 7.2(d), Figure 7.2(e), Table 7.1 and Table 7.2). The referred items result from an intensive study to determine the relationship between an individual's raw personality (Big Five) and her preference for tourist

attractions and travel-related preferences & concerns, having found they are strongly related, resulting in the proposal of structural equation models that confirm that relationship (Alves, Martins, Saraiva, et al., 2023). Those models are used by the MAMS to calculate a prediction on the preference for the aforementioned travel aspects, bypassing the initial learning phase needed by the existing RS (Dara, Chowdary, & Kumar, 2020), solving the cold-start.

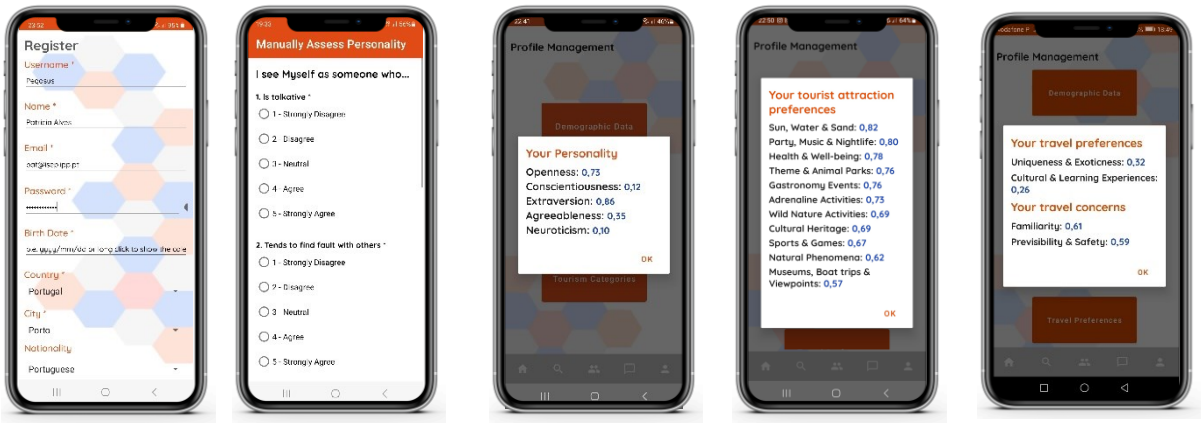


Figure 7.2. Some Grouplanner app screens: (a) new user registration form; (b) personality inventory (BFI); (c) the tourist's personality scores after filling the BFI; (d) the tourist's predicted attraction preference; and (e) the tourist's predicted travel-related preferences & concerns.

As previously mentioned, we adapted the k-means algorithm to aggregate the tourists with similar preferences. If the tourist is the first user registering in the application, a cluster based on his personality scores is created, becoming the centroid[34], otherwise, his similarity to the center of the existing clusters is calculated and, if the similarity is 0.80 or more (see Equation 2), (configurable, to introduce more or less sensitivity), he is added to the most similar one or to a new cluster if not, constituting the proposed d-means algorithm. To maximize the tourists' similarity inside a cluster, the formation of the dynamic clusters is solely based on the tourists' personality. This modification of the k-means algorithm eliminates the need to know the number of clusters in advance, as mandatory by the clustering algorithms (Ezugwu et al., 2022), as we already know the characteristics we want to cluster, i.e., the five dimensions of personality. Also, it solves the k-means problems related to noise and outliers, since the tourists are only assigned to a cluster if they are close to its centroid, not being forced to cluster if they are far away. Therefore, the clusters will contain users with highly similar personalities, and consequently, preferences, which will help mitigate the heter-

[34] The clustering process is only executed if the tourist has filled the BFI first and the respective personality scores calculated.

ogeneity and conflicting preferences associated with casual/large groups. To solve problems related to sparsity (Altman & Krzywinski, 2018), when an excursion group is created, it is divided into subgroups of similar personality, and users that were alone in a cluster will automatically belong to one of those subgroups (see Section 7.3.4).

Table 7.1. Description of the tourism categories available for recommendation, adapted from Alves, Martins, Saraiva, et al. (2023).

Tourism categories	Description
Adrenaline Activities (F1)	Adrenaline promoting activities (hard adventure), like extreme sports, such as aquatic sports (e.g., sailing, canoeing), motor sports (e.g., rally, karting, motocross), under water activities (diving, snorkeling), climbing, bungee jumping, air sports (e.g., skydiving, parachute jumping, gliding), ski.
Wild Nature Activities (F2)	Soft adventure activities related to wild nature, such as to appreciate natural landscapes, hiking, mountaineering, visit nature or wildlife reserves, walk in forests/woods, walk along rivers or seacoasts, visit mountain areas or gorges.
Party, Music & Nightlife (F3)	Events related to celebrations, listening to music, watching movies and nightlife, like attending discos or night clubs, live music bars/places, thematic parades (military, electronic, etc.), film festivals, music festivals, concerts, dance/ballet festivals, balls.
Sun, Water & Sand (F4)	Activities related to relaxing or swimming at a swimming pool or the beach, sunbathing, take vacations on an island.
Museums, Boat Trips & Viewpoints (F5)	Activities involving the visit to museums (historical or scientific), the interest in nature or urban viewpoints, or boat trips to know the coast or to appreciate its historical value.
Theme & Animal Parks (F6)	This category includes activities usually done in family, like going to water parks, funfairs, a zoo or theme parks (like Isla Magica or Disneyland Paris).
Cultural Heritage (F7)	Activities associated with knowing the cultural heritage of a country, like visiting monuments (e.g., castles, monasteries, churches, cathedrals) and historical cities or villages.
Sports & Games (F8)	This category is related to hunting, fishing or assisting to a sporting competition (e.g., football game).
Gastronomy Events (F9)	Events related to gastronomic experiences, like gastronomy tours or festivals involving food (typical and/or gourmet dishes) and wine tasting.
Health & Well-being (F10)	Activities to promote the health & well-being, such as going to a SPA, beauty centers, or do health and wellness treatments (e.g., mineral water resorts).
Natural Phenomena (F11)	Assist to natural events like observing natural phenomena (e.g., volcanic eruptions, northern lights, waterfalls), visit caves, caverns, or volcanoes.

We chose k-means over the other mainstream clustering algorithms because hierarchical clustering algorithms are more suitable for situations where all objects of interest are in a main cluster that needs to be divided into smaller parts, or the opposite, which is not the case in the current problem. This left us with partitional clustering approaches, which are the contrary of hierarchical clustering, where the objects are assigned to a number of clusters determined a priori, according to a criterion function (Lam & Wunsch, 2014), which is what we needed for the tourists registering in the application, i.e., to group them according to their personality similarity using a similarity measure. k-means was therefore chosen, as it is one of the most popular and simple clustering

algorithms (Ezugwu et al., 2022; Saxena et al., 2017), being easier to adapt to the problem in hand.

Table 7.2. Description of the travel-related preferences & concerns considered in the recommendations, adapted from Alves, Martins, Saraiva, et al. (2023).

Travel-related preferences & concerns	Description
Previsibility and Safety (FP1)	Travel-related concerns, like to feel comfort, have mobile phone signal, fear of getting lost, fear of getting ill or having an accident, not to take risks related to the physical integrity.
Cultural & Learning Experiences (FP2)	Travel-related preferences, like studying the destination before traveling, consider the destination's cultural offer by including a cultural/learning component with a visit to iconic monuments or even visit as many attractions as possible.
Uniqueness & Exoticness (FP3)	Travel preferences related to visiting "exotic" points of interest, uncommon places or observe peculiar things.
Familiarity (FP4)	Concerns related to traveling in a familiar environment, with known acquaintances (family, friends, etc.), or not to travel in a group with strangers.

The implemented clustering process is explained next.

Definition 1. Let T_i, $i \in \{1,2,\ldots,n\}$, be a certain tourist i, where n is the number of tourists registered in the application, and p_j, $j \in \{1,2,\ldots,m\}$, be a certain participant j, where m is the number of participants in the conducted simulation (Section 7.4.3).

Definition 2. Let $P \in \{O,C,E,A,N\}$, $T_i.P \in [0,1]$, where P is the personality of tourist's T_i, and $T_i.O$ represents the tourist's Openness to Experience score, $T_i.C$ the Conscientiousness score, $T_i.E$ the Extraversion score, $T_i.A$ the Agreeableness score, and $T_i.N$ the Neuroticism score.

Definition 3. Let $AP_{T_iF_j} \in [0,1]$, $i \in \{1,2,\ldots,n\}$, $j \in \{1,2,\ldots,11\}$, be the tourist's T_i predicted tourist attraction preference AP for a certain tourism category F_j.

Definition 4. Let $TC_{T_iFP_k} \in [0,1]$, $i \in \{1,2,\ldots,n\}$, $k \in \{1,4\}$ be tourist's T_i predicted travel-related concerns TC for a certain travel-related concern factor FP_k, and $TP_{T_iFP_k} \in [0,1]$, $k \in \{2,3\}$, the tourist's T_i predicted travel-related preference for the travel-related preference factor FP_k.

Definition 5. Let C_q, $q \in \{1, \ldots, n\}$ the cluster to which a tourist T_i belongs to and $C_q.centroid = \{O,C,E,A,N\}$ the C_q cluster's centroid personality, where O is C_q tourists' average openness, C is C_q tourists' average conscientiousness, E is C_q tourists' average extraversion, A is C_q tourists' average agreeableness and N is C_q tourists' average neuroticism, all $\in [0,1]$.

To compare a tourist T_j to a cluster's centroid, the dissimilarity between them, $d(T_j, C_q)$, where $j \in \{1, 2, \ldots, n\}$, $d \in [0, \sqrt{5}]$, was calculated, by measuring the Euclidean distance between their personality (5-dimensional), as it is considered the most used metric for numerical data (Ezugwu et al., 2022; Saxena et al., 2017):

$$d(T_j, C_q) = \sqrt{(T_j.O - C_q.O)^2 + (T_j.C - C_q.C)^2 + (T_j.E - C_q.E)^2 + (T_j.A - C_q.A)^2 + (T_j.N - C_q.N)^2} \quad (1)$$

The same formula is applied to measure the distance between two tourists (points). The closer the distance is to zero, the closer the tourists are.

As the Euclidean distance measures the dissimilarity between two points, we used the following formula to calculate the similarity between them (Feldman & Sanger, 2007), so the values were easier to compare:

$$sim(T_j, C_q) = 1/(1 + d(T_j, C_q)), \quad \in [1/(1 + \sqrt{5}), 1] \quad (2)$$

Where $sim(T_j, C_q)$ represents the similarity between tourist T_j and cluster C_q in terms of personality. The closer to 1 the more similar the tourist and the cluster's centroid are. In our algorithm, we consider a tourist's personality is similar to a cluster's personality (or other tourist's personality) if $sim(T_j, C_q) \geq 0.80$ (this value can be changed to increase or decrease the desired similarity and consequently, the clustering sensitivity, being this the most important input parameter that needs to be configured to run the algorithm. All the other application parameters and default values can be consulted in Appendix D Table D-C.2.

The dynamic clustering process is presented in Algorithm 1.

After running Algorithm 1, a tourist that once belonged to a cluster C_x can now belong to a cluster C_y, as the clusters' centroids are recalculated and the tourists' clusters updated.

k-means (Abernathy & Celebi, 2022; Arthur & Vassilvitskii, 2007) is NP-hard and the time complexity is $O(I \times (n \times k \times d))$, where n is the number of points, k the number of clusters, d the number of dimensions of each points, and I the number of iterations performed. In d-means, the main loop iterates until no changes in the centroids are detected, which depends on the number of I iterations. The inside loops iterate over all users and clusters to determine their distance, resulting in a time complexity of $O(n \times k \times d)$ for each main loop iteration. The centroid calculation adds

a complexity of $O(n \times k)$ also for each main loop iteration. This results in a time complexity of $O(I \times (n \times k \times d + n + k))$.

This personality-based dynamic clustering is an innovative approach, used to the best of our knowledge for the first time in GRS, accurately assigning the tourists to clusters of other similar tourists in real-time as they register in the application, eliminating the need for previous interaction data and/or ratings as in the existing RS, solving the cold-start problem. This led to an alternative algorithm to the previously proposed (Alves, Martins, Saraiva, et al., 2023).

Algorithm 1 Dynamic personality-based clustering, d-means

Input: New tourist's T_i personality
Output: Cluster C_q containing tourist T_i and all clusters with centroids updated

1://Assignment of the registering tourist to the initial cluster
2: Obtain tourist's T_i personality
3: $maxSimilarity \leftarrow 0$, $C_c \leftarrow null$
4: **if** $list\langle Cluster\rangle$ is empty
5: create cluster C_1 and set T_i as centroid ($C_1.centroid = \{T_i.O, T_i.C, T_i.E, T_i.A, T_i.N\}$)
6: add C_1 to $list\langle Cluster\rangle$
7: **else**
8: **for each** cluster C_q in $list\langle Cluster\rangle$ **do**
9: calculate normalized Euclidean distance $sim(T_i, C_q.centroid)$ between T_i and C_q centroid
10: **if** $sim(T_i, C_q.centroid) \geq 0.80$ and $sim(T_i, C_q.centroid) > maxSimilarity$ **then**
11: set C_q as closest cluster C_c, $maxSimilarity \leftarrow sim(T_i, C_q.centroid)$
12: **end if**
13: **end for**
14: **if** $C_c \neq null$ **then** //update cluster C_c centroid
15: add T_i to C_c
16: $C_c.O = \frac{\sum_{j=1}^{C_c.size} T_j.O}{C_c.size}$, $C_c.C = \frac{\sum_{j=1}^{C_c.size} T_j.C}{C_c.size}$, $C_c.E = \frac{\sum_{j=1}^{C_c.size} T_j.E}{C_c.size}$, $C_c.A = \frac{\sum_{j=1}^{C_c.size} T_j.A}{C_c.size}$, $C_c.N = \frac{\sum_{j=1}^{C_c.size} T_j.N}{C_c.size}$
17: **else //** T_i was not added to a cluster
18: create new cluster C_x and set T_i as centroid ($C_x.centroid = \{T_i.O, T_i.C, T_i.E, T_i.A, T_i.N\}$)
19: add C_x to $list\langle Cluster\rangle$
20: **end if**
21:**end if**

//Recalculation of the clusters' centroids (adapted from k-means algorithm)
22: **for each** tourist T_j in list<Tourist> **do**
23: $maxSimilarity \leftarrow 0$, $C_c \leftarrow null$
24: **for each** cluster C_q in $list\langle Cluster\rangle$ **do**
25: calculate normalized Euclidean distance $sim(T_j, C_q.centroid)$ between T_j and C_q centroid
26: **if** $sim(T_j, C_q.centroid) \geq 0.80$ and $sim(T_j, C_q.centroid) > maxSimilarity$ **then**
27: set C_q as closest cluster C_c, $maxSimilarity \leftarrow sim(T_j, C_q.centroid)$
28: **end if**
29: **end for**
30: **if** $C_c \neq$ null **then**
31: add T_j to C_c

32: **else //** T_j was not added to an existing cluster
33: create new cluster C_x and set T_j as centroid $\left(C_x.centroid = \{T_j.O, T_j.C, T_j.E, T_j.A, T_j.N\}\right)$
34: add C_x to $list\langle Cluster\rangle$
37: **end if**
35: **end for**
36: **for each** cluster C_q in $list\langle Cluster\rangle$ **do**
37: recalculate cluster C_q centroid (same as step 16)
38: **end for**
39: **repeat** steps 22 to 38 until the existing clusters' centroids no longer change

7.3.3 Determining Rules to Improve Recommendations

To refine the predicted recommendations, using association rules, namely the Apriori algorithm with at least a 95% confidence and support intervals, the MAMS searches for positive and negative rules for each cluster, considering the tourists' profile (demographic data, weather preference, disabilities, fears/phobias (more details in Table 7.3)) and ratings given to (un)visited POI[35]. This process creates a list of positive and negative rules for each cluster. For example, let's imagine several tourists with 45+ years old from cluster C_1 rated positively museums (4 or 5 stars). A positive rule could be: "Tourists with 45+ years old like to visit museums". A negative rule could be: "Tourists who have children do not like to visit Tower of Clérigos". This algorithm is programmed to run as a job during late night, once a day, to update the clusters' rules (parameterizable).

The rules are searched for in a cluster if it has at least 50 members (configurable), otherwise, the rules are searched among all the tourists in the app.

To help kickstart this process and bypass the rules cold-start, as the number of users registered in the prototype was low, we registered the 1035 participants in the dataset[36] from our previous study (Alves, Martins, Saraiva, et al., 2023) in the database, so it could be considered by the MAMS and the clustering process, as it has the participants personality and their tourist preferences.

35 As the ratings in the database are in a 5-point Likert scale, values between 1 and 2 are categorized into "1-Don't like", 3 to "2-neutral", and 4 and 5 to "3-Like". Category 1 is considered negative, and Categories 2 and 3 positive.
36 The dataset is composed of participants mostly from Portugal and between 15 and 68 years old (70% between 23 and 55), being 74% female, 31% from the "Engineering & Technology" area, 26% from "Social ciences", and 43% from other areas. 69% have higher education, 61% are employed workers and 35% students. 60% are in some sort of a relationship and 42% have children. 69% have some sort of fear/phobia (mainly heights). More details can be found at https://www.gecad.isep.ipp.pt/grouplanner/dissemination.html.

Table 7.3. Users' attributes, and respective classes, used by the MAMS to determine the association rules list for each cluster.

Attribute	Classes
Age	≤ 23, between 24 and 34, between 35 and 45, ≥ 46 years old (25% bins)
Gender	Female, Male
Marital status	Single, In a relationship, Married, Other
Children	No, Yes
Educational level	High school, Degree, Master, Ph.D., Other
Formation area	Engineering & Technology, Medical & Health Sciences, Natural Sciences, Exact Sciences, Humanities, Social Sciences, Other, None
Professional situation	Employed, Student, Working student, Self-employed, Other
Live with	Parents, Partner & Children, Partner, Friends, Alone, Children, Other
Liquid income	Not applicable, < 650, between 650 and 1000, between 1001 and 2000, > 2000 €
Professes religion	Yes, No but believe in a superior being, Atheist, Agnostic, Other
Travel companions	Relatives, Partner, Partner & Children, Friends, Other
Disabilities	Physical, Sensorial, Other, None
Fears/phobias	None, Heights, Claustrophobia, Agoraphobia, Other
Weather preferences	No preference, Cold weather, Warm weather, Hot weather
Ratings given to (un)visited POI	Don't like, Neutral, Like

7.3.4 Forming Subgroups to Tackle Heterogeinity and Conflicting Preferences

To help with the heterogeinity and conflicting preferences associated to occasional/large groups of tourists, as the tourists are assigned to a cluster of other similar-personality tourists when they register in the app, that clustering is used by the MAMS as an advantage to divide the excursion groups into subgroups of also similar-personality tourists. This means that tourists from an excursion group who belong to the same cluster are gathered in a subgroup, which will drastically reduce the main group's heterogeneity and conflicting preferences, as they will have similar preferences due to their personality. This can be advantageous, as it is evidenced that smaller groups have higher satisfactory travel experiences and perceived value than larger ones (Su, Cheng, & Huang, 2021). This division is only performed if the subgroups can have at least three members

and at least two subgroups can be formed[37]. The process is detailed next and in Algorithm 2. The creation of similar personality subgroups can be the solution for sparsity issues (sparse users), related to the curse of dimensionality (Altman & Krzywinski, 2018), as users that are alone in a cluster will be forced to belong to a subgroup with the most similar personality.

When a group owner requests a recommendation for an excursion group, Figure 7.4 and Figure 7.5, if at least three tourists in the group belong to the same cluster, a subgroup, C_qSg, where C_q refers to the originating cluster, with the respective tourist agents is created as well as a subgroup Travel Agent, *TrvAg-<GroupID>sub<ClusterID>*, responsible for the subgroup's tourist agents interaction. If there are tourists from clusters that cannot generate a subgroup, i.e., that would create a subgroup of only 1 or 2 members, they are individually compared to the clusters' centroid that originated the already formed subgroups, using the normalized Euclidean distance (Equation 2), and included in the most similar subgroup (Figure 7.3). It is important to notice that neither the subgroup's centroid nor the originating cluster's centroid are updated at this stage. All this guarantees that only the most similar tourists, and consequently with similar tourist preferences, are in the same subgroup and that the corresponding subgroup's and cluster's centroid is not "damaged" by the posteriorly added tourists' personality. If at least two subgroups could not be formed, the main group remains intact, and the recommendations are considered for the full group.

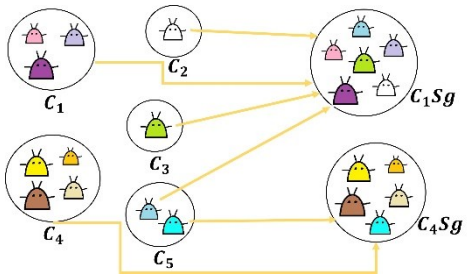


Figure 7.3. Representation of the main excursion division into subgroups with at least 3 tourists from the same cluster.

If a tourist is traveling with his family and/or other companions, and they are registered in the application, he can force the application to pair with their respective users, so when subgroups are formed, they will stay together. If they are not registered, the tourist can add them to the excursion

37 These decisions were made because, for instance, if there is an impasse in a decision, the third person can break a tie. The presence of a third person can also help mediate conflicts. More persons can also help choose more diverse places to visit. The group dynamics can be richer with three persons than with only 2.

group as external members and only fill in the profile mandatory information. It is important to notice that the subgroup's centroid will not consider the family/companion members' personality, so the centroid's personality is not tampered with, to maximize the original subgroup members' satisfaction. However, they can chat and rate together the recommended POI list, as described further in this section. The tourist can also choose not to pair with other excursion members, and his subgroup will only have his family and/or companions.

Algorithm 2 Division of the excursion group into subgroups of similar-personality tourists

Input: Excursion group
Output: Subgroups of similar-personality tourists or the main excursion group

```
1:  ExcursionGroup excursionGroup;
2:
3:  //to form at least 2 subgroups of 3 tourists or more, the excursion group needs to have 6 or more members
4:  if excursionGroup.size ≥ 6 then
5:
6:     Hashtable clustersHash = new Hashtable();
7:
8:     for each T_i in excursionGroup.tourists do //count the number of tourists from same cluster
9:      if T_i.C_q not in clustersHash then
10:        clustersHash.add(T_i.C_q, 1); //Cluster C_q is the key
11:     else
12:        clustersHash[T_i.C_q] += 1;
13:     end if
14:  end for
15:
16:  count number of clusters with at least 3 tourists
17:
18:  if count ≥ 2 then //guarantees there will be at least 2 subgroups
19:     for each C_q in clustersHash do
20:        if clustersHash[C_q] > 2 then //form subgroups of at least 3 similar-personality tourists
22:           create subgroup C_qSg with the corresponding tourists //C_q refers to the originating cluster
22:           create travel agent TrvAg-<ExcursionGroupID>subC_q.id
23:           add TrvAg-<ExcursionGroupID>subC_q.id to excursionGroup.subgroups[C_qSg];
24:           add subgroup C_qSg to excursion.subgroups list;
25:        end if
26:     end for
27:
28:     for each C_q in clustersHash do
29:        if clustersHash[C_q] < 3 then //if only 1 or 2 tourists are from the same cluster
30:           for each T_i in C_q do
31:              int maxSimilarity ← 0;
32:              for each C_qSg in excursionGroup.subgroups do
33:                 calculate normalized Euclidean distance sim(T_i, C_qSg.centroid) between T_i and C_qSg centroid
34:                 if sim(T_i, C_qSg.centroid) > maxSimilarity then
35:                    set C_qSg as closest subgroup C_qSg_closest
```

```
                    maxSimilarity ← sim(T_i, C_qSg.centroid) ;
                end if
            end for
            if C_qSg_closest ! = null then
                add T_i to C_qSg_closest //add tourist T_i to closest subgroup
                update excursionGroup.subgroups accordingly
            end if
        end for
    end if
end for
else
    keep main excursion group intact
end if
```

The Subgroup Travel Agents are responsible for getting the respective subgroup members' travel history (already visited POI and the ratings given, revisit intention, and rating interest for unvisited POI). The rating interest for unvisited POI, if available, comes from previous recommendations the tourists rated as interesting to visit or not, or from the average rating of the other tourists in the same cluster if the tourist has not rated those POI yet (visited or not).

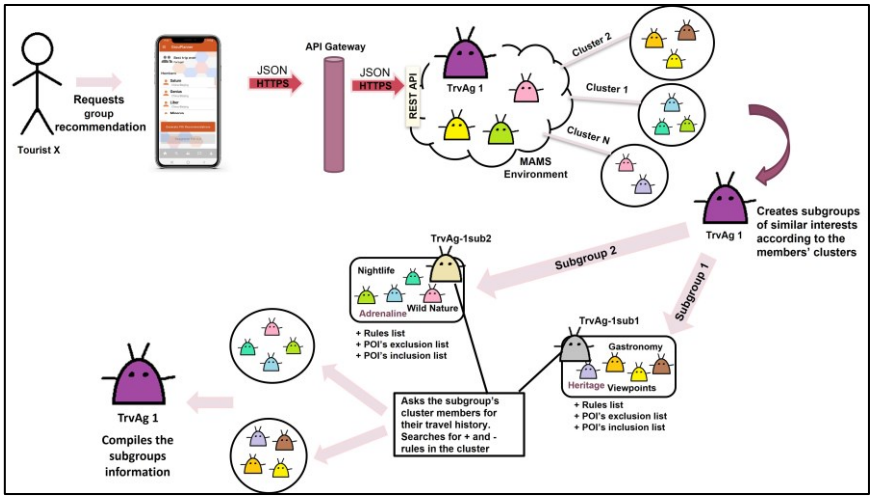


Figure 7.4. Diagram representing the request of a group recommendation to the MAMS.

If at least 50% of the tourists in a subgroup match a rule in the originating cluster for a certain POI in the destination, that POI is added to a POI exclusion or inclusion list of the subgroup, depending on whether it is a negative or positive rule, respectively (see Algorithm 3). This simple process will help the Recommendation Engine to (not) include that and other equivalent POI (i.e., with the

same attraction type, for example, all motor sports activities, see Appendix D Table D-C.1) in the subgroup recommendation list.

To further refine the recommendations, the subgroups' agents use the ratings given to (un)visited POI (in this case, only by the subgroups' members that originated from the same cluster, contrary to the rules, which consider all the subgroup's members). For example, if those subgroup's members rated a (un)visited POI with a mean of less than 3 stars, that POI is added to the subgroup's POI exclusion list. Negatively rated POI and positively rated but that the majority does not want to visit again, are also added to the subgroup's POI exclusion list. Positively rated POI and that the subgroup's majority never visited are added to the inclusion list, otherwise (if visited) are added to the subgroup's exclusion list. This helps increase the recommendation diversity, which is in line with the observation made by Ricci (2022) that suggesting unknown POI should be a priority to diversify recommendations. That is, although a tourist says she wants to revisit a certain POI, that POI is only recommended if the majority never visited it and after the never visited POI have been recommended first. For all other POI in the excursion destination with ratings in the corresponding cluster, but not rated by the subgroup's members, the cluster's average rating is calculated (again, only for the subgroups' members that originated from the same cluster) and added to the exclusion or inclusion lists.

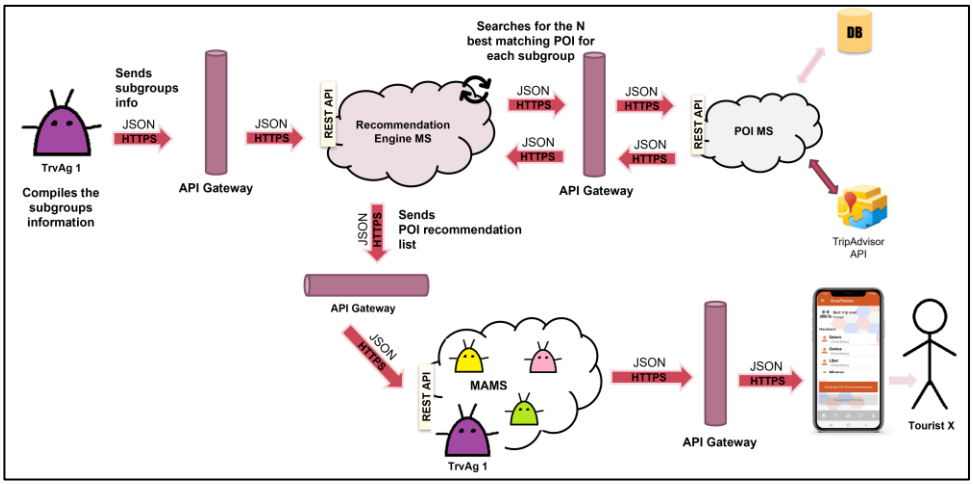


Figure 7.5. Diagram representing the continuation of the group recommendation request.

After creating the subgroups (named after the best scoring category concatenated with the corresponding cluster's ID) and their respective POI's inclusion and exclusion lists, the MAMS sends a

JSON via HTTPS POST to the REMS (Figure 7.5), containing the subgroups formed (or the main group if all tourists have similar personality), their average scores on the tourism categories and on the travel-related preferences & concerns, the corresponding members' profile, and the respective POI's inclusion and exclusion lists.

Algorithm 3 Construction of the POI inclusion and exclusion lists for the subgroups

Input: Subgroups of the main excursion group
Output: Subgroups, or the main excursion group, with POI exclusion and inclusion lists

```
1:  for each subgroup C_qSg in excursionGroup.subgroups do
2:
3:      Hashtable rulesCounter = new Hashtable(); //hash with matching rules count
4:      int count ← 0;
5:
6:      //find matching rules for each subgroup, only the subgroup's originating cluster matters
7:      for each rule R_i in C_qSg.cluster.aprioriRulesList do
8:          for each T_i in C_qSg do
9:              if T_i.profile matches rule R_i then
10:                 count++;
11:             end if
12:         end for
13:
14:         rulesCounter.add(R_i, count);
15:
16:         //if 50% or more tourists in a subgroup match a rule for a certain POI
17:         if rulesCounter[R_i] ≥ C_qSg.size / 2 then
18:             if R_i.rating < 3 then
19:                 add R_i.POI to C_qSg.POIExclusionList
20:             else
21:                 add R_i.POI to C_qSg.POIInclusionList
22:             end if
23:         end if
24:     end for
25:
26:     //obtains already visited POI and the ratings given, revisit intention, and rating interest for unvisited POI
27:     for each T_i in C_qSg do
28:         int ratingCount ← 0;
29:         Dictionary<POI, int[ ]> POIDictionary = new Dictionary<POI, int[ ]>( );
30:
31:         for each POI_i in T_i.travelHistory do //the POI is only iterated if it wasn't considered before
32:             POIDictionary.add(POI_i, new ratingCount[ ]{POI_i.rating, 1,0,0,0}; //ratingCount = 1
33:
34:             if (POI_i.revisit and POI_i.rating > 2) then
35:                 POIDictionary[POI_i].ratingCount[2] += POI_i.rating; //sum ratings
36:                 POIDictionary[POI_i].ratingCount[3]++;
37:             end if
38:
39:             if POI_i.visited then
40:                 POIDictionary[POI_i].ratingCount[4]++;
41:             end if
```

```
42:
43:         for each T_j in C_qSg do
44:           if (i ≠ j) then
45:             for each POI_j in T_j.travelHistory do //only consider POI not already added to the lists
46:               if POI_j = POI_i then
47:                 POIDictionary[POI_i].ratingCount[0] += POI_j.rating; //sum ratings
48:                 POIDictionary[POI_i].ratingCount[1]++;
49:                 if (POI_j.revisit and POI_j.rating > 2) then
50:                   POIDictionary[POI_i].ratingCount[2] += POI_j.rating;
51:                   POIDictionary[POI_i].ratingCount[3]++;
52:                 end if
53:               end if
54:             end for
55:           end if
56:         end for
57:
58:         float POIMeanRating = POIDictionary[POI_i].ratingCount[0] / POIDictionary[POI_i].ratingCount[1]
59:         float POIMeanRevisitInterest = POIDictionary[POI_i].ratingCount[2] /
            POIDictionary[POI_i].ratingCount[3];
60:         int POIMeanVisited = POIDictionary[POI_i].ratingCount[4];
61:
62:         if POIMeanRating < 3 or POIMeanRevisitInterest < 3 or POIMeanVisited ≥ C_qSg.size / 2 then
63:           add POI_i to C_qSg.POIExclusionList
64:         else
65:           add POI_i to C_qSg.POIInclusionList
66:         end if
67:       end for
68:     end for
69:  end for
```

7.3.5 Assigning the Best Matching POI

When the Recommendation Engine receives a group recommendation request, it navigates the POI ontology (D. L. C. d. Silva, 2023), with the leaves ordered by descending relevance for each tourism category (see *ratio_evaluation* attribute in Table 7.4), in the POI Microservice to find the 10 (configurable) best matching POI for each subgroup, and considering the received information. The used POI were classified according to the proposed 11 categories of tourism, the 4 travel-related preferences & concerns, if they were adequate for persons with the considered disabilities and/or fears/phobias, the average rating ratio, and other attributes (Table 7.4). These classifications were first performed by the authors and validated by three experts from the tourism area (please refer to Alves, Martins, Saraiva, et al. (2023) for more details).

Table 7.4. Points of Interest main attributes.

Attribute	Description
number_evaluations	Number of evaluations retrieved from TripAdvisor (posteriorly also from the Grouplanner app)
overall_rating	Mean rating given by the users in TripAdvisor (posteriorly also from the Grouplanner app)
ratio_evaluation	number_evaluations / overall_rating (Relative importance. This ratio is used to order the POI from the best to the worst evaluated inside a category, as it is more representative of the real evaluation. For example, a POI with an average rating of 5 stars but with only 10 raters can be less interesting than a POI with 5 stars and 100 raters)
country	Country of the POI
city	City of the POI
address	Address of the POI
latitude	Latitude coordinates of the POI
longitude	Longitude coordinates of the POI
category	Main tourism category the POI fits into from the 11 available
attraction_type	Type of attraction inside a tourism category (see Appendix D Table D-C.1)
travel_pref	Main travel-related preference the POI fits into (see Table 7.2)
fears	List of fears/phobias the POI is not suitable for (heights, claustrophobia, agoraphobia)
limitations	List of disabilities the POI is not suitable for (wheelchairs, blind, deaf, heart conditions)
indoor_outdoor	If the POI is indoor, outdoor or both
visit_duration	Estimated time for visit, in hours (not in use at the moment)
danger_rate	How much dangerous it is to visit/do in a scale from [0..1] (not in use at the moment)
adrenaline_rate	How much emotion it causes in a scale from [0..1] (not in use at the moment)
engagement_level	How much engagement/attention is needed when visiting/performing [0..1] (not in use at the moment)
min_age	Minimum allowed age (not in use at the moment)
max_age	Maximum allowed age (not in use at the moment)
price_level	The price range (0 – is free, 0.2 – up to 5€ per ticket/meal/etc., 0.4 – between 6 to 10€, 0.6 – between 11 and 20 €, 0.8 – between 21 and 35 €, 1 – if 36 or more €) (not in use at the moment)
schedule	(Seasonal) visit intervals. For example: Summer (10:00-20:00); Winter (10:00-18:00) 8:00-12:30, 14:00-18:00 Summer (10:00-12:00, 14:00-20:00); Winter (10:00-18:00)

Taking into consideration the subgroups' POI's inclusion and exclusion lists and the travel-related preferences & concerns average score (more accurate than the respective cluster's average), the POI are assigned to each subgroup's top-3 preferred tourism categories and that have a score of at least 0.49 (configurable). A tourist T_i is considered to have a certain travel-related preference if $TP_{T_iFP_k} \geq 0.50$, otherwise he does not have (much) interest in that factor. A tourist T_i is considered to have a certain travel-related concern if $TC_{T_iFP_k} \geq 0.50$, otherwise she doesn't care (much) about that factor. The travel-related preferences & concerns are used to further refine the recommendations and better match the POI for each subgroup. It is also in this process that the weather conditions and the tourists' disabilities and fears/phobias are considered.

If a certain member of a subgroup has a disability that impedes the visitation of a certain POI, that POI is not recommended, regardless of the other members having the same disability or not. The same is not applicable for fears/phobias. For instance, only if the majority in a subgroup is afraid of heights a POI not suitable for acrophobic will not be recommended by the REMS. These decisions were made because a disability can be more restrictive and cumbersome for a tourist than a fear or phobia. However, the logic is a proof of concept and can be easily changed to meet the application's future users' feedback and needs.

The REMS consults an external API (via HTTP REST) that returns weather forecasts for the next 5 days (storms, rain, snow, and extreme meteorological phenomena) in JSON. If the excursion starts in the next five days, the POI are recommended based on their suitability for the forecasted weather conditions, during the opening hours (as default, between 8 a.m. and 6 p.m.). For instance, in the timespan, if it is going to rain on one of the excursion days, the REMS will first search for POI allowing for indoor visits/activities. Let´s suppose a subgroup has Cultural Heritage as a top category. POI that only have outdoor activities will not be recommended. For instance, instead of recommending the visitation to an archeological site, a church or castle will be recommended instead, according to the subgroups' preferences. The weather conditions are checked every 24 hours and only if the excursion starts within the next 5 days and until the excursion's end date. If a list of POI has already been suggested, the suggested POI are replaced accordingly if the group owner so wishes, i.e., a notification is sent to the group owner to decide with the excursion group if they want to replace the affected POI or not.

As is evidenced in literature and in real-life, individuals generally have a combined preference of tourism categories (Alves, Martins, Saraiva, et al., 2023; Gretzel et al., 2006; Sertkan et al., 2019), i.e., they don't just like Adrenaline activities or Cultural Heritage attractions, they have a combined weighted preference for each of them. This is why we decided to assign weights to the tourism categories preference according to the subgroup's predicted score for the top-3 preferred categories F_j, to introduce further variability in the recommended POI. This means the relative importance (percentage) of a tourism category score is used to decide how many POI will be recommended for that category, which resulted in the following formula:

$$N_{F_j} = round.up\left(\frac{\overline{AP}_{C_q Sg F_j}}{\sum_{j=1}^{3} \overline{AP}_{C_q Sg F_j}} \times N_{POI}\right) \quad (3)$$

Where N_{F_j} is the rounded-up integer number of POI to recommend for the tourism category F_j, $\overline{AP}_{C_q Sg F_j}$ the average attraction preference score of subgroup $C_q Sg$, $q \in \{1, \ldots, n\}$, for the top category F_j; $\sum_{j=1}^{3} \overline{AP}_{C_q Sg F_j}$ the sum of the top-3 categories average scores of subgroup $C_q Sg$; and N_{POI} the total number of POI to recommend for each subgroup (10 by default).

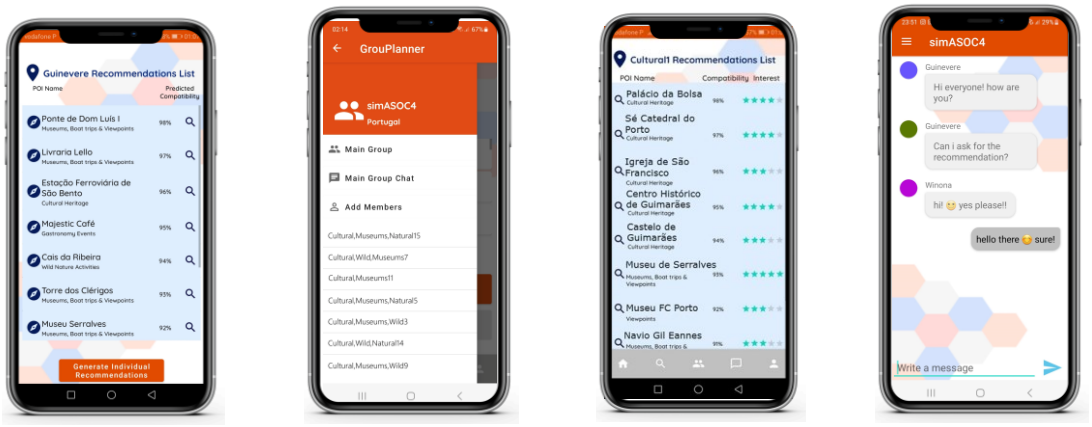
For example, by consulting Table 7.10 left-side, Subgroup $C_7 Sg$ has the following top-3 categories: F_7, F_2, F_5. If we sum up the respective scores (2.24), the number of POI to recommend for category F_7 would be $N_{F_7} = round.up(0.82/2.24 \times 10) = 4$, $N_{F_2} = 3$ and $N_{F_5} = 3$. In case one of the top categories' score is tied with a fourth category, 4 categories are considered, and so on. As the number of POI to recommend for a category results from a rounding operation, extra POI can happen to be recommended.

The order by which the best categories are recommended is important because, for instance, if two subgroups like F_7 (Cultural heritage) and F_5 (Museums, boat trips & viewpoints), but one of them scores higher on F_7, more POI can be recommended for the F_7 category than for the F_5 one, which was the case, for example, of Subgroups $C_{15} Sg$ and $C_5 Sg$ in the conducted simulation (see Table 7.9).

After determining the best matching POI, the recommendation engine answers to the requesting Travel Agent with a JSON containing the list of POI suggested for each subgroup (or the main group), along with a justification for each recommended POI (e.g., "This POI was recommended

because the subgroup likes Adrenaline activities"), and a name for the subgroup containing the top-3 category names concatenated.

The subgroups' members can then rate the suggested POI, chat if necessary (Figure 7.6(d)), and reach a consensus. When all members have rated the recommended POI, the group's average rating for each POI is displayed in the recommendation list (Figure 7.6(c)). The group owner is responsible for asking in the main excursion chat if all subgroups want to keep their recommendations or ask for new ones. If any subgroup wants new recommendations, the group owner asks for new ones, and all POI rated below 3 (configurable) will be replaced by other POI, following the previously mentioned criteria.



(a) (b) (c) (d)

Figure 7.6. Some Grouplanner's app screens used in the recommendation process: (a) partial list of individual POI recommended to user Guinevere and the corresponding main tourism category; (b) list of the 7 subgroups formed for the excursion group simASOC4; (c) partial list of recommendations suggested to Subgroup $C_{11}Sg$ and respective average rating given by all subgroup members; (d) main group chat screen.

The POI rated in the recommendation lists and that were not registered as visited by a tourist, are added to his respective POI history but marked as not visited. If a tourist registers a visited POI and rates it, that rating replaces the previous rating.

Grouplanner allows to see the public profile of the other group members, as well as the ratings they gave to previously visited POI, as mutual awareness is important in groups (Y. Chen & Pu, 2012; Guzzi et al., 2011; Jameson et al., 2003). However, as previously mentioned, this mutual awareness needs to be carefully considered, as the group members can manipulate the others to meet their preferences (Delic & Masthoff, 2018; Delić et al., 2020; Jameson et al., 2003). That is why the group interest in the suggested recommendations is only visible when all tourists in the

(sub)group have rated the recommended POI, which can be less biasing than allowing a full awareness of the other members' ratings.

7.3.6 Requesting Individual Recommendations

Grouplanner is suitable for individual recommendations, as the individual personality is the core feature to build dynamic clusters. When a tourist requests an individual recommendation, a JSON message is sent from the client app via HTTPS POST to her Travel Agent, $TrvAg$, in the MAMS. Her corresponding $TrvAg$ determines to which cluster the tourist belongs to and asks for her travel history. The logic followed for the remaining process is similar to the group recommendations but when a tourist rates a (un)visited POI that was never rated by other tourists in her cluster, that rating is replicated to those tourists.

The recommendation list suggested by the REMS is then sent to the tourist's $TrvAg$ which then sends it to the requesting user in the application through the API Gateway. An example of an individual recommendation list can be observed in Figure 7.6(a).

7.4 Experimentation and Evaluation

In this Section, we describe how we evaluated the proposed clustering algorithm and the GRS. We present the datasets used, the protocol followed to evaluate d-means, and the conducted simulation with real participants (n = 35).

7.4.1 Datasets

To test the algorithms, beside the sample obtained in the simulation with real participants (n = 35) (Section 7.4.3), we used the 1035 participants dataset from our previous study (Alves, Martins, Saraiva, et al., 2023), which were named as "userCSV<id>", and a Personality dataset obtained from kaggle[38] (Tunguz, 2018) with more than 1M answers.

The Personality dataset was collected worldwide between 2016-2018 (Tunguz, 2018) through an interactive on-line personality test, constructed using "Big-Five Factor Markers" from the International Personality Item Pool (IPIP)[39], being composed of 10 items per personality dimension, using

38 https://www.kaggle.com/datasets/tunguz/big-five-personality-test/data
39 https://ipip.ori.org/newBigFive5broadKey.htm

a 5-point Likert scale. As the dataset was too large to deal with, we split it in half. We only used records where the IPC value was 1, as suggested by the dataset authors. Answers to questions EXT2, EXT4, EXT6, EXT8, EXT10, EST2, EST4, AGR1, AGR3, AGR5, AGR7, CSN2, CSN4, CSN6, CSN8, OPN2, OPN4, OPN6 were reverted, and the average score of each personality dimension was calculated. Some answers had 0 as value, which was not according to the scale the authors claimed to use, so we decided to remove those participants' answers. All the scores were normalized between 0 and 1, so they could be used in the same conditions as the other datasets in the calculations.

The next step was to create the correspondent users in the MAMS database. We selected ca. 10% of the main dataset (n = 127907). The participants from the simulation and from the previous study had already been registered before. So, we created a .NET script to import and insert the Personality dataset's users in the MAMS database, naming them as "userIPIP<id>".

7.4.2 d-means Evaluation

To evaluate the quality of the d-means algorithm, several experiments were conducted. Also, the algorithm was compared with two baseline algorithms, k-means and k-means++ (Arthur & Vassilvitskii, 2007). k-means was chosen because it was the base to develop the proposed algorithm and it was therefore important to determine if d-means could improve it. k-means++ was chosen for being an improvement of the original k-means, generating better quality clusters, so, it was a mandatory choice to be compared.

The algorithms were manually implemented in the MAMS (in .NET), as described in Ackermann et al. (2012); Arthur and Vassilvitskii (2007), so they could be compared in the same conditions as d-means. An incremental version of each of them was also implemented (Pham, Dimov, & Nguyen, 2004), i.e., the code was adapted so the base algorithms could allow the insertion of a new user considering the existence of clusters in the database without generating again all the clusters. This was necessary to compare the 3 algorithms in the experiments related to assigning a new user when there were already clusters in the database (more details next).

The following experiments were conducted to evaluate the proposed d-means algorithm:

E1. Time taken by each algorithm to cluster 35, 1000, 5000, 10k, 50k, and 100k users, for $sim \geq 0.80$;

E2. Time taken by each algorithm to assign a new user when there were already k clusters formed in the database, for 1000, 5000, 10k, 50k, and 100k users, for $sim \geq 0.80$ (the incremental version of k-means and k-means++ was used when adding the new user to make a fair comparison with our algorithm);

E3. Time taken by d-means to cluster 35, 1000, 5000, 10k, 50k, and 100k users, for different sensitivities: $sim \geq 0.70$, $sim \geq 0.80$, and $sim \geq 0.90$;

E4. Number of k clusters formed by d-means, for an increasing number of users in the database (35, 1000, 5000, 10k, 50k, and 100k), for each sensitivity: $sim \geq 0.70$, $sim \geq 0.80$, and $sim \geq 0.90$.

Experiments E1 to E3 were run 3 times for each set of users and the average time was considered.

For E1 and E2, as d-means dynamically determines the number of clusters according to the defined similarity (sim), the number of clusters k obtained in each run, for each set of users, was used as input for the runs with the baseline algorithms.

In experiments E1, E3, and E4, the clusters formed were deleted and disassociated from the corresponding user between each run, to start from scratch for each run. In experiment E2, the clusters formed were only deleted and disassociated after assigning the new user, i.e., first each clustering algorithm was run for the defined set of users, then the new user was added considering the clusters formed, and only after that, the clusters were deleted and disassociated, proceeding to the next set of users.

The experiments were run in an Intel Xeon Silver 4210 CPU @2.20 GHz (4 cores), with 16 GB of RAM, running a 64-bit Windows Server 2022 Standard version.

There are several validation measures that can be used to evaluate the goodness of clustering, which are divided into three main categories: external, internal, and relative clustering validation (Ezugwu et al., 2022; Saxena et al., 2017; H. Zhang, Sun, Zhao, Chow, & Wu, 2019). Internal validation measures how compact a cluster is (intra-cluster homogeneity/cohesion) and/or how separated they are from each other (inter-cluster separability), like the Sum of Squared Error (SSE),

Silhouette Index, etc. External validation assesses how well a cluster's structure matches a predefined structure of the known dataset, such as Rand Index, Entropy, etc. Relative clustering validation is generally used to determine the optimum number of clusters (Ezugwu et al., 2022; Rousseeuw, 1987; Saxena et al., 2017). With the conducted experiments, beside comparing our algorithm's performance, sensitivity, and scalability with the baselines, we wanted to determine if the users were better clustered, i.e., if the clusters were more compact and had higher silhouettes, as to aggregate users with similar personalities was the main focus of the proposed algorithm. To do so, for each formed cluster by each algorithm, we determined the following metrics (Rousseeuw, 1987):

- How compact it was by measuring the average squared distance of the cluster's users, to the respective cluster's centroid, where T_i represents the tourist user $i \in \{1, \dots, n\}$, n is the number of users in cluster C_q. The smaller the value the more cohesive the cluster is:

  $$\alpha = (\sum_i^n \|T_i - C_q\|^2)/n, \quad \begin{cases} if\ C_q.size > 2 \\ else\ \alpha = 0 \end{cases} \tag{4}$$

- How well each cluster C_q was separated from the other clusters C, by determining the squared distance to the closest cluster. The greater the value, the more distant is the closest cluster:

  $$\beta = min\|C_q - C\|^2 \tag{5}$$

- Its Silhouette (s) value, that is a measure of the compactness against the separability. The closer to 1 the better the members are clustered. By default, a cluster with one member as s=0:

  $$s = (\beta - \alpha)/\max(\alpha, \beta) \tag{6}$$

For that, an Excel file was generated after each run with the following metrics for interpretation, for each user: user ID, username, cluster membership (cluster ID), user's personality values (OCEAN), cluster's average distance to centroid (α), closest cluster (β), cluster's Silhouette (s), user's Euclidean distance to the corresponding cluster's centroid.

As some runs took more than 7 hours to complete, and the generation of the Excel files for 100k users was taking between 2 to 3 hours, we only conducted the experiments for a maximum of 100k users, which took in total more than 4 weeks to complete.

7.4.3 Simulation with Real Participants

To test how accurate and satisfactory the preliminary individual and group recommendations of POI were, as well as the prediction of the users' tourism categories preference and travel-related preferences & concerns, we planned an experiment with real users to simulate a large excursion group (at least 30 participants). To gather participants, a wave of emails asking to participate in the study was sent to research fellows and professors of different departments of the Institute of Engineering of Polytechnic of Porto (ISEP). Some relatives and friends were also asked to participate, resulting in a total of n = 35 participants. Although the objective was to gather participants from different formation areas to get more diversity in terms of personality, most participants were from the "Engineering and Technology" area (77%) as can be seen in Table 7.6. However, the participants personality followed a normal distribution as shown in Figure 7.13.

The participants were invited to bring an Android smartphone to the research facilities, otherwise one was provided.

First, the participants filled a pre-questionnaire composed of demographic, disabilities and fears/phobias related questions (see Table 7.6); a section to classify, in a 5-point Likert scale, how much they enjoy the type of attractions in the 11 tourism categories ($F_1, \dots, F_{11}$) when on vacations; and a section to classify, also in a 5-point Likert scale, how much they care for the 4 travel-related preferences & concerns ($FP_1, \dots, FP_4$) when on vacations (see Table 7.10 and Appendix D Table D-B.1). The simulation dataset can be consulted at https://www.gecad.isep.ipp.pt/grouplanner/dissemination.html under the "Simulations" tab.

Then, the participants were asked to install and register in the Grouplanner application, fill in the basic profile information and indicate possible fears/phobias and disabilities (Figure 7.2(a)). After registering in the app, they were asked to navigate into the personality assessment BFI questionnaire (Figure 7.2(b)) and answer the questions, so their scores in the five dimensions of personality could be assessed. After filling in the BFI, the participants were told to verify the obtained personality scores in their profile (see Figure 7.2(c) and Table 7.7).

The next step was to request individual recommendations for the North of Portugal, for the next 7 days, and analyze the suggested POI, rating them from 1 to 5 stars (Figure 7.6(a)). They were also

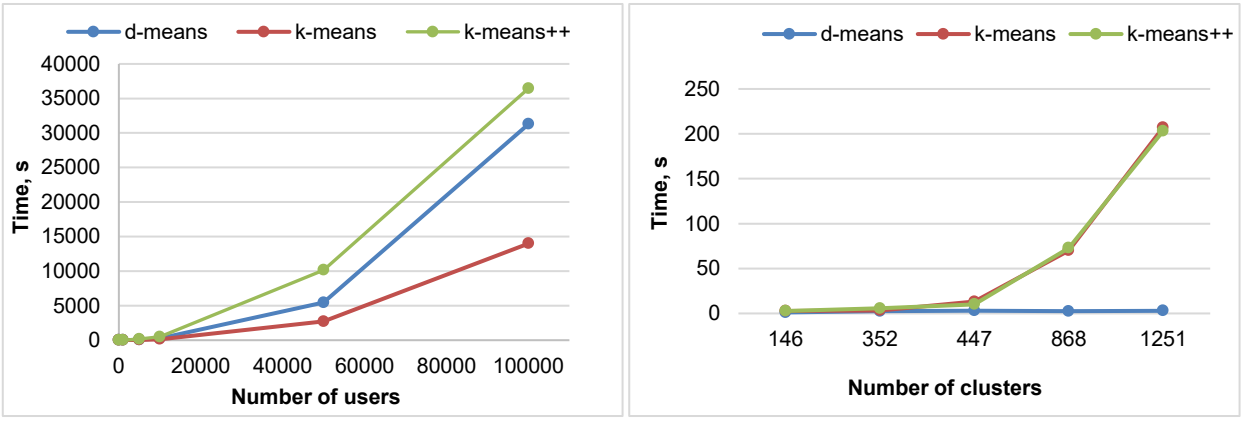
asked to check their predicted scores for the 11 tourism categories and 4 travel-related preferences & concerns (Figure 7.2(d)).

After that, one of the participants created an excursion group, added the other participants, and requested recommendations for the group, also for the North of Portugal, for the next 7 days. Each participant was asked to check the respective subgroup's POI recommendations and rate them, also from 1 to 5 stars (see Figure 7.6(c) and Table 7.9).

7.5 Results and Analysis

7.5.1 d-means Evaluation Results

Experiment E1: Regarding the experiments conducted to evaluate the proposed d-means algorithm, in experiment E1, we can see the time to cluster the users increases as the number of users increases (Figure 7.7(a)). From n=35 to n=1000, the algorithms took almost the same time to create the clusters, but from n=5000, k-means performed faster than d-means and k-means++, and d-means faster than k-means++. Although k-means++ was made to improve k-means, our algorithm outperformed k-means++, clustering the users faster and without needing to know the number of clusters a priori like the other two algorithms. As expected, k-means performed faster because it already knows the number of clusters to assign at the beginning. k-means++ took the longest time, because, although optimized for creating better quality clusters, it takes longer in the optimization phase of selecting the initial clusters.



(a) (b)

Figure 7.7. (a) Time taken, in seconds, by each algorithm to cluster 35 to 100k users, for $sim \geq 0.80$; (b) Time taken, in seconds, by each algorithm to assign a new user when there were already k clusters (x-axis) in the database, from 1000 to 100k users, for $sim \geq 0.80$.

Experiment E2: In terms of scalability, our algorithm scaled significantly better than the baselines with the increasing number of clusters (Figure 7.7(b)), following a linear trend, while k-means and k-means++ followed a polynomial trend of approximately order 3. So, roughly, the more clusters to "compare", the more time the baseline algorithms take. Although slower than k-means to create the initial clusters, d-means outperforms the baselines by adding a new user in a few seconds, < 3s, independently of the number of clusters in the database. This incredible gain comes from the d-means greatest impact being mostly related to the similarity restriction and the nearest cluster when a new user is added (or to the creation of a new cluster), as only clusters whose centroid's $sim \geq 0.80$ are seen and compared by the algorithm, instead of all existing clusters like in the baselines. This reduces the overall computational load compared to the baselines, where adding a new user might require multiple iterations to stabilize the centroids across all clusters, as happened for 447 clusters and up.

Experiment E3: Comparing the clustering time taken by d-means for different sensitivities, the greater the sensitivity the more time d-means takes to cluster the users, as would be expected, as it becomes more difficult to find users similar to each other, which was the case of $sim \geq 0.90$ (Figure 7.8(a) and Table 7.5) which took more than 18 hours to run for 100k users.

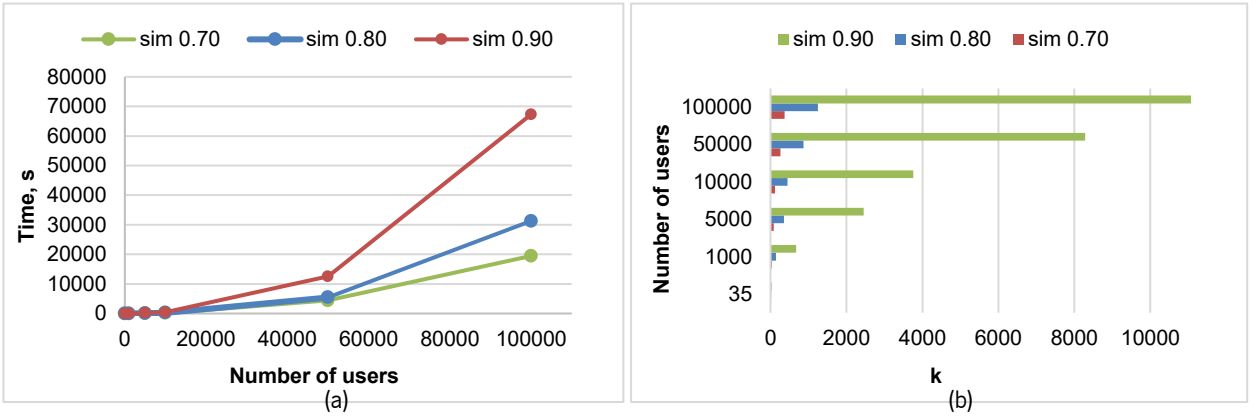


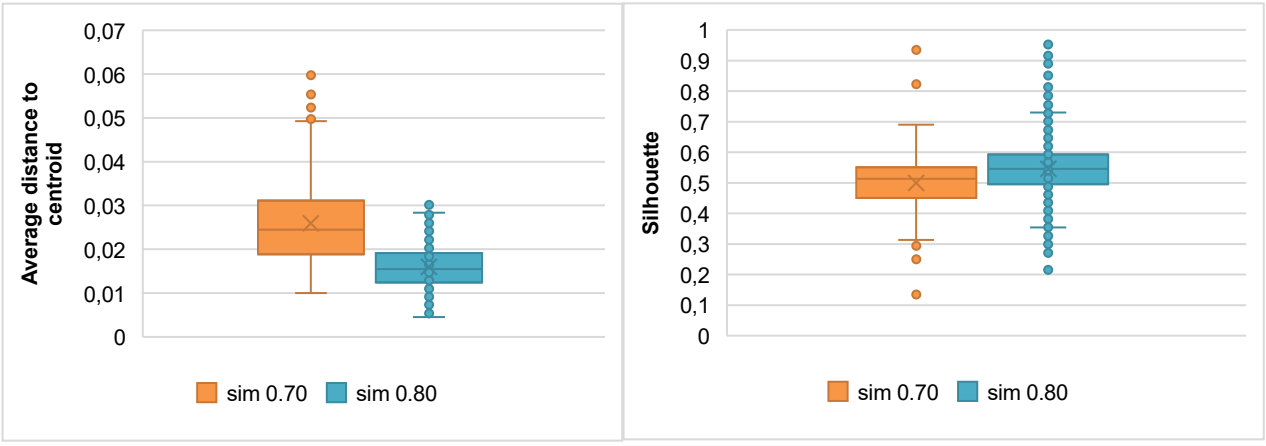
Figure 7.8. (a) Time taken, in seconds, by d-means to cluster 35 to 100k users for different sensitivities; (b) Number of clusters formed by d-means for an increasing number of users in the database for each sensitivity.

Experiment E4: The greater the sensitivity, the more clusters are created by d-means (Figure 7.8(b) and Table 7.5). For instance, the number of clusters drastically increases, in the order of thousands, for $sim \geq 0.90$, as it becomes harder to find very similar users, which is not acceptable. As the clusters formed for $sim \geq 0.80$ are much more compact and have higher silhouette

values than $sim \geq 0.70$ (Figure 7.9), we decided to use $sim \geq 0.80$ as the default value for our algorithm.

Table 7.5. Average time taken, in seconds, and number of clusters formed by d-means to cluster 35 to 100k users for different sensitivities.

n	k ($sim \geq 0.70$)	mean time, s ($sim \geq 0.70$)	k ($sim \geq 0.80$)	mean time, s ($sim \geq 0.80$)	k ($sim \geq 0.90$)	mean time, s ($sim \geq 0.90$)
35	10	0,267	21	0,193	35	0,215
1000	35	1,99	146	3,62	678	3,99
5000	86	36,43	352	60,86	2453	118,77
10000	117	120,48	447	251,72	3758	426,66
50000	258	4395,42	868	5439,30	8287	12538,62
100000	369	19463,52	1251	31278,00	11161	67304,40



(a) (b)

Figure 7.9. (a) Boxplots comparing the d-means clusters compactness for the similarity thresholds of $sim \geq 0.70$ and $sim \geq 0.80$ for 50000 users. (b) Boxplots comparing the d-means clusters silhouette for the similarity thresholds of $sim \geq 0.70$ and $sim \geq 0.80$ for 50000 users.

Clusters' Cohesion: Comparing the clusters' average distance to the respective centroid for d-means and the baselines (Figure 7.10(a)), except for n=35, where d-means has the most cohesive clusters of all 3, it can be seen the cohesion values increase for d-means and k-means++ until 5k users, inclusive, and start to decrease after 10k users, curiously it starts do decrease after 5k for k-means. Starting from 1000 users, d-means seems to "imitate" k-means++ in terms of cohesion, having very similar values for each set of users. It is clear that k-means has the largest interquartile range until 10k users, showing greater disperse values, starting to approximate of d-means and k-means++ after 50k users. k-means has also considerably the largest whiskers, especially for 5k users, showing the cohesion values are more dispersed and therefore the algorithm is less consistent. d-means and k-means++ have very similar interquartile ranges and medians,

and smaller whiskers compared to k-means, showing the cohesion values are less dispersed and the algorithms are more consistent. We can therefore create very compact clusters like the optimized version of k-means, i.e., like k-means++ , without the need to define the initial k clusters just by defining a similarity threshold.

Closest Cluster: As for the clusters' separability (Figure 7.10(b)), for a small set of users (n=35) and considering the interquartile range, the closest clusters are more distant and dispersed for d-means and k-means compared to the other sets of users. The distance to the closest clusters decreases as the number of users increases. This might be due to the increasing number of clusters, augmenting the chance of having closer neighbors. k-means has again the largest interquartile range in all cases, although decreasing with the number of users, and the largest whiskers for 5k users. We can see that although 50% of the clusters are closer, the other 50% are quite dispersed for all algorithms. The maximum and minimum values are also for k-means, having the greatest range at all cases. d-means and k-means++ are very similar in terms of interquartile range and median values, but d-means can have farther clusters than k-means++, showing again d-means competes with k-means++, gaining advantage with the dynamic clustering and scalability capability without compromising the clustering quality.

Silhouette: Regarding the clusters silhouette values (Figure 7.10(c)), d-means and k-means++ have always the greatest silhouette values, revealing a very good/good clustering quality for the upper 50% values in all cases, being the clusters cohesive and well separated. k-means starts to have fair clustering quality after 5k users. For the 3 algorithms, the silhouette values decrease as the number of users increases. Once again, d-means competes with k-means++, being a better choice due to the less time it takes to form clusters for high sets of users, the linear scalability, and without needing to define the initial clusters.

For curiosity, the number of users in each cluster was determined for each sensitivity for each set of users (Figure 7.10(d)). As was expected, the higher the sensitivity the less users were aggregated in a cluster. So, the tradeoff of searching for the most possible similar users does not compensate what we can achieve by having acceptable clustering times and a similarity of at least 0.80, as the users are still very similar, and we can have much more (similar) users in a cluster.

We also determined the optimal number of clusters for the baseline algorithms using the average silhouette method (Kaufman & Rousseeuw, 2009) and compared their clustering quality against our algorithm, for two small sets of users (n=50 and n=150) as the graphics would become very complex for large sets. The results are presented in Figure 7.11 and Appendix D Table D-A.2 to Table D-A.7.

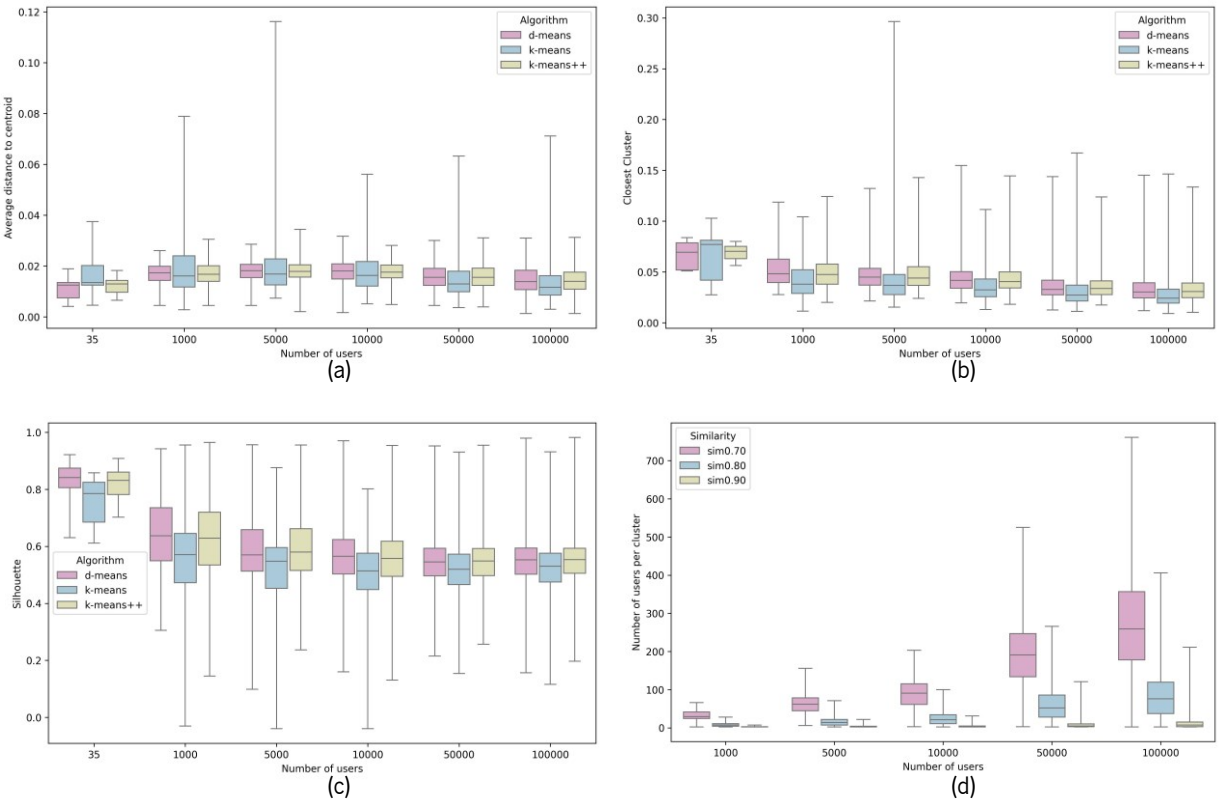


Figure 7.10. (a) Boxplots comparing the 3 algorithms in terms of the clusters' users' average distance to the respective centroid; (b) closest cluster; (c) silhouette values, from 35 to 100k users, for $sim \geq 0.80$; and (d) d-means number of users per cluster for each sensitivity, from 1000 to 100k users. Only clusters with 2 or more users were considered.

Observing Figure 7.11 graphics, we can perfectly see the clusters formed. For d-means, in Figure 7.11(a), clusters C_7 and C_{16} have the greatest number of similar members, although some overlapping can be seen mainly between these 2 clusters and between C_{16} and C_{14}. As an example, user 37 was assigned to cluster C_{11} be could also belong to C_{16}. However, the graphics only have 2 dimensions and clusters that seem to overlap may not be overlapping. This is confirmed by the high values obtained for the clusters' compactness and silhouette (Appendix D Table D-A.2), showing the clusters are very cohesive and with a good to very good clustering quality. When we ran d-means for 150 users (Figure 7.11(b) and Appendix D Table D-A.5), 50 clusters were formed. Sev-

eral clusters seem to overlap and some users that were alone in a cluster or with other users in Figure 7.11(a), were assigned to different clusters, as more similar users appeared, rearranging the clusters and creating new ones. For instance, users 18 and 20 left C_{10} and were assigned to another cluster, C_1, with higher similarities, and user 47 remained alone.

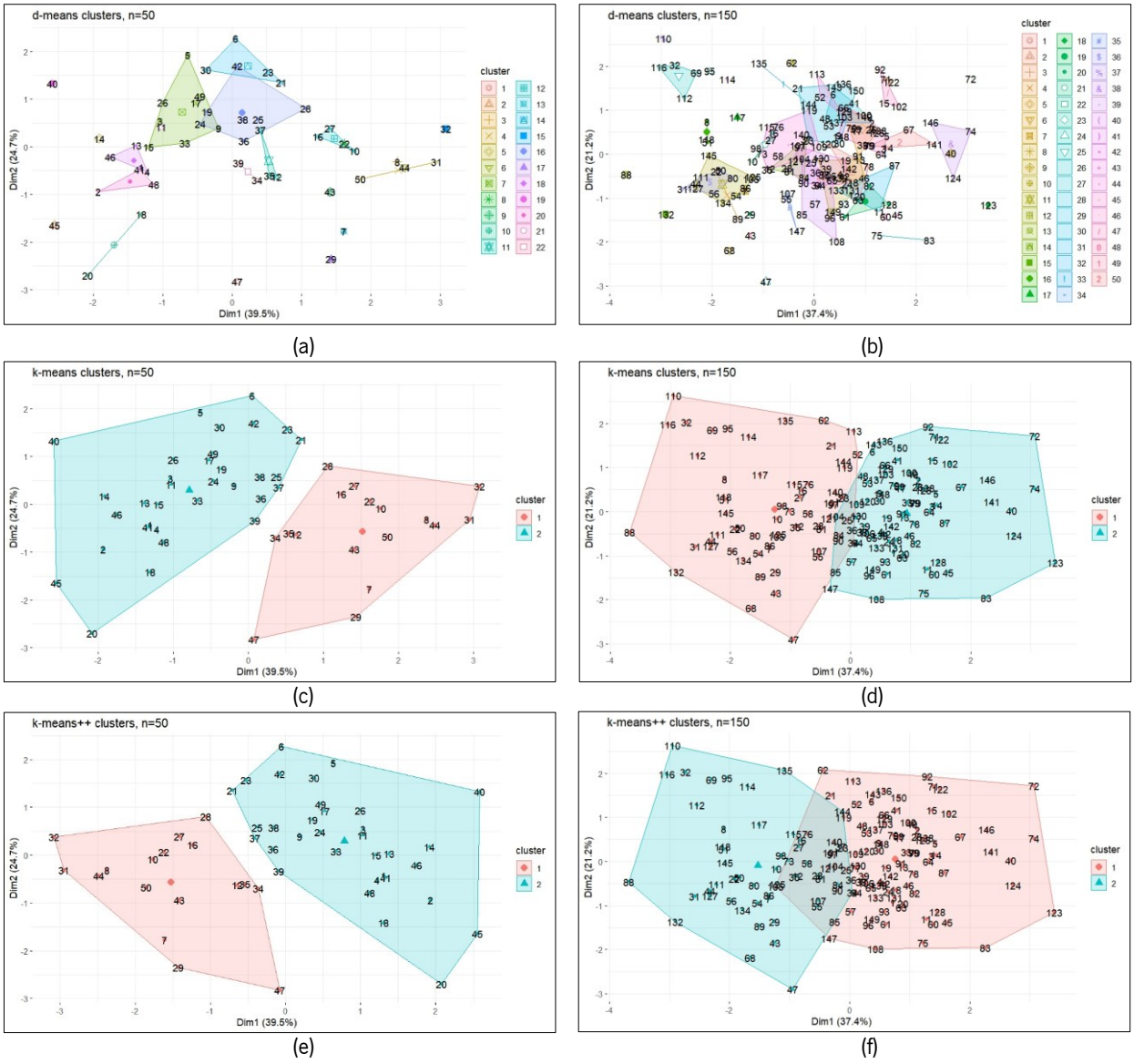


Figure 7.11. Comparison of the clusters 2D spatial distribution for d-means and the 2 baselines, for n= 50 and n = 150.

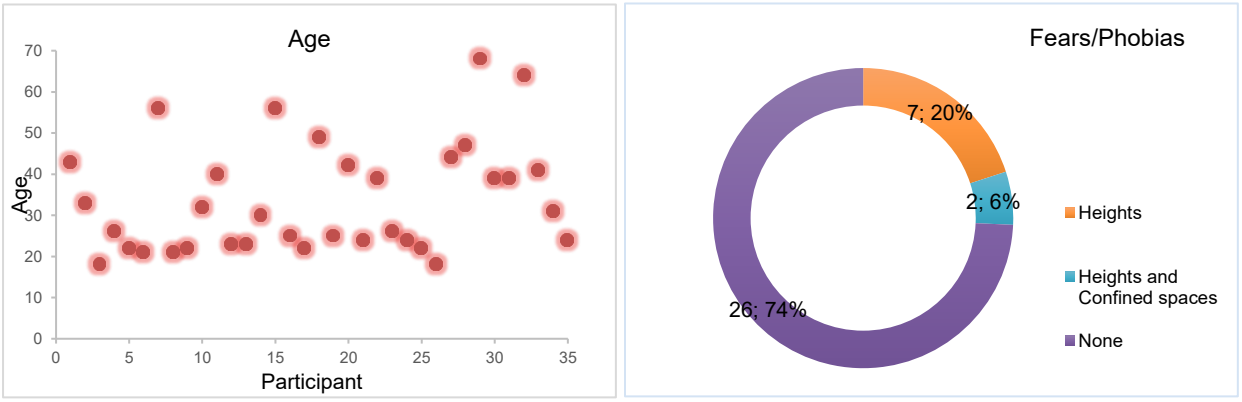
As for k-means and k-means++ (Figure 7.11(c)(d)(e)(f)), for both sets of users, we can see the members are more dispersed inside the same cluster, having several members far from the respective cluster's centroid. We can also see there are more users closer to the respective cluster's centroid for n = 150 than for n = 50, but there is also supposedly a cluster overlap. The members

of each cluster are exactly the same for k-means and k-means++ for n = 50. The same almost happens for n = 150, but some changes occurred like users 62, 21, 144, 119, 52, and 113 changed from one cluster to the other, and the overlap seems to diminish, which may be the result of the k-means++ clusters initialization based on probabilities.

Comparing the clustering metrics for the three algorithms (see Appendix D Table D-A.2 to Table D-A.7), d-means clearly outperforms the baselines, showing high cohesive clusters and a good to very good clustering quality for both sets of users. In comparison, all the baselines, for both sets of users, have lower cohesion values and a weak clustering quality. This confirms d-means fulfilled its intended objective of clustering only the most similar users.

7.5.2 Simulation's Sample Characterization

As can be seen in Table 7.6, the simulation participants' gender is almost equilibrated (57% males vs 43% females) with a mean age of 34 years old, being most of them in the 20-35 (54%) age range (Figure 7.12(a)). 54% of the participants are in some sort of a relationship and the majority do not have children (63%). The great majority have higher education (86%) and are from the Engineering & Technology formation area, as most of the participants were from ISEP. Regarding the professional situation, the great majority (63%) have a job, 34% are only students, and 3% are unemployed. 26% are afraid of heights and 6% are claustrophobic. In Figure 7.12(b), it can be seen that the participants who are claustrophobic are also afraid of heights. None of the respondents had the considered disabilities (physical impairments, sensorial (deafness, blindness), heart conditions), therefore, they were not an influencing factor for the group recommendations.



(a) (b)

Figure 7.12. Participants' (a) age range, (b) fears/phobias; n = 35.

The participants personality, assessed with the BFI, revealed the same type of distribution as in the previous studies (Alves, Martins, Saraiva, et al., 2023; Alves et al., 2020) (see Figure 7.13), with the same 3 dimensions, openness, conscientiousness and agreeableness, having responses above the mid-point, revealing a negative skewness, i.e., participants situated themselves more between "3- Neither agree nor disagree" and "5-Agree strongly", reflecting the same social desirability bias common in self-reporting questionnaires (Pedregon et al., 2012), e.g. like the desire of being more intellectual in the case of openness to experience; effortful, self-effective and truthful in the case of conscientiousness; and moral and kind in the case of agreeableness. The other two dimensions, extraversion and neuroticism, had the mean value near the scale mid-point. All five distributions follow the shape of a normal curve, and according to the values of skewness and kurtosis obtained, and respective standard errors, although some having a slight skew and kurtosis, they are in acceptable ranges and the data are considered not significantly different from a normal distribution (Field, 2013; Gravetter et al., 2020; Sposito et al., 1983).

7.5.3 Simulation Results and Analysis

For the 35 participants, the dynamic clustering algorithm, d-means (Algorithm 1) created 21 clusters at the registration phase, as can be observed in Table 7.7. As expected in large groups, a great number of clusters was formed, revealing their members heterogeinity. However, even in a small sample, 23 of 35 participants (66%) could be fitted into the same cluster (9 clusters in total). This is curious, meaning 66% of the random participants had a personality similarity above 0.80 (Figure 7.14(c)), which is reflected in the participants' personality scores, predicted factors' scores (Table 7.7), and in the radar charts of Figure 7.17, for each cluster. This could be confirmed by the similarity measure between the participants inside each cluster. For example, $sim(p_8, p_{13})$ is 0.83, and $sim(p_8, p_4)$ is 0.85 (cluster C_{11}). This similarity can be due to most of the participants being from the same formation area.

The participants who did not match the similarity criteria (Algorithm 1) were assigned to a new cluster or remained in their individual cluster if already in one. For example, users 28 and 34 were assigned to the same cluster C_7 but user 26 remained alone in a cluster, C_4, because there were no participants with $sim(p_{26}, p_j) \geq 0.80$.

Table 7.6. Participants descriptive statistics (n=35).

		n	%
Age	Min = 18, Max = 68, Mean = 33.7		
Gender	Female	15	42.9
	Male	20	57.1
Marital status	Single	13	37.1
	In a relationship	7	20.0
	Non-marital partnership	6	17.1
	Married	6	17.1
	Divorced/Separated	3	8.6
Children	No	22	62.9
	Yes	13	37.1
Educational level	High school	5	14.3
	Bachelor	1	2.8
	Degree	17	48.6
	Master	10	28.6
	Ph.D.	2	5.7
Formation area	Engineering & Technology	27	77.1
	Exact Sciences	1	2.9
	Humanities	2	5.7
	Natural Sciences	1	2.9
	Social Sciences	2	5.7
	Other	2	5.7
	None	1	2.9
Professional situation	Employed	17	48.6
	Student	12	34.3
	Working student	3	8.6
	Employer	2	5.7
	Unemployed	1	2.9
Fears/phobias	Heights	9	25.7
	Claustrophobia	2	5.7
	None	26	74.3

Some total percentages do not match 100% because the corresponding questions allowed multiple answers.

With the d-means dynamic clustering process, there was no need to define the initial number of clusters required, as is mandatory for the existing clustering algorithms, since the number of clusters were dynamically generated/updated at the participants' registration process, according to the clustering iterations and the 0.80 similarity restriction. In Table 7.8 and Figure 7.14, we can see the clusters have a low α value showing a good compactness and that they are very close to the respective centroid (Euclidean similarity close to 1). It can also be seen that the clusters that aggregated more participants have the highest average distance to the respective cluster's centroid, being less compact than the ones with less participants. Pertaining to the clusters' separability from the neighbor cluster, there are closer clusters where the participants could have been assigned to. However, d-means guarantees the users are clustered with the most similar ones (it is

possible, but improbable, to have several clusters with equal similarity as neighbor clusters, so the first one is chosen).

The participants that got alone in a cluster are not shown (n=11). These participants affect the closest cluster and silhouette values, as they are considered clustering possibilities for the d-means algorithm, but they are not aggregated because they do not match the similarity criteria of at least 0.80. We also do not merge close clusters, to preserve the members' similarity as much as possible. Nevertheless, the formed clusters have very high silhouette values, all superior to 0.60 and most of them with $s \geq 0.80$ (Figure 7.14(b)), showing a great clustering quality.

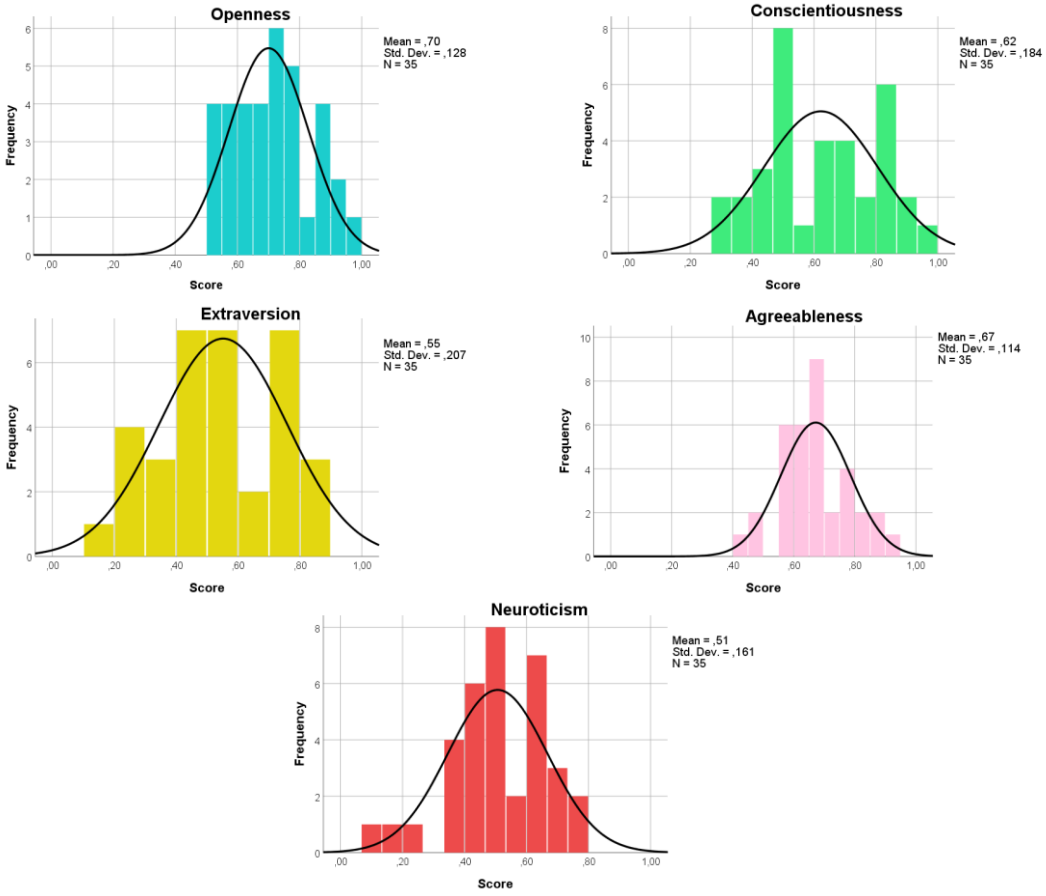


Figure 7.13. Distribution of the participants' five personality dimensions scores.

We are not forcing users that are alone to cluster with other users like usually happens in the other clustering algorithms, to have higher cohesions, which is the purpose of d-means, to have the most similar personality users in the same cluster. The fact we force a minimum similarity greatly improves the tourists' proximity in the same cluster (Figure 7.14(c)), guarantying that tourists with

very different personalities are not grouped together like may happen in k-means and k-means++, eliminating the noise and outlier issues associated to the baseline algorithms.

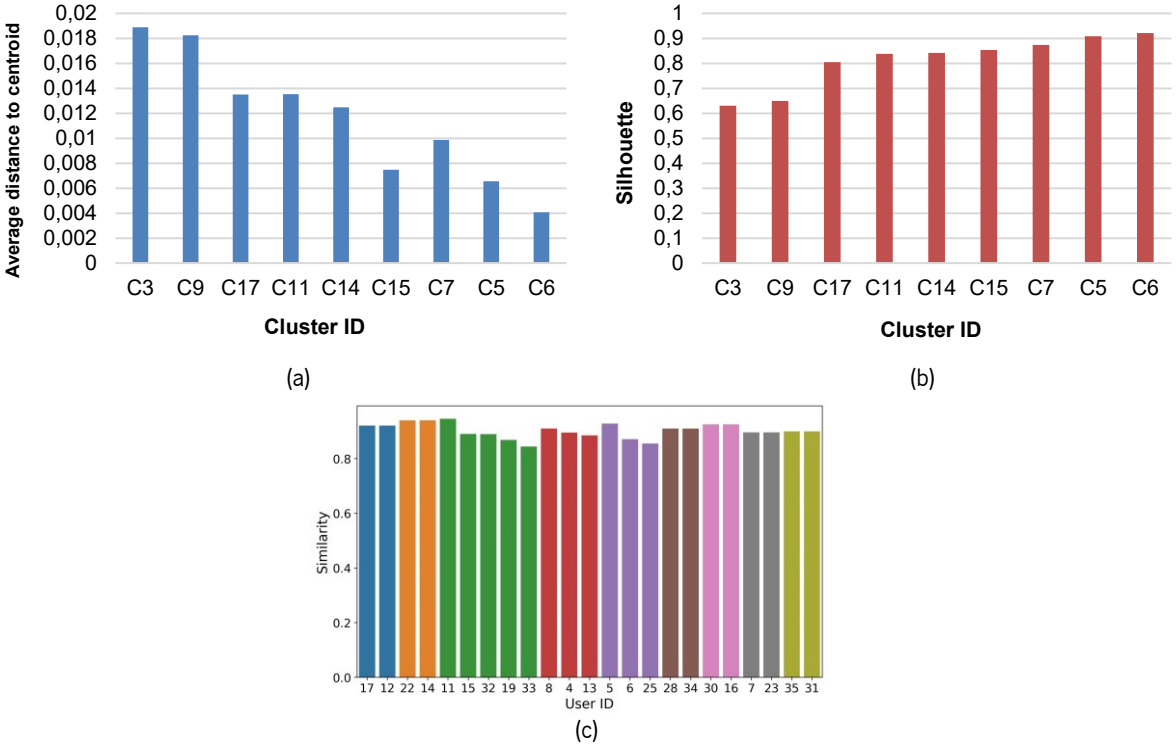


Figure 7.14. (a) Participants' clusters' average α; (b) Participants' clusters' silhouette; (c) Participants' Euclidean similarity to the corresponding cluster's centroid, grouped by their respective cluster. Only clusters with more than one member are shown.

When the participants asked for group recommendations, the MAMS detected that the excursion group could be divided into different subgroups, forcing the main group members that were alone or with only another member from the same cluster to pair with each other or other subgroups, being assigned to the one with the closest centroid until forming subgroups of at least 3 members. Seven subgroups were created, as can be seen in Figure 7.6(b) and Table 7.9, meaning the participants were sufficiently different to divide the main group. Also, at least 2 participants from the same cluster were placed in the same subgroup, meaning they had similar preferences for the 0.80 similarity threshold (Table 7.7).

For example, participant p_1 (from cluster C_{21}) was forced to pair with participants p_4, p_8, and p_{13} (from C_{11}) in subgroup $C_{11}Sg$, as he was more similar to their subgroup's centroid than to the others. This led to some subgroups ending up with tourists not so similar to the other members, but that were the most similar possible, like subgroup C_7Sg.

As there was not a group member that could be grouped with participants p_7, and p_{23}, that came from the same cluster C_{17}, they were separated into different subgroups, C_3Sg and $C_{14}Sg$ respectively, being assigned to the subgroup with the most similar centroid personality, as imposed by the implemented algorithm.

To determine the clustering quality of the subgroups formed, their compactness, separability, and silhouette values were calculated, revealing very compact subgroups with a very good clustering quality, all with s > 0.80 with an average silhouette s = 0.91 (see Figure 7.15 and Appendix D Table D-A.1), confirming the intra-subgroups personality similarity. The formation of the subgroups revealed to be advantageous as the subgroups (clusters) formed became more compact and with higher silhouettes than the originating clusters. The formed subgroups can be better visualized in the radar charts at Figure 7.17. For each subgroup, the similarity between the participants belonging to the same cluster can be perfectly seen. Also, the personality of the participants that came from another cluster(s) is close to their subgroup's members, which is in line with the obtained silhouette values.

As for the rules, Figure 7.16 shows some of the rules found with the Apriori algorithm run by the MAMS for the 1035 users from the previous study dataset (Alves, Martins, Saraiva, et al., 2023). In 10 000 rules, most were between the tourist attractions preference. No rules relating to the other attributes, such as age, marital status, children, etc., could be found in the rules set. This may be due to the large number of variables in comparison, or some variables needed to be differently binned, being a subject for further research. All the rules found had a great confidence level, with 119 rules having a 100% confidence, 568 rules 99%, and so on, until a 91% confidence. To validate the algorithms correctness, the Apriori algorithm was also run in Weka® 3.8.6 for the same sample, resulting in the same rules. The generated rules can be consulted at https://www.gecad.isep.ipp.pt/grouplanner/dissemination.html under the "simulations" tab.

Table 7.7. Personality, predicted tourist attraction preference and predicted travel-related preferences & concerns of the participants in the clusters formed, grouped by the corresponding subgroup (C_qSg).

User #	C_qSg	Cluster#	O	C	E	A	N	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	FP1	FP2	FP3	FP4
1	11	C21	**0.95**	**0.83**	**0.50**	**0.58**	**0.69**	0.40	0.48	0.44	0.40	0.54	0.42	0.58	0.39	0.42	0.48	0.44	0.68	0.63	0.63	0.61
4	11	**C11**	**0.75**	**0.81**	0.28	0.47	**0.63**	0.25	0.35	0.32	0.30	0.45	0.33	0.47	0.32	0.31	0.39	0.34	0.54	0.63	0.46	0.64
8	11	**C11**	**0.78**	**0.75**	0.34	**0.58**	**0.53**	0.31	0.44	0.34	0.33	0.52	0.34	0.58	0.33	0.37	0.39	0.43	0.59	0.56	0.52	0.55
13	11	**C11**	**0.78**	**0.61**	0.25	0.47	**0.53**	0.29	0.38	0.30	0.27	0.49	0.31	0.47	0.33	0.31	0.34	0.39	0.53	0.51	0.45	0.56
26	7	C4	**0.63**	**0.86**	**1.00**	**0.69**	**0.72**	0.73	0.69	0.80	0.82	0.57	0.76	0.69	0.67	0.76	0.78	0.62	0.73	0.71	0.81	0.58
28	7	**C7**	**0.83**	**0.67**	**0.88**	**0.75**	**0.63**	0.71	0.72	0.70	0.68	0.66	0.66	0.75	0.59	0.70	0.66	0.67	0.77	0.56	0.83	0.47
34	7	**C7**	**0.88**	**0.72**	**0.78**	**0.89**	**0.56**	0.63	0.74	0.61	0.60	0.73	0.57	0.89	0.49	0.66	0.57	0.69	0.82	0.54	0.84	0.40
5	3	**C3**	**0.85**	**0.61**	**0.53**	**0.67**	**0.63**	0.49	0.57	0.48	0.44	0.62	0.45	0.67	0.42	0.49	0.47	0.56	0.69	0.53	0.65	0.48
6	3	**C3**	**0.73**	**0.64**	**0.63**	**0.69**	**0.59**	0.48	0.58	0.41	0.34	0.70	0.38	0.67	0.37	0.44	0.36	0.62	0.68	0.55	0.67	0.48
7	3	C17	**0.70**	**0.47**	**0.78**	**0.56**	**0.66**	0.70	0.63	0.68	0.65	0.58	0.65	0.56	0.62	0.64	0.64	0.61	0.65	0.52	0.69	0.49
14	3	**C6**	**0.68**	**0.61**	**0.59**	**0.61**	0.41	0.53	0.56	0.52	0.51	0.55	0.50	0.61	0.49	0.54	0.51	0.54	0.60	0.47	0.62	0.47
22	3	**C6**	**0.65**	**0.69**	**0.59**	**0.64**	**0.50**	0.50	0.56	0.52	0.52	0.56	0.51	0.64	0.48	0.54	0.52	0.53	0.61	0.55	0.62	0.50
25	3	**C3**	**0.85**	**0.50**	**0.50**	**0.78**	**0.78**	0.50	0.63	0.48	0.44	0.73	0.45	0.78	0.39	0.51	0.45	0.63	0.76	0.55	0.68	0.42
2	14	C10	**0.93**	**0.53**	0.47	**0.75**	0.25	0.47	0.60	0.40	0.35	0.66	0.37	0.75	0.37	0.48	0.37	0.60	0.68	0.33	0.67	0.35
3	14	C1	**0.50**	0.47	**0.81**	**0.64**	0.16	0.72	0.68	0.66	0.68	0.56	0.64	0.64	0.64	0.70	0.61	0.65	0.56	0.34	0.68	0.36
9	14	C8	**0.55**	**0.53**	**0.81**	**0.58**	0.44	0.70	0.64	0.68	0.69	0.54	0.66	0.58	0.64	0.67	0.65	0.61	0.59	0.48	0.67	0.46
23	14	C17	**0.63**	0.36	**0.78**	**0.75**	**0.63**	0.74	0.74	0.69	0.66	0.71	0.64	0.75	0.59	0.70	0.61	0.73	0.71	0.48	0.73	0.36
31	14	**C14**	**0.70**	**0.72**	**0.78**	**0.86**	0.34	0.63	0.73	0.61	0.62	0.68	0.57	0.86	0.52	0.68	0.57	0.68	0.73	0.48	0.79	0.38
35	14	**C14**	**0.68**	**0.53**	**0.75**	**0.81**	0.44	0.66	0.73	0.62	0.62	0.69	0.59	0.81	0.54	0.68	0.57	0.70	0.71	0.45	0.75	0.35
36	14	C16	**0.85**	0.44	**0.72**	**0.67**	0.47	0.67	0.67	0.60	0.56	0.64	0.56	0.67	0.55	0.61	0.55	0.65	0.70	0.40	0.73	0.39
11	9	**C9**	**0.58**	**0.86**	0.47	**0.69**	0.44	0.37	0.51	0.42	0.45	0.54	0.43	0.69	0.39	0.48	0.46	0.48	0.59	0.60	0.57	0.52
15	9	**C9**	**0.68**	**0.75**	0.47	**0.64**	0.41	0.40	0.51	0.42	0.43	0.54	0.42	0.64	0.40	0.46	0.45	0.49	0.59	0.53	0.58	0.50
19	9	**C9**	**0.70**	**0.83**	0.47	**0.69**	0.53	0.38	0.52	0.42	0.43	0.57	0.42	0.69	0.38	0.46	0.46	0.49	0.64	0.61	0.60	0.53

User #	$C_q Sg$	Cluster#	O	C	E	A	N	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	FP1	FP2	FP3	FP4
20	9	C19	**0.90**	**0.81**	**0.59**	**0.72**	0.38	0.47	0.58	0.47	0.45	0.59	0.44	0.72	0.42	0.51	0.48	0.54	0.70	0.50	0.71	0.48
29	9	C18	**0.75**	**0.97**	**0.72**	**0.61**	0.09	0.51	0.54	0.52	0.55	0.45	0.52	0.61	0.51	0.56	0.56	0.48	0.59	0.47	0.69	0.53
32	9	**C9**	**0.55**	**0.89**	0.44	**0.58**	0.38	0.34	0.45	0.40	0.44	0.46	0.41	0.58	0.40	0.44	0.46	0.41	0.52	0.59	0.51	0.57
33	9	**C9**	**0.52**	**0.89**	**0.63**	**0.67**	0.34	0.47	0.55	0.52	0.57	0.51	0.52	0.67	0.48	0.56	0.55	0.50	0.58	0.58	0.62	0.52
10	15	C12	**0.5**	0.36	0.19	0.44	**0.75**	0.33	0.39	0.34	0.31	0.52	0.35	0.44	0.36	0.33	0.36	0.43	0.46	0.55	0.35	0.53
12	15	**C15**	**0.7**	**0.50**	0.34	**0.61**	**0.69**	0.39	0.50	0.39	0.36	0.60	0.38	0.61	0.37	0.41	0.40	0.51	0.60	0.54	0.52	0.48
17	15	**C15**	**0.7**	**0.53**	**0.50**	**0.56**	**0.66**	0.49	0.52	0.49	0.46	0.56	0.48	0.56	0.46	0.48	0.49	0.52	0.60	0.54	0.57	0.51
16	5	**C5**	**0.50**	**0.56**	0.31	**0.72**	0.47	0.35	0.53	0.36	0.37	0.62	0.36	0.72	0.34	0.44	0.36	0.54	0.56	0.51	0.49	0.41
18	5	C13	**0.75**	0.42	0.22	**0.83**	0.41	0.33	0.58	0.28	0.24	0.73	0.26	0.83	0.25	0.40	0.25	0.60	0.65	0.38	0.55	0.30
21	5	C2	**0.60**	0.33	0.44	**0.94**	0.66	0.51	0.72	0.47	0.45	0.83	0.43	0.94	0.37	0.57	0.40	0.74	0.73	0.48	0.64	0.27
24	5	C20	**0.58**	0.28	0.47	**0.69**	0.47	0.55	0.62	0.48	0.46	0.67	0.46	0.69	0.46	0.54	0.43	0.64	0.59	0.31	0.59	0.26
30	5	**C5**	**0.60**	0.44	0.28	**0.69**	0.47	0.37	0.53	0.34	0.33	0.63	0.34	0.69	0.33	0.42	0.33	0.55	0.57	0.45	0.49	0.38

Where O = Openness, C = Conscientiousness, E = Extraversion, A = Agreeableness, N = Neuroticism; F1 = Adrenaline activities, F2 = Wild Nature activities, F3 = Party, Music & Nightlife, F4 = Sun, Water & Sand, F5 = Museums, Boat trips & Viewpoints, F6 = Theme & Animal parks, F7 = Cultural heritage, F8 = Sports & Games, F9 = Gastronomy events, F10 = Health & Well-being, F11 = Natural phenomena ; FP1 = Previsibility & Safety, FP2 = Cultural & Learning experiences, FP3 = Uniqueness & Exoticness, FP4 = Familiarity. Personality dimensions scores equal or superior to 0.5 are in bold.

Table 7.8. Clusters formed by the proposed d-means algorithm and their respective average distance to the centroid (α), closest cluster (β, separability), silhouette values (s), and Euclidean similarity (sim) between the participant p_i and the corresponding cluster's centroid. Only clusters with more than one member are shown.

p_i	$cluster\ C_q.id$	α	Closest cluster, β	$sim\ (p_i, C_q.centroid)$	Silhouette, s
5	C_3	0,0189	0,0511	0,927678125	0,6303
6	C_3	0,0189	0,0511	0,87106191	0,6303
25	C_3	0,0189	0,0511	0,855179517	0,6303
11	C_9	0,0183	0,0520	0,945643965	0,6491
15	C_9	0,0183	0,0520	0,889973882	0,6491
32	C_9	0,0183	0,0520	0,889399342	0,6491
19	C_9	0,0183	0,0520	0,868055569	0,6491
33	C_9	0,0183	0,0520	0,844076439	0,6491
7	C_{17}	0,0135	0,0693	0,895905223	0,8052
23	C_{17}	0,0135	0,0693	0,895905223	0,8052
8	C_{11}	0,0135	0,0838	0,909922294	0,8385
4	C_{11}	0,0135	0,0838	0,894875885	0,8385
13	C_{11}	0,0135	0,0838	0,884655094	0,8385
35	C_{14}	0,0125	0,0786	0,899530081	0,8413
31	C_{14}	0,0125	0,0786	0,899530081	0,8413
17	C_{15}	0,0075	0,0511	0,920422077	0,8537
12	C_{15}	0,0075	0,0511	0,920422077	0,8537
28	C_7	0,0099	0,0786	0,909609356	0,8744
34	C_7	0,0099	0,0786	0,909609356	0,8744
30	C_5	0,0066	0,0712	0,925127505	0,9081
16	C_5	0,0066	0,0712	0,925127505	0,9081
22	C_6	0,0041	0,0520	0,939994755	0,9217
14	C_6	0,0041	0,0520	0,939994755	0,9217

Table 7.9. List of POI recommended to each subgroup with the respective POI tourism category, POI Id, POI description and average rating given by the simulation participants (from 1 to 5 stars).

Subgroup 11				Subgroup 3			
Category	Id	Name	Mean rating	Category	Id	Name	Mean rating
F7	652	Palácio da Bolsa	**4**	F7	652	Palácio da Bolsa	**4**
F7	885	Sé Catedral do Porto	**4**	F7	885	Sé Catedral do Porto	**4**
F7	382	Igreja de São Francisco	3	F7	382	Igreja de São Francisco	3
F7	170	Centro Histórico de Guimarães	**4**	F7	170	Centro Histórico de Guimarães	3
F7	135	Castelo de Guimarães	3	F5	588	Museu FC Porto	**4**
F5	606	Museu Serralves	**5**	F5	624	Navio Gil Eannes	**4**

F5	588	Museu FC Porto	3	F5	174	Centro Português de Fotografia	**4**
F5	624	Navio Gil Eannes	3	F2	486	Mata Nacional do Buçaco	**4**
F5	174	Centro Português de Fotografia	**4**	F2	519	Montanha-Parque da Penha	**4**
F5	580	Museu do Douro	**4**	F2	33	Arouca Geopark	3

Subgroup 7				Subgroup 14			
Category	Id	Name	Mean rating	Category	Id	Name	Mean rating
F7	57	Bom Jesus do Monte	**5**	F7	652	Palácio da Bolsa	**5**
F7	652	Palácio da Bolsa	**5**	F7	885	Sé Catedral do Porto	**4**
F7	885	Sé Catedral do Porto	**4**	F7	382	Igreja de São Francisco	3
F7	382	Igreja de São Francisco	**5**	F7	170	Centro Histórico de Guimarães	**5**
F2	486	Mata Nacional do Buçaco	**4**	F2	683	Passadiços do Paiva	**5**
F2	519	Montanha-Parque da Penha	**4**	F2	486	Mata Nacional do Buçaco	**5**
F2	283	Excursão de meio dia ao Palácio Bussaco, jardins e floresta	**5**	F2	33	Arouca Geopark	**5**
F5	588	Museu FC Porto	**5**	F11	690	Pateira de Fermentelos	**5**
F5	624	Navio Gil Eannes	**4**	F11	708	Poço Negro	**5**
F5	174	Centro Português de Fotografia	3	F11	692	Pedra Bolideira	2

Subgroup 9				Subgroup 5			
Category	Id	Name	Mean rating	Category	Id	Name	Mean rating
F7	652	Palácio da Bolsa	**4**	F7	652	Palácio da Bolsa	**4**
F7	885	Sé Catedral do Porto	**4**	F7	885	Sé Catedral do Porto	**4**
F7	382	Igreja de	3	F7	382	Igreja de	**4**

		São Francisco				São Francisco	
F7	170	Centro Histórico de Guimarães	**5**	F7	170	Centro Histórico de Guimarães	**5**
F5	588	Museu FC Porto	2	F5	588	Museu FC Porto	3
F5	624	Navio Gil Eannes	**4**	F5	624	Navio Gil Eannes	**4**
F5	174	Centro Português de Fotografia	3	F5	174	Centro Português de Fotografia	**4**
F2	683	Passadiços do Paiva	**4**	F11	690	Pateira de Fermentelos	**5**
F2	486	Mata Nacional do Buçaco	**4**	F11	708	Poço Negro	**5**
F2	33	Arouca Geopark	**4**	F11	692	Pedra Bolideira	3

Subgroup 15

Category	Id	Name	Mean rating
F7	885	Sé Catedral do Porto	**4**
F7	382	Igreja de São Francisco	**4**
F7	170	Centro Histórico de Guimarães	**4**
F7	135	Castelo de Guimarães	**4**
F5	588	Museu FC Porto	2
F5	624	Navio Gil Eannes	3
F5	174	Centro Português de Fotografia	**4**
F11	690	Pateira de Fermentelos	**5**
F11	457	Lagoas Naturais Fafião	**5**

Values in bold represent positively rated POI and bold underlined POI with a rating of 5 stars. The ratings in a subgroup correspond to the average rating given by the members belonging only to the same cluster. POI names are in Portuguese. The individual ratings given by each subgroup member can be consulted in Appendix D Table D-B.2.

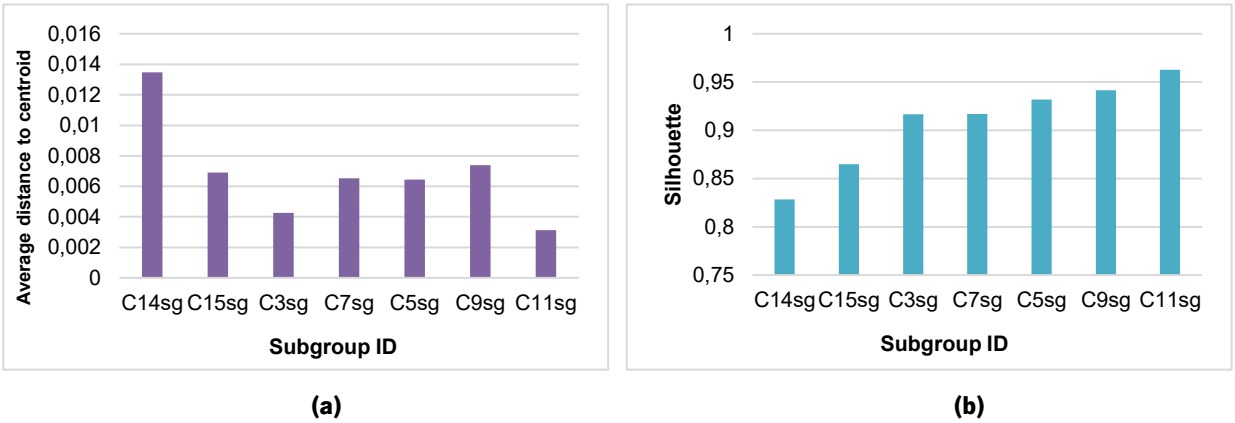


Figure 7.15. (a) Formed subgroups average distance to the corresponding subgroup's centroid; (b) Formed subgroups silhouette values.

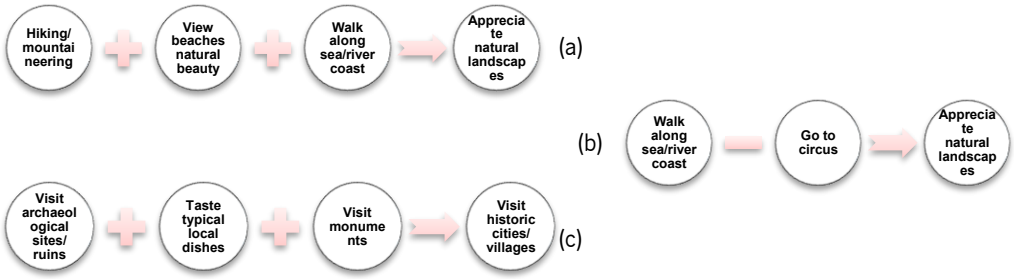


Figure 7.16. Example of some rules found with the Apriori algorithm. (a) 71% users who like to do hiking/mountaineering, visit beaches for their natural beauty and walk along the sea/river coast, like to appreciate natural landscapes, with a 100% confidence; (b) 71% users who like to walk along the sea/river coast and do not like to go to the circus, like to appreciate natural landscapes, with a 98% confidence; (c) 71% users who like to visit archaeological sites/ruins and taste typical dishes of the destination and visit monuments, like to visit historic cities/villages, with a 98% confidence.

The average personality and predicted tourism categories preference for the subgroups formed can be consulted in Table 7.10 (Left side)[40]. Table 7.10 right side shows the average ratings participants gave to the same categories in the pre-questionnaire. The list of POI suggested for each subgroup and the respective average rating can be consulted in Table 7.9. The individual ratings given by each group member to each recommended POI can be consulted in Appendix D Table D-B.2.

40 More details on how the predicted scores were calculated can be consulted in Alves, Martins, Saraiva, et al. (2023), Section 5.

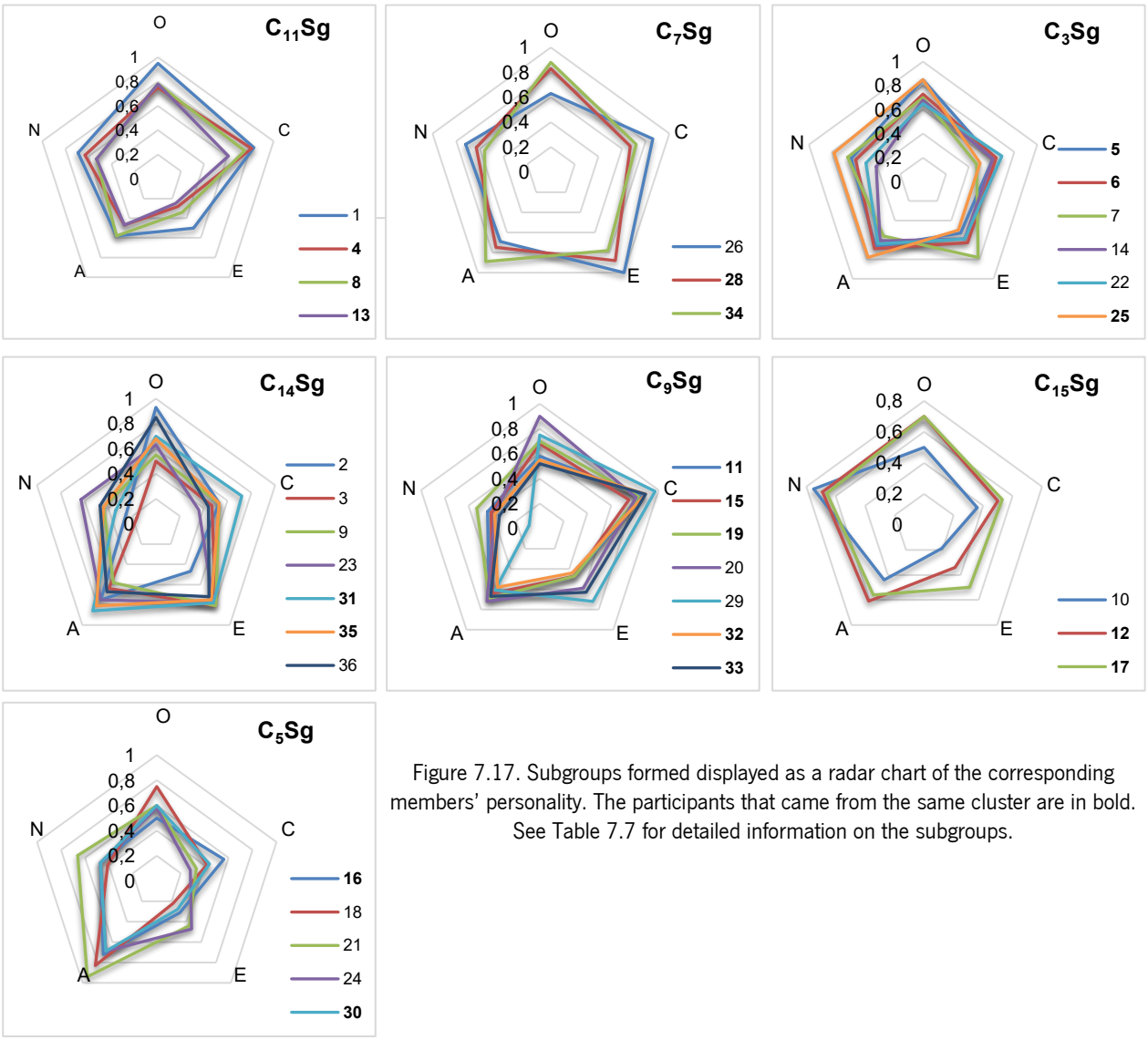


Figure 7.17. Subgroups formed displayed as a radar chart of the corresponding members' personality. The participants that came from the same cluster are in bold. See Table 7.7 for detailed information on the subgroups.

The predicted tourism categories that subgroup $C_{11}Sg$ scored higher and with a score of at least 0.49 were only two, "Cultural Heritage" and "Museums, Boat Trips & Viewpoints". The 3 predicted categories C_3Sg and C_9Sg scored higher were "Cultural Heritage", "Museums, Boat Trips & Viewpoints" and "Wild Nature", respectively. C_7Sg had higher predicted values for "Cultural Heritage", "Wild Nature" and "Museums, Boat Trips & Viewpoints". For $C_{14}Sg$, the predicted top-3 categories were "Cultural Heritage", "Wild Nature" and "Natural Phenomena". Finally, $C_{15}Sg$ and C_5Sg had a higher predicted score on "Cultural Heritage", "Museums, Boat Trips & Viewpoints" and "Natural Phenomena", being those categories the ones selected for the preliminary recommendations. Although subgroups C_3Sg and C_9Sg, and $C_{15}Sg$ and C_5Sg, have the same top-3

categories, they have different personalities, which is the reason why they are distinct subgroups, as we believe it is important to preserve the intra-subgroup's similarity to mitigate the heterogeneity problems associated with large excursion groups, as the members will have more similar preferences and therefore can reach a faster consensus in the final recommendation list.

To visit monuments and historical cities/villages (F_7) are the predicted top preferred activities for all subgroups. To visit museums, go on a boat trip or visit viewpoints (F_5), activities in the wild nature (F_2) or to appreciate natural phenomena (F_{11}), are the next predicted most preferred tourist attractions. These preferences were also the participants' top-rated tourism categories in the pre-questionnaire[41]. This is in line with the results previously found (Alves, Martins, Saraiva, et al., 2023), that, regardless the person's personality, everyone likes to visit/do those types of tourist attractions when on vacation, along with theme & animal parks (F_6), relax/swim at the beach/swimming pool (F_4), taste typical dishes (F_9), and party, music & nightlife events (F_3). Only subgroups C_7Sg and C_3Sg would like to experience adrenaline activities (F_1), approximately to the predicted. Sports & games (F_8) had a negative prediction for all subgroups, although $C_{14}Sg$ and C_5Sg would like to include that sort of activities in their vacations as mentioned in the pre-questionnaire. Nonetheless, it is easy to observe that the predicted scores for other categories in a subgroup only differ one-tenth from the ones suggested for the top. For instance, C_7Sg could easily have F_9, F_{11}, F_1 or even F_3 and F_4 as top categories, confirming the given ratings in the pre-questionnaire. The same happens for C_3Sg, $C_{14}Sg$ and C_9Sg for the same or other categories. This means a small variation in the BFI answers can change that order, and that the suggested POI can be further refined by using the ratings given by the users when using the application. This proximity can also be used to change the recommended POI variability.

[41] The individual ratings given by each participant to the tourism categories and travel-related preferences & concerns can be consulted in Appendix D Table D-B.1.

Table 7.10. Left side: predicted average preference for the tourism categories and the travel-related preferences & concerns for the formed subgroups (C_qSg), from 0.0 to 1.0, followed by the corresponding rating from 1 to 5 stars in parenthesis. Right side: average ratings for the tourism categories and travel-related preferences & concerns given by the members in the pre-questionnaire, from 1 to 5 stars. Both sides show the subgroups average personality for easier comparison, from 0.0 to 1.0 (only calculated for members belonging to the same cluster).

	Predicted average preferences								Average ratings given						
	$C_{11}Sg$	C_7Sg	C_3Sg	$C_{14}Sg$	C_9Sg	$C_{15}Sg$	C_5Sg		$C_{11}Sg$	C_7Sg	C_3Sg	$C_{14}Sg$	C_9Sg	$C_{15}Sg$	C_5Sg
O	0.77	0.86	0.73	0.69	0.61	0.70	0.55	O	0.77	0.86	0.73	0.69	0.61	0.70	0.55
C	0.72	0.70	0.64	0.63	0.84	0.52	0.50	C	0.72	0.70	0.64	0.63	0.84	0.52	0.50
E	0.29	0.83	0.59	0.77	0.50	0.42	0.30	E	0.29	0.83	0.59	0.77	0.50	0.42	0.30
A	0.51	0.82	0.65	0.84	0.65	0.59	0.71	A	0.51	0.82	0.65	0.84	0.65	0.59	0.71
N	0.56	0.60	0.53	0.39	0.42	0.68	0.47	N	0.56	0.60	0.53	0.39	0.42	0.68	0.47
F1	0.29 (2)	**0.67 (4)**	0.52 (3)	**0.64 (4)**	0.39 (3)	0.44 (3)	0.36 (3)	F1	3	**4**	**4**	3	2	2	2
F2	0.39 (2)	**0.73 (4)**	**0.58 (3)**	**0.73 (4)**	**0.51 (4)**	0.51 (3)	0.53 (3)	F2	**4**	**5**	**4**	**4**	**4**	**4**	**4**
F3	0.32 (2)	**0.66 (4)**	0.52 (3)	**0.62 (4)**	0.44 (3)	0.44 (3)	0.35 (2)	F3	**4**	**5**	**4**	**4**	3	3	3
F4	0.30 (2)	**0.64 (4)**	0.50 (3)	**0.62 (4)**	0.46 (3)	0.41 (3)	0.35 (2)	F4	**5**	**5**	**5**	**4**	**4**	**5**	**4**
F5	**0.49 (3)**	**0.69 (4)**	**0.59 (3)**	**0.68 (4)**	**0.52 (3)**	**0.58 (3)**	**0.63 (4)**	F5	**4**	**4**	**4**	**4**	**4**	**4**	**4**
F6	0.33 (2)	**0.61 (4)**	0.50 (3)	0.58 (3)	0.44 (3)	0.43 (3)	0.35 (2)	F6	**4**	**5**	**4**	**4**	**4**	**4**	**4**
F7	**0.51 (3)**	**0.82 (5)**	**0.65 (4)**	**0.84 (5)**	**0.65 (4)**	**0.59 (3)**	**0.71 (4)**	F7	**4**	**4**	**4**	**4**	**5**	**4**	**5**
F8	0.33 (2)	0.54 (3)	0.47 (3)	0.53 (3)	0.41 (3)	0.41 (3)	0.34 (2)	F8	3	2	3	**4**	3	3	**4**
F9	0.33 (2)	**0.68 (4)**	0.53 (3)	**0.68 (4)**	0.48 (3)	0.45 (3)	0.43 (3)	F9	**4**	**4**	**4**	**4**	**4**	3	**4**
F10	0.37 (2)	**0.62 (4)**	0.51 (3)	0.57 (3)	0.48 (3)	0.44 (3)	0.35 (2)	F10	**4**	**4**	3	3	**4**	3	2
F11	0.39 (2)	**0.68 (4)**	0.55 (3)	**0.69 (4)**	0.47 (3)	**0.51 (3)**	**0.54 (4)**	F11	**4**	**4**	**4**	**4**	**4**	**5**	3
FP1	**0.55 (3)**	**0.80 (4)**	**0.64 (4)**	**0.72 (4)**	**0.58 (3)**	**0.60 (3)**	**0.57 (3)**	FP1	**4**	3	**4**	3	**4**	**4**	**4**
FP2	**0.57 (3)**	**0.55 (3)**	**0.53 (3)**	0.47 (3)	**0.58 (3)**	**0.54 (3)**	0.48 (3)	FP2	**4**	**4**	**4**	**4**	**4**	**4**	**4**
FP3	0.48 (3)	**0.83 (5)**	**0.64 (4)**	**0.77 (4)**	**0.57 (3)**	**0.54 (3)**	0.49 (3)	FP3	**4**	**5**	**5**	**4**	**4**	**5**	**4**
FP4	**0.59 (3)**	0.43 (3)	0.48 (3)	0.36 (2)	**0.53 (3)**	**0.50 (3)**	0.40 (2)	FP4	2	3	3	3	**4**	3	**4**
								Fears							heights

Left side: The values in bold underlined represent the top tourism categories (F_1 to F_{11}) for each subgroup superior or equal to 0.49. The values in bold represent the travel-related preferences & concerns (FP_1 to FP_4) superior or equal to 0.50. The scale binning corresponds to: 0.0-0.20 (1), 0.21-0.40(2), 0.41-0.60(3), 0.61-0.80(4), 0.81-1.0(5). **Right side:** The values in bold represent positively rated factors and bold underlined the ones rated with 5. The presented fears are only for subgroups where at least 50% of the members said to have that fear.

To validate these results and determine if the predicted ratings were not statistically different from the real ratings given in the pre-questionnaire, the paired samples t-test to compare their means was performed in SPSS. The results can be found in Table 7.11. The predicted ratings for the tour-

ism categories F_1 (Adrenaline Activities), F_5 (Museums, Boat trips & Viewpoints), F_7 (Cultural heritage), F_8 (Sports & Games), F_{10} (Health & Well-being) and F_{11} (Natural phenomena) were not statistically different from the real ratings. The same applies to the travel-related concerns FP_1 (Previsibility & Safety) and FP_4 (Familiarity). For the other factors, the difference is small for F_3 (Party, Music & Nightlife), and medium for F_9 (Gastronomy events) and FP_3 (Uniqueness & Exoticness) (J. Cohen, 2013), and therefore can be considered for this study and context, meaning 11 of the 15 categories had valid predictions, validating the used structural equation models (Alves, Martins, Saraiva, et al., 2023).

Comparing the given to the predicted preferences for the tourism categories (Table 7.10 left and right sides), in a 1 to 5 stars scale, almost all categories (F_1, F_3, F_5, F_7, F_8, F_9, F_{10} and F_{11}) have similar mean ratings, confirming the predictions. F_4 and F_6 were the less accurate predicted categories, followed by F_2, which is reflected in the paired samples t-test results (Table 7.11), having a high effect size. We can also see that no tourism category had an average predicted preference or given rating lower than 2. This may be a consequence of the small sample used for the simulation, as it was impossible to have a significant number of participants for each type of personality combination. For example, if there were a greater number of participants with low openness, conscientiousness or agreeableness values, or higher neuroticism, the categories that were less chosen would increase their scores for those participants, namely F_1, F_3, F_8, or F_{10}. The same applies to the predicted ones.

Analyzing Table 7.10 right side, all subgroups want to have cultural & learning experiences (FP_2) and visit unique & exotic places (FP_3), especially C_7Sg, C_3Sg and $C_{15}Sg$. It was only for one-tenth that all those preferences would have been predicted for the suggested POI, as can be observed on the left side of the table, also confirming the paired samples t-test results. All subgroups want safety & previsibility (FP_1) when on vacations, except C_7Sg and $C_{14}Sg$ which were neutral. Only C_9Sg and C_5Sg are concerned about familiarity (FP_4) and would prefer not to travel with strangers.

Table 7.11. Paired samples t-test of the means between the real ratings given by the participants to the tourism categories and the travel-related preferences & concerns in the pre-questionnaire and the predicted ones.

				95% Confidence Interval of the Difference					
Pairs	Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)	Cohen's D
F_1 real - F_1 predicted	**-0,057**	**1,282**	**0,217**	**-0,498**	**0,383**	**-0,264**	**34**	**0,794**	**-0,04**
F_2 real - F_2 predicted	0,857	1,141	0,193	0,465	1,249	4,443	34	0,000	0,75
F_3 real - F_3 predicted	0,514	1,040	0,176	0,157	0,871	2,927	34	0,006	**0,49**
F_4 real - F_4 predicted	1,486	1,197	0,202	1,074	1,897	7,341	34	0,000	1,24
F_5 real - F_5 predicted	**0,286**	**0,926**	**0,156**	**-0,032**	**0,604**	**1,826**	**34**	**0,077**	**0,31**
F_6 real - F_6 predicted	0,943	0,906	0,153	0,632	1,254	6,159	34	0,000	1,04
F_7 real - F_7 predicted	**0,314**	**0,796**	**0,135**	**0,041**	**0,588**	**2,336**	**34**	**0,026**	**0,39**
F_8 real - F_8 predicted	**0,343**	**1,552**	**0,262**	**-0,190**	**0,876**	**1,307**	**34**	**0,200**	**0,22**
F_9 real - F_9 predicted	0,543	1,094	0,185	0,167	0,919	2,936	34	0,006	0,50
F_{10} real - F_{10} predicted	**0,400**	**1,193**	**0,202**	**-0,010**	**0,810**	**1,983**	**34**	**0,055**	**0,34**
F_{11} real - F_{11} predicted	**0,371**	**1,262**	**0,213**	**-0,062**	**0,805**	**1,741**	**34**	**0,091**	**0,29**
FP_1 real - FP_1 predicted	**0,171**	**0,985**	**0,166**	**-0,167**	**0,510**	**1,030**	**34**	**0,310**	**0,17**
FP_2 real - FP_2 predicted	1,086	0,951	0,161	0,759	1,412	6,755	34	0,000	1,14
FP_3 real - FP_3 predicted	0,629	0,910	0,154	0,316	0,941	4,085	34	0,000	0,69
FP_4 real - FP_4 predicted	**0,400**	**1,311**	**0,222**	**-0,050**	**0,850**	**1,806**	**34**	**0,080**	**0,31**

The categories with mean differences not statistically different at a significance level of α = 0.025 (2-tailed) are in bold. The Cohen's small effect sizes are in bold, the medium are underlined, and the remaining are the high effect sizes (J. Cohen, 2013).

As most of the members of $C_{15}Sg$ were afraid of heights (in fact all members), the REMS did not suggest POI for acrophobic, and therefore only 2 were available in the POIMS under those criteria and thus recommended (Table 7.9).

Some participants referred they did not agree with the predicted tourism categories individual preference order (screen in Figure 7.2(d) from the user's profile in the app). This reflects the same

observations already made for the subgroups' predicted preferences. Besides, these are only the initial recommendations which will be improved with the rules, the ratings given by the users to the recommendation lists and already visited POI. Also, all the presented predictions are a reflection of the models used (Alves, Martins, Saraiva, et al., 2023), which had an acceptable fit (CFI=0.771 and $PCFI$ = 0.721 for the "Personality vs Tourism Categories Preference model", and CFI=0.809 and $PCFI$ = 0.716 for the "Personality vs Travel-related Preferences & Concerns" model, among other metrics). A larger sample (at least the triple (Marôco, 2010)) was needed to increase the models' goodness-of-fit and consequently the predictions. However, we believe it is a great help and contribution to GRS for tourism, and in general, to be able to present these first recommendations to excursion groups, as well as divide them into subgroups of similar personalities, mitigating the cold-start problem and diminishing the excursion group's heterogeneity and conflicting preferences. This is confirmed by the high ratings the participants gave to the individual POI recommendation list (Figure 7.18(a)): 74% of the recommended POI had 4 to 5 stars, and if we include ratings from 3 to 5 stars, 92%, meaning the participants were highly satisfied with the recommendations suggested. Only 8% of the POI were not an option to visit.

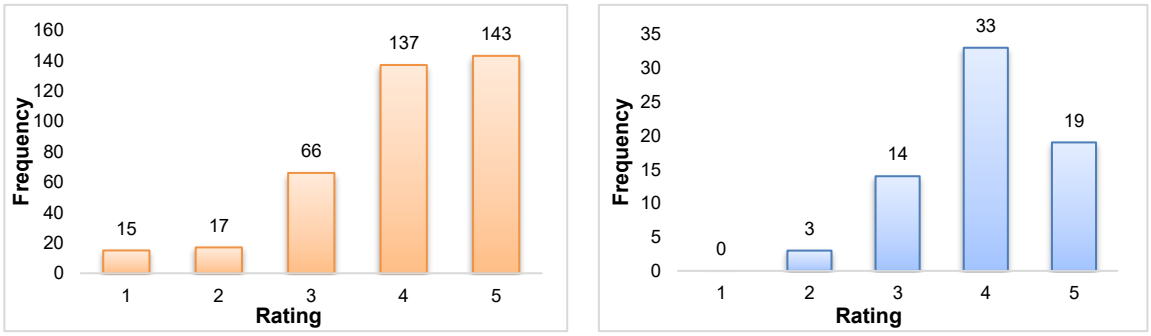


Figure 7.18. (a) Ratings (1 to 5 stars) given by the participants to the individual POI recommendations; (b) Average ratings given to the suggested POI by the excursion subgroups' members.

It is important to mention that during the simulation some participants gave lower rates to POI they already visited (because they didn't like or just didn't want to revisit) or just because they didn't know what the POI was. These situations can be easily resolved if we add the option to indicate if the POI has already been visited and a representative picture of the POI to the recommendation lists (under development).

According to the MAMS implemented algorithms, if the group owner is asked to retrieve new recommendations, all the POI with a rating below 3 (configurable) will be replaced by new ones. According to this criterion, only subgroups $C_{14}Sg$, C_9Sg and $C_{15}Sg$ would have POI replaced, namely the "588-FC Porto Museum" for subgroups C_9Sg and $C_{15}Sg$, and "692-Boulder Stone" for subgroup $C_{14}Sg$. This is a great result, meaning 96% of the participants were satisfied with the suggested POI group recommendations (Figure 7.18(b)). If we also replaced the POI rated with 3 stars, 75% of the participants would be very satisfied. Interestingly, the preference for visiting the FC Porto Museum was below 3 stars for several participants, either from different clusters or from the same, which might indicate the preference for a football team is not personality dependent.

7.6 Reflections and Future Work

In this work, we present a novel approach to solve the main challenges associated with GRS for tourism. A GRS prototype, based in a microservices architecture, Grouplanner, was improved and uses intelligent agents deployed in a Multi-Agent Microservice (MAMS) modeled with the tourists and (sub)groups' profile. The agents provide a faster access to the tourists and (sub)groups data using asynchronous tasks, facilitating the communication between the agents themselves and the other microservices and clients. The MAMS is implemented in a simpler way than the conventional MAS used in RS, as only two types of agents are created, the ones that represent the tourists, and the ones that represent the excursion groups.

A novel dynamic clustering technique, d-means, based on a modification of the k-means algorithm, to dynamically aggregate tourists with similar personalities into new or existing clusters at the registration phase, is proposed, as individuals with similar personalities tend to choose similar tourist attractions (Alves, Martins, Saraiva, et al., 2023). The dynamic clustering is performed by the MAMS in real-time when a new tourist user registers in the application, without needing to define and initialize the number of initial clusters like in the conventional clustering algorithms, not wasting time in the clusters initialization, or perform the clustering in offline and online phases, as we create clusters on the fly or go directly to the existing ones and add the new user, updating its centroid. d-means offers a different approach to handling new users, without necessarily discarding existing clusters or recomputing centroids from scratch, which showed to have advantages in

terms of efficiency, scalability and a higher clustering quality. The proposed d-means clustering algorithm guarantees there are no outliers and large distances between the clusters' members, as the tourists are assigned to an existing cluster only if their similarity to the cluster's centroid is of at least 0.80 (configurable), making the clustering process much more precise. The ones that do not meet the criterion are assigned to a new cluster, which can then have other similar tourists as new tourists register in the app which partially solves sparsity issues.

Therefore, in this work, the clustering process is performed dynamically (fully online and incrementally) because it allows to assign the tourists in real-time to a cluster of similar tourists as they register, benefiting from the following advantages: 1) the clusters are scaled in real-time, incrementally updating the clusters' pool used by the recommendations without affecting the clustering quality; 2) saves processing time when dividing the excursion groups into smaller groups of similar-personality tourists, which also helps solve sparsity issues, as all tourists will be assigned to the most similar personality subgroup; and 3) helps refine the ratings and rules prediction in the recommendation process as they will be more targeted towards people of the same type and therefore similar preferences, managing to satisfy more users, or even all of them, in the same group.

Comparing our algorithm with two baselines (k-means and k-means++), although not surpassing k-means for the time needed to create clusters in bulk (which is not the purpose of d-means in the GRS prototype), d-means greatly competes with k-means++ (the optimized version of k-means), creating similarly cohesive clusters, closest clusters, and revealing a good to very good clustering quality (silhouette), substantially outperforming k-means++ in the time needed to create clusters in bulk, and k-means and k-means++ in scalability without prejudicing the clustering quality. It would be interesting to compare the proposed algorithm with other clustering algorithms like DBSCAN or BIRCH, or even decision-trees.

This new algorithm can be expanded to other contexts where other attributes instead of personality can be used, for example the users' preference for music or movie genres, etc. Another advantage is that the users' personality only needs to be assessed once and can be reused across different research domains. Although the proposed algorithm gave great results, it would be interesting to find the dynamic similarity threshold (on the fly) to balance the accuracy/time tradeoff according to the business needs. For a commercial version, load tests should also be performed.

Another novelty is the way the main excursion group members are divided and processed by the MAMS. To solve the (large/occasional) group members' conflicting preferences, heterogeneity and to decrease the sense of misplacement and increase socialization and companionship, the main group is divided into subgroups of similar personalities based on the members corresponding clusters. If at least three members come from the same cluster, they are maintained together in a subgroup. The other members are distributed to the most similar subgroup's centroid. The subgroups' centroid personality is calculated only considering the members that came from the same cluster, so the similarity is not prejudiced by the tourists coming from the other clusters, otherwise the logic of forming clusters of tourists with similar personalities would lose its purpose, although we could see in the results of the simulation with real participants that the subgroups had higher cohesions and silhouette values than the originating clusters.

The subgroups' personality is used to predict the subgroups' tourism categories preference and travel-related preferences & concerns, based in the models obtained from our previous work (Alves, Martins, Saraiva, et al., 2023). For instance, as the members in a subgroup are very similar in personality and therefore have similar preferences[42], if a subgroup has elements that enjoy playing Pokémon Go, they can chat with each other, organize raids and conquer gyms together, or enjoy the company of each other when visiting a museum or going to a restaurant, promoting socialization and the sense of belonging/companionship. This strategy solves the cold-start problem, implicitly determining the preliminary tourists' preferences and allowing to create initial recommendations without the need for the tourists interaction with the application, negotiation or feedback.

Each cluster is assigned a list of association rules, using the Apriori algorithm. The rules and the ratings given by the subgroup's members, that came from the same cluster, to previous recommendation lists and visited POI, are considered to build inclusion and exclusion POI lists for the subgroups. This also guarantees the recommendations for the subgroups are not hampered by the tourists from other clusters. All these strategies were implemented to facilitate the recommendation process in the recommendation Engine (REMS). Taking the subgroups' inclusion and exclusion POI lists into account, the top predicted preferred tourism categories and travel-related preferences

42 It is important to refer that similar personalities do not mean compatible personalities.

& concerns, their disabilities and fears/phobias, the REMS assigns the best matching POI to each subgroup by navigating the existing POI. This approach takes the subgroups' members' needs into account, suggesting only POI adequate for each subgroups' characteristics. As future work, if rules are not found in a cluster, they will be searched for in the closest cluster and so on, instead of searching in all the other clusters. This way, the rules will be more similar to the closest cluster tourists' profile and therefore more exact.

In this work, we show we don't need previous data to build the users' initial profile, like the filtering techniques used in the conventional (G)RS that need large amounts of data. Also, the implemented strategies showed the participants were highly satisfied with the initial recommendations, without needing to previously classify or negotiate any POI. Although there is a chat screen for each subgroup and main group to exchange opinions, etc., the way the recommendation lists are presented facilitates the choice process and the consensus reaching, minimizing the need for long and tedious negotiations.

During the POI recommendation lists classification, it was possible to observe that some participants were rating lower some POI because they had already visited them and didn't want to go again (because that information wasn't added in the POI history by the tourist), or because they didn't know what the POI was. Therefore, we are currently improving the information displayed in the app, to allow users to indicate whether a POI in a recommendation list has already been visited and if the tourist wants to revisit it, similar to the POI history functionality. Also, a representative image for each POI will be included in the recommendation lists.

Some tourism categories have a combination of tourist attractions, like "Museums, Boat Trips & Viewpoints" or "Party, Music & Nightlife". In these cases, the REMS should recommend 2 or more POI of each type, to introduce more variability and because the tourists might prefer one type over another. For example, a tourist might prefer to go to museums than do boat trips or visit viewpoints. Also, in the tourist's profile screen, the user should be able to rearrange the predicted tourism categories to help improve the type of recommended POI.

Although the simulation participants were satisfied with the recommended POI, the predicted tourism categories and travel-related preferences & concerns, 4 factors (in 15) were statistically different from the real participants' average preferences. This was mainly due to the used models' satis-

factory goodness-of-fit. To increase the models' accuracy and predictability, a larger sample was needed. Also, as it is evidenced in our previous study (Alves, Martins, Saraiva, et al., 2023), almost everyone likes to include almost all types of tourist attractions in their vacations, which could be somehow biasing the participants' ratings. Nevertheless, although everyone likes to include certain types of attractions, some attraction types are not for all, like adrenaline activities or sports & games. That is why the division of the main excursion group into subgroups of similar personalities is so important, as the ones who like adrenaline or sports & games will be placed in a subgroup with their peers and will be able to perform those exclusive activities without constraining the other group members who don't like that sort of activities. Also, excursion members with disabilities will have accessible POI to visit and if most of the members in a subgroup have a certain fear/phobia, they will receive POI recommendations that will not affect their fears, without impacting the other excursion members experience. It would have been interesting to test the prototype with real excursion groups.

Although we are using the BFI to determine the tourists' personality, which is fast to answer (< 5 minutes), we are working on creative and compelling ways of implicitly acquiring the tourists' personality to replace the personality questionnaire, not only to avoid the weight associated to filling questionnaires, but also to avoid the desirability bias associated to personality questionnaires and to provide a more granular way of obtaining the personality 30 traits instead of the 5 dimensions (Alves, Trindade, et al., 2024). We hope these can be generalized to all types of recommender systems, as well as the novel strategies implemented to provide the individual and group recommendations.

It is also important to work on ways of guaranteeing the anonymity and confidentiality of the users' personal data, especially regarding their personality.

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8

IMPROVING GROUP RECOMMENDATIONS USING PERSONALITY, DYNAMIC CLUSTERING AND MULTI-AGENT MICROSERVICES



A photograph of “Gardens by the Bay” in Singapore, photo from Pixabay (royalty-free)

Paper Title	**Improving Group Recommendations using Personality, Dynamic Clustering and Multi-Agent Microservices**
Authors	Patrícia Alves, André Martins, Paulo Novais, Goreti Marreiros
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Abstract

The complexity associated to group recommendations needs strategies to mitigate several problems, such as the group's heterogeinity and conflicting preferences, the emotional contagion phenomenon, the cold-start problem, and the group members' needs and concerns while providing recommendations that satisfy all members at once. In this demonstration, we show how we implemented a Multi-Agent Microservice to model the tourists in a mobile Group Recommender System for Tourism prototype and a novel dynamic clustering process to help minimize the group's heterogeneity and conflicting preferences. To help solve the cold-start problem, the preliminary tourist attractions preference and travel-related preferences & concerns are predicted using the tourists' personality, considering the tourists' disabilities and fears/phobias. Although there is no need for data from previous interactions to build the tourists' profile since we predict the tourists' preferences, the tourist agents learn with each other by using association rules to find patterns in the tourists' profile and in the ratings given to Points of Interest to refine the recommendations.

CCS Concept: Computing methodologies → Multi-Agent systems • Information systems → Clustering; Association rules; Recommender Systems • Computer systems organization → Cloud computing

Additional Keywords and Phrases: Group Recommender Systems, Multi-Agent Microservices, Personality, Dynamic clustering, Affective computing, Leisure tourism

8.1 Introduction

The travel and tourism domain is very complex and the emergence of Group Recommender Systems (GRS) (Alves et al., 2019; Ardissono et al., 2003; Garcia et al., 2009; Leon, 2022; T. N. Nguyen & Ricci, 2018) came to help tourists plan their trips and provide better and more personalized recommendations. Due to that complexity, like the groups' heterogeneity and conflicting preferences (especially in occasional groups), several GRS are being proposed to improve recommendations, using different techniques like preference negotiation, emotions, pairwise preferences, location-based social networks (Abolghasemi, Engelstad, et al., 2022; Álvarez Márquez & Ziegler, 2016; Bekkerman et al., 2006; Garcia et al., 2009; T. N. Nguyen & Ricci, 2018; M.-H. Park et al., 2008; Sojahrood et al., 2023), or even Multi-Agent Systems (MAS) (Batet et al., 2012; Borràs et

al., 2014; Julian & Botti, 2023; Lorenzi et al., 2012; Neto et al., 2022b; Ravi et al., 2021; Selmi, Brahmi, & Gammoudi, 2014; Wallinger et al., 2023). However, issues like (i) providing the first recommendations independently of the users interaction with the system, negotiation or feedback, (ii) diminishing the group's heterogeinity and conflicting preferences, (iii) providing (explainable) recommendations at a certain destination while caring for the tourists' needs, and (iv) avoiding the emotional contagion phenomenon usual in groups (Delic & Masthoff, 2018; Delić et al., 2020) are still open in GRS (Alves et al., 2019; Delić et al., 2020; Masthoff, 2015; Ricci, 2022).

Hoping to tackle some of the open issues, we improved our previous work (Alves et al., 2022), a GRS for tourism prototype, Grouplanner, that beside using Multi-Agent MicroServices (MAMS), introduces three other novelties in GRS: the prediction of the tourists' attraction preference and travel-related preferences & concerns based in their five dimensions of personality, dynamic clustering to group tourists with similar personalities, and association rules to refine the recommendations.

Several studies show that personality is strongly related to the users' preferences in several domains (Alves, Martins, Saraiva, et al., 2023; Cantador et al., 2013; Martijn et al., 2022; Tkalcic & Chen, 2015), including tourism, which can be a leverage to solve the cold-start problem. Based in our previously proposed models (Alves, Martins, Saraiva, et al., 2023), which predict tourist attraction preferences[43] and travel-related preferences & concerns[44] just by knowing the tourists' five dimensions of personality (Costa & MacCrae, 1992), the developed GRS provides a preliminary list of POI to visit. Besides using the tourists' personality for the referred predictions, the agents use their communication skills to ask for the other tourists' knowledge and travel experience to help improve the recommended list of POI. Using the tourists' personality, the MAMS dynamically creates clusters of tourists with similar personalities which are then used to divide the main excursion group into subgroups of similar personalities and therefore similar tourist preferences, diminishing the group's heterogeinity and conflicting preferences. We believe this can also reduce the time needed to reach a consensus on the final list of POI to visit, the number of interactions and reduce

43 Adrenaline Activities; Wild Nature Activities; Party, Music & Nightlife; Sun, Water & Sand; Museums, Boat Trips & Viewpoints; Theme & Animal Parks; Cultural Heritage; Sports & Games; Gastronomy Events; Health & Well-being; Natural Phenomena
44 Previsibility and Safety; Cultural & Learning Experiences; Uniqueness & Exoticness; and Familiarity

or even eliminate the negotiation phase. This paper briefly describes the referred implemented improvements, more detailed in the demonstration video[45].

8.2 The GroupPlanner Prototype

The developed GRS prototype is intended to help (occasional) groups of tourists choose which POI to visit at a certain destination based on their profile, mainly their personality, disabilities and fears/phobias. The prototype is fully functional and can be installed and used by any potential users or groups of users to get individual or group recommendations[46].

8.2.1 The Microservices Architecture

The GRS is based on a microservices architecture, implemented using .NET, composed of five microservices published in a Microsoft Azure server: the User Management MS (UMMS), the Social Network MS (SNMS), the POI MS (POIMS), the Multi-Agent MS (MAMS), and the Recommendation Engine MS (REMS). The MAMS was developed using the ActressMAS (Leon, 2022) multi-agent framework. More details are further described in (Alves et al., 2022).

8.2.2 Using MAMS, Personality, Dynamic Clustering and Association Rules to Improve Recommendations

8.2.2.1 User Registration with Dynamic Clustering

When a tourist registers in the app, his profile is first sent in a JSON via HTTPS POST to the UMMS (https://<domain>/gp/user/registerUser), and then to the MAMS, responsible for creating a matching agent (TourAg X) modeled with his initial profile (demographic data, personality, disabilities, fears/phobias). If the tourist is the first person to register in the app, a cluster, using his five dimensions of personality scores as the centroid, is dynamically created (Figure 1). When another tourist registers, her similarity to the center of the existing cluster is calculated (normalized Euclidean distance). If her personality is at least 80% similar to the existing tourist, she is added to the same cluster. If not, a new cluster is created based on her personality, and so on.

45 Accessible at https://youtu.be/up0A3B_e6zU
46 Available at http://www.gecad.isep.ipp.pt/grouplanner/dissemination.html as an installable Android APK. The API can be provided on request.

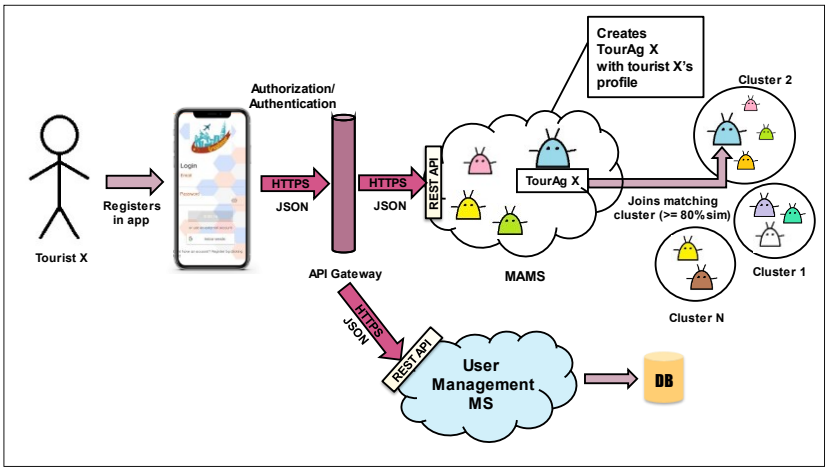


Figure 8.1. Registering a tourist user in the application with dynamic clustering (simplified diagram).

Grouplanner allows tourists to register visited POI and rate them from 1 to 5 stars, as well as define if they want to visit the same POI again. These functionalities, along with the tourists' profile, are important to improve the recommendation process, i.e., an agent can learn from the other agents' travel experience and profile.

8.2.2.2 Group Recommendations

When a tourist creates an excursion group (group owner), a JSON containing the group's data is sent via HTTPS POST to the MAMS (https://<domain>/mams/agents/groups/registerGroup), which then creates a Travel Agent Y (TrvAg-<GroupID>) representing the group. When the group owner requests a group recommendation, an HTTPS request is sent to the respective TrvAg (https://<domain>/mams/agents/groups/<groupID>/requestRecommendation). At the moment a group recommendation is received, to help minimize the group's heterogeneity and conflicting preferences, if at least three tourists belong to the same cluster, a subgroup with the agents belonging to that cluster is created, with a centroid based in their average personality scores, as well as a Subgroup Travel Agent (TrvAg-<GroupID>Sub<clusterID>) responsible for the subgroup members communication (Figure 2). Using the previously proposed models (Alves, Martins, Saraiva, et al., 2023), each subgroup's tourist attractions preference and travel-related preferences & concerns are predicted by the subgroup's centroid score in the five dimensions of personality, and posteriorly sent to the REMS to build the first recommendations.

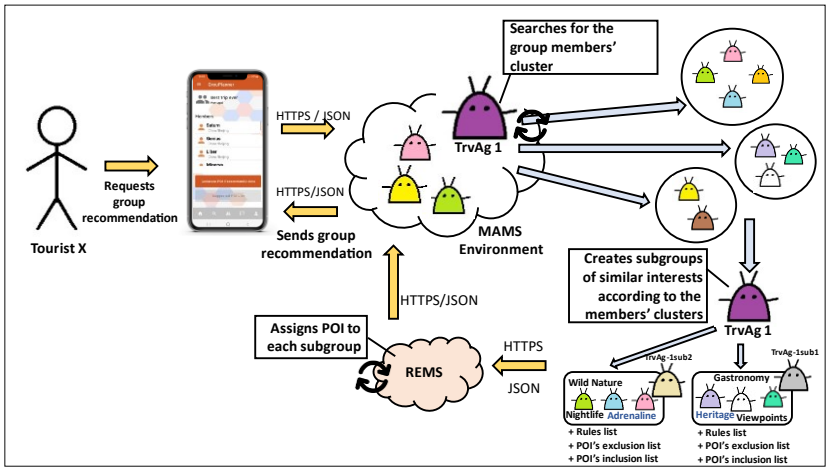


Figure 8.2. Simplified diagram for the group recommendation process.

The Subgroup TrvAg then asks the subgroup's cluster members for their travel history (visited POI, respective rating, revisit intention, and rating preference for unvisited POI), if available, and searches for positive and negative association rules in the respective cluster using the apriori algorithm, adding them to a list of rules. If 50% or more tourists in a subgroup match a certain rule for a POI, that POI is added to a POI exclusion or inclusion list, whether it is a negative or positive rule, respectively, so that and other similar POI are (not) included by the REMS in the recommendation list for that subgroup. Also, if a POI in the subgroup's members travel history has a mean rating of less than 3 stars, that POI is added to the subgroup's POI exclusion list. If all tourists have similar personalities, the main group will prevail, and the recommendations will be for the whole group. In case there are tourists from different clusters that were not enough to create a subgroup, they are compared to the existing subgroups and added to the most similar one, but without changing the subgroup's centroid. The same applies to tourists with a similarity below 80%. After creating the subgroups, the TrvAg sends a JSON via HTTPS POST to the REMS containing the subgroups characteristics and their POI lists.

The REMS then searches for the N best matching POI for each subgroup in a POI ontology, considering the respective POI lists, the preferred predicted tourism categories and travel related preferences & concerns, and possible disabilities and fears/phobias. Then, it answers the requesting TrvAg with the list of POI suggested for each subgroup. The TrvAg then answers to the GRS app, which creates the suggested subgroups and presents them in the subgroup's interface along with their respective POI recommendation list, allowing each subgroup's members to anonymously rate

the recommended POI. If at least 50% of the members in a subgroup rate a POI below 3 stars, it is added to the subgroup's POI exclusion list and to the respective rater and cluster's members POI history. If the group owner asks for new recommendations, all POI rated below 3 will be replaced by new POI.

8.2.2.3 Individual Recommendations

The prototype also allows requesting individual recommendations. The recommendation process is the same as for the group recommendations, but the recommendation request is directly asked to the tourist's agent (https://<domain>/mams/agents/tourists/<username>/requestRecommendation). If the tourist rates (un)visited POI that were never rated by tourists in his cluster, the rating is replicated for those tourists and replaced by the real rating if the tourist visits and rates them.

8.3 Conclusions

In this demonstration, we briefly described Grouplanner, a GRS for tourism prototype, that can be used by individuals or (casual) groups of tourists to obtain recommendations of POI to visit. The microservices architecture allows requests from any HTTP client, namely: tourist registration, request of individual recommendations, creation of excursion groups, request of group recommendations, and rating of the recommendation lists and visited POI.

The first POI recommendations are provided without the need for the users interaction, negotiation or feedback, solving GRS open issue (i); the dynamic clustering and division of the main group into subgroups of similar personality tourists diminishes the group's heterogeinity and conflicting preferences, tackling issue (ii); all presented recommendations consider the tourists' travel-related preferences & concerns, disabilities and fears/phobias, are accompanied by a description of the tourism category they belong to, and the 3 top tourism categories that characterize each subgroup (or the main group) are presented to the tourists, solving issue (iii); and finally, the emotional contagion phenomenon, issue (iv), is mitigated by dividing the main excursion group into subgroups of similar tourists and forcing the tourists to anonymously rate the recommended POI lists, only presenting the (sub)groups overall rating when all tourists have individually rated the suggested POI.

To test the prototype, a simulation with real users (n = 35) was performed. The results are currently in a work that is under peer review, but the dataset used can be consulted at the Grouplanner website[47].

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47 Under the "Simulations" tab at http://www.gecad.isep.ipp.pt/grouplanner/dissemination.html

9

"YOU WANT TO PLAY A GAME?" DETECTING TWO PERSONALITY TRAITS WITH SHORT-DURATION MOBILE GAMES



Image of a poster used to gather participants for the serious games' experiments.

Paper Title	**"You Want to Play a Game?" Detecting Two Personality Traits with Short-Duration Mobile Games**
Authors	Patrícia Alves, João Trindade, Gonçalo Monteiro, Pedro Campos, Pedro Saraiva, Goreti Marreiros, Paulo Novais
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Abstract

To accurately determine someone's personality is complex, such as the need for long personality questionnaires, which are subject to social desirability bias, or a great amount of users' interactions with the system. Also, most existing works focus on broader personality dimensions instead of the more granular traits, which better characterize a person, and, so far, there are no short-duration mobile games that can accurately predict personality.

In this work, we propose to implicitly acquire users' more granular personality traits in less than five minutes, namely cautiousness and achievement-striving as a first concept proof, by using short-duration mobile serious games, in an attempt to also replace self-reporting personality questionnaires.

Two platform mobile games were developed, one for each trait, Which Way and Time Travel, respectively. Then, an experiment with real participants (n=100) was conducted. Time Travel proved to be capable of detecting achievers, while Which Way couldn't effectively measure cautiousness, although it seems promising. Interesting significant correlations with other personality traits, such as anger, modesty, friendliness, excitement seeking, cheerfulness, adventurousness, and others were also found. The results show short-duration mobile minigames are a viable way of unobtrusively determining the users' more granular personality, being the path to replace personality questionnaires.

Keywords: Big five; personality; cautiousness; achievement-striving; personality acquisition; serious games; human factors

9.1 Introduction

Several researchers are trying to implicitly determine the users' personality in different domains such as music, tourism, games, social networks, or even in general (Alves, Martins, Saraiva, et al., 2023; Birk, Toker, Mandryk, & Conati, 2015; Cantador & Fernández-Tobías, 2014; Ferwerda et al., 2015; Haizel, Vernanda, Wawolangi, & Hanafiah, 2021; Yee et al., 2011). However, to accurately acquire someone's personality is a great challenge. The existing techniques are still intrusive and time-consuming in the ways they gather the users' personality, need great amounts of data, or involve filling tedious and long self-reporting questionnaires, which are known for being susceptible

to the social desirability bias (Pedregon et al., 2012) and fake responses (Bhatia & Ryan, 2018). Also, they are mainly focused in broader personality dimensions instead of the more granular personality traits, which are better for characterizing a person (Costa & MacCrae, 1992), and the ones who intend to determine the more granular traits are not that accurate (F. Y. Wu et al., 2022). The challenge is therefore to accurately gather the users' personality non-intrusively and in a less time-consuming and more compelling way, without the need for machine learning (ML) techniques, which need great amounts of data and user interactions to provide accurate predictions.

An application example are Recommender Systems (RS) for tourism. Travelling is an emotional experience (Volo, 2021) and therefore, personalization is a key factor for the success of RS in tourism (Gavalas & Kenteris, 2011; Ricci, 2002; Schmidt-Belz et al., 2002). The more information about the tourist is known, the better recommendations can be made. For instance, personality is strongly related to the users' preferences (Alves, Martins, Saraiva, et al., 2023; Cantador et al., 2013; Friedman & Schustack, 1999; Tkalcic & Chen, 2015) and has been evidenced to improve recommendations and tackle the cold-start problem (Alves, Martins, et al., 2024; Feil et al., 2016; Tkalcic & Chen, 2015). Therefore, the users' personality can help build a more robust profile, and it somehow needs to be obtained by the system.

Gamification and serious games can be the leverage we are looking for. In fact, gamification techniques will be a major trend for the future of tourism (Mortara et al., 2014; Xu et al., 2017; Xu et al., 2016). For example, Dunn et al. (2009) compared three different interfaces for acquiring personality in RS: explicitly, using the NEO PI-R personality questionnaire, and implicitly, with the Commons Fishing (computer) Game and the Implicit Association Test. They found the game was a good predictor of the Agreeableness and Extraversion dimensions but needed to be improved for accuracy. They said it would be promising to explore other game (theory) alternatives that could be applied to RS. Thus, adding serious games to profile users can be the twist needed in the history of RS and of other personality-based systems/applications.

Several attempts of profiling players have been made (Diamond, Tondello, Marczewski, Nacke, & Tscheligi, 2015; Halim, Atif, Rashid, & Edwin, 2017), starting with Bartle (1996), who proposed a player typology for multiplayer games composed of four player types: achievers, explorers, socializers and killers. However, in this work, we intend to profile players based on their crude (and more

granular) personality traits, using the most used and best recognized personality model, the Big Five (Digman, 1990), so their profile can be used across multiple domains.

Thus, we propose to implicitly acquire the individual's more granular Big Five personality traits in less than five minutes, by using short-duration mobile games, to motivate and challenge the users at the same time, as a means of substituting the self-reporting personality questionnaires, starting with two traits as a first proof of concept: cautiousness and achievement-striving. Two 2D platform minigames were developed, one more focused in the detection of the cautiousness trait, and the other in the achievement-striving trait. An experiment with real users (n = 100) from different ages, formation areas, and professions was conducted. The International Personality Item Pool (IPIP) IPIP-NEO-120 personality questionnaire was then used to assess the participants' personality granular traits and compared with the minigames results. The achievement-striving trait could be successfully associated with game behaviors, but cautiousness could not, although it seemed to be promising with the right improvements and a larger sample. Statistically significant correlations with other personality traits were also found, namely: anger, modesty, friendliness, excitement seeking, cheerfulness, adventurousness, anxiety, imagination, intellect, self-conscientiousness, and vulnerability.

In Section 9.2 we introduce the concept of personality and its relationship to the users' preferences, and the different techniques used to acquire the users' personality, including serious games, and some related works. Section 9.3 exposes the used methodology. Section 9.4 shows the obtained results and respective analysis, and finally, Section 9.5 reflects on the study results and describes what will be done as future work.

9.2 Background and Related Work

9.2.1 Personality and User Preferences

Psychological aspects, such as personality, moods and emotions, are being perceived to influence the variance in the individual's preferences and behavior (Dhelim et al., 2021; T. T. Nguyen, Maxwell Harper, Terveen, & Konstan, 2018; Tkalčič et al., 2016), and their consideration is evidencing to show better results than generic approaches (Castells & Jannach, 2024; Nunes et al., 2008; Tondello et al., 2017; Waris et al., 2024).

As defined by H. Eysenck and Rein (1998), "personality is the sum-total of the actual or potential behavior-patterns of the organism, as determined by heredity and environment". Each person has her own behavior patterns, which are rather stable over time in different situations (McCrae & Costa Jr, 1997). These patterns can be summarized into personality dimensions (or factors), being the Five Factor Model, OCEAN, or Big Five, recognized as the best model to represent them (Digman, 1990): Openness to Experience (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Emotional Stability/Neuroticism (N). Each factor is further refined into six facets or traits[48] (Costa & MacCrae, 1992), which are more granular and can be used to better portray a person. The thirty traits are presented in Table 9.1, with the studied two traits in bold.

Table 9.1. Big Five Personality dimensions and Corresponding six traits, Adapted From Costa and MacCrae (1992).

Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Imagination	Self-efficacy	Friendliness	Trust	Anxiety
Artistic interests	Orderliness	Gregariousness	Morality	Anger
Emotionality	Dutifulness	Assertiveness	Altruism	Depression
Adventurousness	**Achievement-striving**	Activity level	Cooperation	Self-consciousness
Intellect	Self-discipline	Excitement-seeking	Modesty	Immoderation
Liberalism	**Cautiousness**	Cheerfulness	Sympathy	Vulnerability

In bold the two studied personality traits.

For instance, as noted by Tkalcic and Chen (2015), personality can be useful in many areas of RS, since it is strongly connected to the users' choices (Martijn et al., 2022). Users with similar personalities have a great tendency to choose similar contents or items. For example, in tourism, highly extraverted and low conscientiousness individuals tend to take more risks and prefer adrenaline activities (Alves, Martins, Saraiva, et al., 2023). In the music field, popular music is tendentially sought by extraverted persons who are in need of positive emotions, gregariousness, and warmth, and rock music is tendentially enjoyed by persons who score high on excitement seeking (Rawlings & Ciancarelli, 1997). Even the characteristics of users' pictures on Instagram are related to personality dimensions (Ferwerda et al., 2015). Therefore, personality is a powerful trait in humans that can be leveraged to predict their preferences across various areas.

In this work, we proposed to detect two personality traits from the Conscientiousness dimension of the Big Five, cautiousness and achievement-striving, through two minigames developed for Android mobile devices. The choice of these traits was mainly because, based on our experience with vide-

[48] For simplicity, from now on called traits.

ogames, there are several popular videogames that seem easier to "mimic", having features that we think could help measure those traits, and, to the best of our knowledge, there are a few studies that try to implicitly acquire the players' cautiousness and achievement-striving with serious games, but without much success (see Section 9.2.2).

We can describe someone cautious as prudent, thoughtful, and deliberate in the decisions, making plans carefully (Costa Jr et al., 1995). Cautious individuals prefer to avoid unnecessary risks, are attentive to details, prefer well-established routines, and may lack spontaneity. This trait is associated with a desire for security. Persons with a high level of achievement-striving are often ambitious, persistent, and dedicated to their pursuits (Costa Jr et al., 1995; Elliot & McGregor, 2001). They set demanding standards for themselves and actively seek success and accomplishment in various aspects of their lives. Individuals with this trait are typically focused on continuous improvement, are willing to put in effort and hard work, being often "workaholic", and are driven by a desire to attain excellence. The opposite can be said for individuals low on the referred traits.

9.2.2 Personality Acquisition

There are two ways of acquiring the user's personality (Tkalcic & Chen, 2015): by using (1) explicit techniques – usually by means of Psychology questionnaires[49]; or (2) implicit techniques: for example by data mining emails or social media like Facebook.

An increasing number of studies show that personality dimensions can be recognized from several human cues and that different kinds of (combination of) methods can be used to automatically acquire them (Finnerty et al., 2016; Mohammadi, Vinciarelli, & Mortillaro, 2010; K. A. Smith, Dennis, Masthoff, & Tintarev, 2019; Tkalcic & Chen, 2015). Finnerty et al. (2016) compiled five different approaches that can be used to implicitly recognize someone's personality:

1. Audio and/or visual approaches: Cues like a person's speaking rate, eye gaze, facial expressions, postures, gestures, voice tone and pitch, among others, can exteriorize personality dimensions. For instance, extroverted persons tend to speak more, faster and hesitate less than introverted (Scherer, 1979). Inspired in the HCRC Map Task of Anderson et al. (1991), Batrinca, Lepri, Mana, and Pianesi (2012) recognized four personality dimensions

49 To measure personality several items and scales exist and can be consulted at the IPIP website at https://ipip.ori.org/

from the interaction of test participants with a map in a computer (visual and acoustic cues), by giving verbal instructions via Skype. They used the Abridged Big Five-dimensional Circumplex model personality questionnaire as a baseline to directly measure the personality dimensions. They found Extraversion and Emotional Stability were the easiest dimensions to detect, followed by Agreeableness and Conscientiousness.

2. Wearable devices: Data can be recorded from wearable devices with sensors, like smartwatches, electronically activated recorders or sociometric badges, without interrupting the user's daily life (Finnerty et al., 2016). Olguın, Gloor, and Pentland (2009) showed that it is possible to identify personality dimensions by using a sociometric badge. They instrumented 67 nurses in a Hospital from Boston and recorded their activities while they worked. 39 participants answered the NEO-FFI personality questionnaire (60 items). For instance, they found that nurses who spent more time of the day on a face-to-face interaction, and that had more variation across days in the daily percentage of face-to-face interaction time, the more neurotic they were.

3. Smartphones: We can say smartphones are a kind of portable multi-sensor device almost everyone carries. Due to their increasing processing and memory capacities, and number of built-in sensors, they can be used to record and sense a panoply of data related to a user's daily life, like his precise location, other devices in his vicinity, communication data and their content (e.g. phone calls logs, text messages, emails), time of day, weather, mood, or even movement patterns. For instance, it is evidenced that extroverts tend to receive more calls and spend more time on them (Chittaranjan, Blom, & Gatica-Perez, 2013).

4. Text: Written texts can be used to predict personality by using text-mining techniques. Texting merges oral and written communication and can be of extreme interest (Finnerty et al., 2016). For example, extraverts text more frequently and use more personal pronouns (Holtgraves, 2011).

5. Social Media: Social media like Facebook, Twitter, or Instagram, can also be a means of showing someone's personality. Several characteristics can be extracted from the users' profiles, like the number of followers, the network's density, number of posts or links (Gol-

beck, Robles, Edmondson, & Turner, 2011), number of likes, number and type of shares, number of groups (Kosinski, Bachrach, Kohli, Stillwell, & Graepel, 2014), etc. Many social contacts (popular users) can be a signal of extraversion and less neuroticism (Golbeck et al., 2011). Celli, Bruni, and Lepri (2014) showed that even profile pictures from Facebook can reveal a lot of information about a user. For instance, those who are "not open to experience tend to have strong spots of light and sometimes darkened figures. Affective people tend to smile in profile pictures. Dominant people tend to have very bright, visible or attractive pictures" (Celli et al., 2014). The authors used the BFI-10 questionnaire to measure the participants' personality and the IPIP Interpersonal Circumplex IPIC-IPC-32 to assess their interaction styles.

6. *(Serious) Games:* It has also been found that a person's behavior in (computer) games reveals their personality (Cowley & Charles, 2016; Van Lankveld et al., 2011; Vinciarelli & Mohammadi, 2014; Yee et al., 2011). The study of the players static behavioral patterns, such as personality, in the context of playing a computer game, is called player profiling (Yannakakis, Spronck, Loiacono, & André, 2013). Although Finnerty et al. (2016) do not refer this approach in their survey, it is referred by other authors (Tkalcic & Chen, 2015; Vinciarelli & Mohammadi, 2014). So, we decided to include it in this section.

   For instance, Van Lankveld et al. (2011) made a very interesting study by creating a module for the Massively Multiplayer Online Role-Playing Game (MMORPG) Neverwinter Nights to predict the gamers' personality. They concluded that all the five personality dimensions could be predicted from the participants' interactions with the game storyline. They also evidenced that each dimension can be better predicted if situations optimally suited for each dimension are inserted in the game. They used the NEO-PI-R personality questionnaire to assess the participants' personality dimensions.

   Yee et al. (2011) used the behaviors from 1040 players in Word of Warcraft, also a MMORPG, to determine if they were related to their personality. For four months, they collected the players data and compared the results with the participants' Big Five personality dimensions, obtained from a 20-item scale retrieved from the IPIP. They found many behavioral cues were related to the players' personality and therefore could be used to implic-

itly detect it. For instance, group activities were preferred by extraverted persons and solo by introverted. High openness to experience individuals had more characters and a higher interest in exploring the surroundings, the less conscientious seemed to be less careful and died more often from falls from high locations.

Santos, Hutchinson, Khan, and Markopoulos (2019) tried to detect two abstract personality traits, need for cognition and self-esteem, through the players' game behavior, in a simple strategy game and in a 2D platformer, respectively. They discovered that players with low need for cognition used more hints in the game than high need for cognition players. Self-esteem seemed to be related to the players' pace in the game.

Palomäki et al. (2021) studied how extraversion and conscientiousness were related to online race horse betting in a sample of 11217 Finnish males online horse bettors. They found high extraversion individuals were more prone to being bettors, placing more bets per day, and with a greater betting volume. High conscientious persons (more cautious) were less likely to be bettors, placing less bets per day, with less money, and playing fewer days.

Click Town and Word Find are two game-based assessments developed by F. Y. Wu et al. (2022) in an attempt to measure three traits of Conscientiousness: achievement-striving, self-discipline, and cautiousness. They used the 50-item NEO-PI-R to assess the participants' personality. However, they found the games were measuring the participants cognitive ability instead of the intended traits, giving several recommendations for future research.

Quwaider et al. (2023) developed and published in the Google Play Store a mobile first-person shooter game, "The Protector", where the main goal is to kill zombies to save several cities, to predict the players' Big Five personality dimensions. To determine each dimension, they used three different customizable scenarios, each to represent one trait of the corresponding dimension, being one of them the achievement-striving trait. They used the accuracy of zombies killed as a metric to measure that specific trait. They also compared several machine learning methods to predict the players' personality. However, how the participants personality was obtained and compared to the measured metrics is not re-

vealed, and therefore, how the achievement-striving metric in the game is correlated to the participants' corresponding trait is not known, and thus cannot be used for comparison.

The use of explicit techniques to acquire the users' personality is intrusive, time-consuming, and not everyone is willing to answer a series of intimate questions, being subject to the well-known desirability bias and fake responses, which generally prejudice systems that rely on a questionnaire to acquire personality. To tackle this limitation, researchers have started to work on ways of gathering the users' personality in implicit ways, like using serious games. Serious games are becoming popular and increasingly being used for educational and training purposes in a great variety of domains (Arif et al., 2024; de Carvalho, Braz, dos Santos, Ferreira, & Prates, 2024; Djaouti et al., 2011; Susi et al., 2007; Xu et al., 2017).

To assess and validate their results, researchers frequently use a personality questionnaire, usually extensive, to obtain "ground truth" data and then correlate those values with the data extracted by the method they want to study, usually applying correlation or regression analysis. Depending on the study purpose, the data obtained can be further subjected to ML techniques to make predictions. However, ML techniques present limitations: they need a great number of interactions and input from the user to obtain enough data to determine the users' behavior, others are not very practical, and they are not very accurate yet. Moreover, social media data is being questioned about its reliability in terms of personality cues, since the information presented is selected by the user and therefore, it represents what the user wants to reveal to the others and not her true self (Finnerty et al., 2016; Gosling, Vazire, Srivastava, & John, 2004). Also, not everyone interacts in the same way with a social network: some are mere observers, others only "like" certain posts/items, which poses a problem for approaches that need that knowledge to make predictions.

Another limitation found is that most of the existing studies are based on the broader five dimensions of personality or on other personality scales, and not on the more granular thirty traits. We believe the thirty Big Five's traits should be assessed instead if we want to predict more accurately the users' personality, which can then be used across a variety of domains. Another limitation that stands out is that the personality traits are treated separately as if there was no correlation between them (Finnerty et al., 2016), which is not always the case (Vinciarelli & Mohammadi, 2014).

For example, inside the same personality dimension Conscientiousness, someone who is cautious might not be ambitious, and vice-versa. So, it is important to keep in mind that relationship and that it may be complex, or not even possible, to measure just a single personality trait in a game, as other traits are certainly related (positively or negatively).

To find a way of predicting someone's personality with enough knowledge without the need for a great number of interactions and continuous inputs from the user, in an unobtrusive manner, is therefore a challenge. We propose to overcome those limitations by using short-duration mobile serious games. Since mobile devices can be taken anywhere and (supposedly) be used anytime, they are a perfect and practical means for acquiring the users' personality and other user-centric information. In sum, with this study, we intend to introduce short-duration mobile games to implicitly detect the users' granular personality traits, so they can be generalized to any type of domain, such as tourism, educational, healthcare, corporate, among others, and integrated into personality-based systems.

So, do you want to play a game?

9.3 Methodology

9.3.1 The Personality Minigames Design

To try to determine the players' cautiousness and achievement-striving, two minigames, Which Way (WW) and Time Travel Mania (TT), respectively, planned to take no more than 5 minutes each to complete, were developed using Unity[50]. Both are 2D platform games and have the same main character, Berry, that the player must control through the map, using the same type of game controls, to avoid a different learning curve between the games. Both games have an energy bar, which represents how much life Berry has and a counter of gold coins, as well as background music to try to make the game more immersive and enjoyable to play. WW game has a black key icon that turns yellow when the player catches it, opening the end door, and TT game has a diamonds counter and a timer in seconds (see

50 The games APK can be downloaded in the supplementary material (APK folder). Please accept the warnings in order to install.

Figure 9.1). Contrary to other works that used games to determine personality, the proposed games aimed to detect personality traits at the first interaction, without needing to be played several times to build ground truth data. The characteristics of the two personality traits (described in Section 9.2.1) served as basis for the reasoning behind the games design.

The data collected in both games was recorded in a CSV file at the end of each full game attempt, on the players' mobile phone, and is detailed in Section 9.3.6.

We tried to make the minigames easy to play for any age group, so that they were not skill dependent to avoid introducing a skill bias. However, due to the traits that were being measured, some difficulties had to be introduced. The minigames are detailed next.

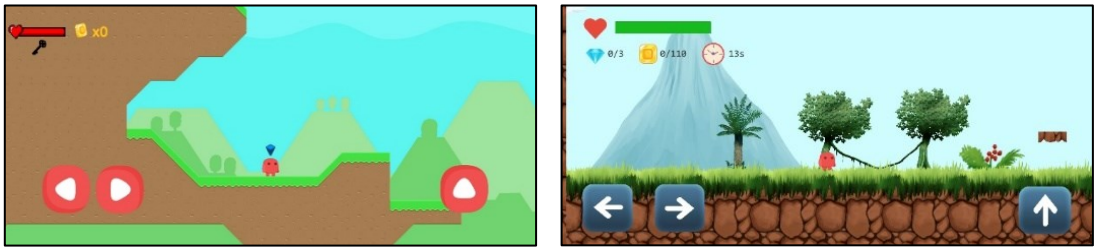


Figure 9.1. (Left) Initial scene of the cautiousness personality minigame. (Right) Achievement-striving minigame initial screen.

9.3.1.1 Cautiousness Minigame

In this game, the goal was to finish the game by finding a hidden key to unlock the final door. As cautious persons are associated with risk-aversion and low impulsivity in different life-style choices (Palomäki et al., 2021), being considered prudent and careful (Costa Jr et al., 1995), eight special monitoring sections (MS) were designed to try to measure that risk aversion and carefulness. They consisted of bifurcations, one of them leading to an easy path and the other to a hard path. The easy paths were fast, straightforward, with no obstacles and no risk of death, usually with one or two easy to catch gold coins. This could attract more cautious people. The hard paths had at least the double of gold coins to give an extra motive to follow that path, and hard obstacles to pass through, like spikes, water, fog, or lava, which became harder as the game progressed, with an elevated death risk. The spikes and lava killed instantly. The difference between the paths and the chance to die on the hard paths was intentional, giving an extra reward for risking the hard path, otherwise everyone could choose the easiest. At the beginning of the game, the player could go

down and explore to the left, which would reveal two hidden MS (Figure 9.2), this could also be an indicator of curiousness.

To avoid the player's frustration in the hard paths, there were checkpoints (red floating inverted pyramids that turned blue after touched) before entering them, which saved the player's latest progress in case of death allowing to start from the last checkpoint and to choose between the easy and hard path again, as the intention here was not to measure their ambition or perseverance nor make the player give up a hard path due to frustration sentiments. Figure 9.2 shows a bifurcation example.

For those who risked going through the hard path, a health potion could be caught at the end to recover the lost energy, if any, being the only way of recovering energy in the game, to try to make the more cautious players avoid the hardest paths. After taking a path, the player could not return to the other, so we could calculate the right metrics on each MS. This was accomplished with strategically placed invisible walls (see vertical red lines in Figure 9.2) that did not let the player change the course chosen after passing the first wall. Also, the walls were used as limits for counting the time taken to cross each MS path. Only if the player completed the monitoring section the respective metrics were recorded.

Along the map, there were also five trap zones that the player could explore to catch extra coins, which randomly released a lethal gas instantly killing the player (see Figure 9.3), i.e., when inside the trap, the gas could be released, killing the player, or not, and the player could catch the coins. We believed this could introduce a sense of insecurity and hesitation in the cautious players.

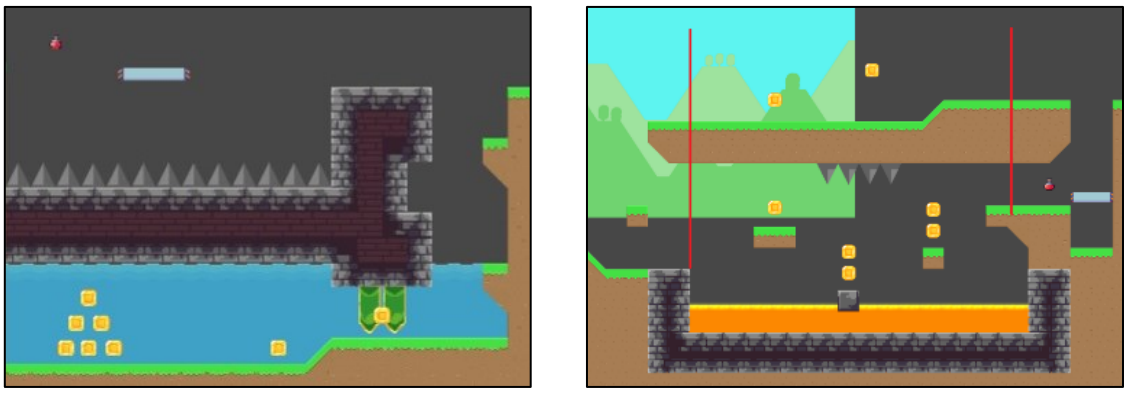


Figure 9.2. Cautiousness game scenes. (Left) One of the hidden MS. (Right) Example of a bifurcation. The top path is an easy path, and the bottom one, a hard path, with a health potion at the end. The vertical red lines mark the invisible walls.

To introduce the surprise element and some additional risk, the potions, number of coins, deadly obstacles, and traps were not in the paths' initial field of view, being only gradually visible as the player advanced in a path, as we believed cautious players would not advance in a hard path if they couldn't have a clear view of the path ahead.

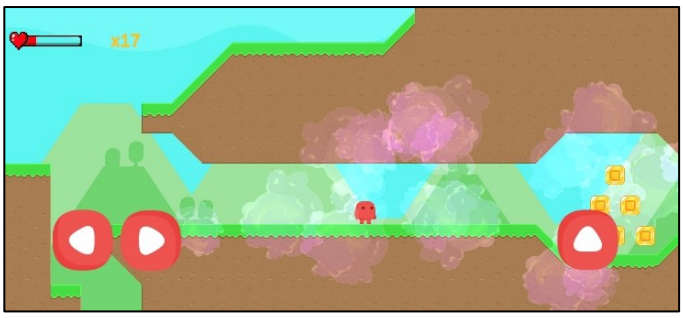


Figure 9.3. Example of a trap with poisonous gas activated (pink fog) in the cautiousness minigame.

To increase the difficulty and sense of insecurity (hoping to further distinguish the cautious from the non-cautious players), one of the last hardest paths had an enemy that used the A* (A-Star) artificial intelligence algorithm to pursuit and kill the player, and fog to decrease the visibility (Figure 9.4). The A* algorithm is a popular pathfinding algorithm to determine the shortest path between two nodes, widely used in the videogames industry (Abd Algfoor, Sunar, & Kolivand, 2015; Foead, Ghifari, Kusuma, Hanafiah, & Gunawan, 2021). It repeatedly examines the most favorable unexplored nodes until finding the destination node, in this case, the player character.



Figure 9.4. Scene of a hard path showing fog and an AI moved enemy in the cautiousness game.

9.3.1.2 Achievement-Striving Minigame

The Time Travel Mania game's main goal was to reach the end of the game. To measure the players' achievement-striving personality trait, the game had three different levels the player had to complete, starting in the Mesozoic Era and ending in the First Humanity Era. The game started with a main menu containing a section with a fake high scores table, to see if the player was moti-

vated to beat the record (see Figure 9.5), which could reveal an achiever, as they are characterized for being ambitious and persistent (Costa Jr et al., 1995; Elliot & McGregor, 2001). This demanded the player to type a username before starting to play.

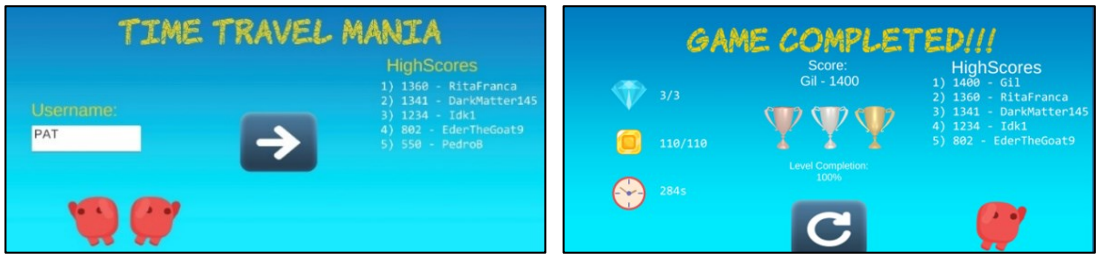


Figure 9.5. (Left) Achievement-striving game start menu. (Right) Achievement-striving game end panel.

Like in the WW game, there were two kinds of coins. The easy coins, which were in the straightforward path, and the hard coins, which involved exploring long and tedious areas to catch them, as we believed only the more ambitious and excellence-driven players would go to, revealing the achievement-striving trait. To see if the players were even more ambitious, a diamond was hidden in each scenario, in a very long and frustrating path, existing a total of three diamonds in the game. This decision was made because we believed achievers would insist and try to catch all diamonds, even if they were hard to obtain, as achievers are also known for putting effort to fulfill their goals (Costa Jr et al., 1995; Elliot & McGregor, 2001). An example can be seen in Figure 9.6.

Along the way, on the hard paths, there were enemies that increased in speed from level to level and inflicted damage. The player would bounce back if touched them, losing more than 50% of his life. Contrary to the WW game, the player's life self-regenerated with time, but there were no checkpoints, and therefore, if the player died, she had to start all over again from the first scenario. This was intentional, to frustrate the players more and see if they persisted in finishing the game or getting better scores, revealing the achievers. The hard paths also had traps, like pits with lava that killed instantly, and spikes that took more than 50% life, to also frustrate the players and reveal the more persistent ones. In the final level, the player had to pass through a giant to reach the final door to make the end more challenging.

To reward the best players and test their achievement-striving trait, a trophy system was also implemented. If the player finished the game in 400 seconds or less, catching all coins and diamonds, would win a gold trophy. If the player finished the game in 450 seconds or less, catching

at least 2 diamonds, would win a silver trophy. If finished in 500 seconds or less catching at least 1 diamond, would receive a bronze trophy. Otherwise, no trophy was awarded.

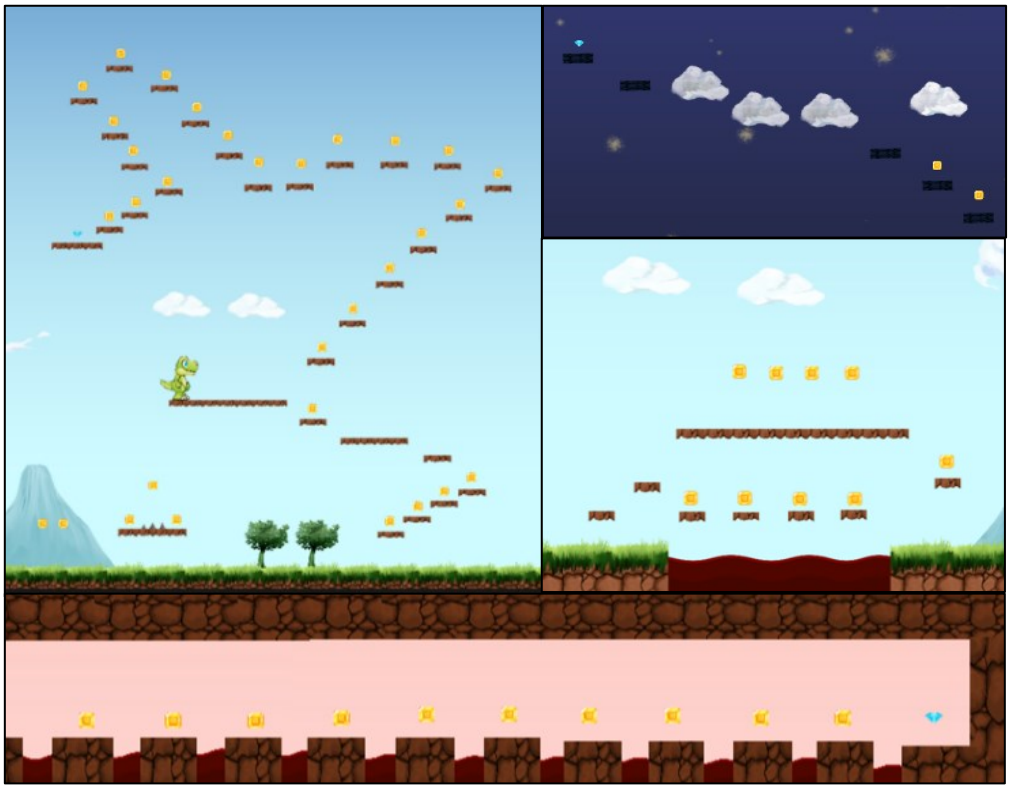


Figure 9.6. Scenes of the Time Travel game. (Top left) A long and tedious path that allows catching many hard coins and a diamond, only partially seen as the player advances. (Top right-top) Path hidden in the clouds leading to a diamond. (Top right-bottom) Bifurcation with an easy and hard path. (Bottom) Part of a hidden long path leading to a diamond.

The type of games and corresponding features were reasoned based on the thesis that someone striving for accomplishment might be someone who strives to get all diamonds, coins, and a better game time, as described by Bartle (1996) and Heeter, Lee, Medler, and Magerko (2011) for the achievers player type. Persons who present high levels of cautiousness tend to be careful with their behaviors and therefore we thought would risk less in the WW game and avoid the unknown and hard paths, contrary to the less cautious ones.

9.3.2 Hypotheses

Building on the two personality traits' characteristics, and the reasoning described in Sections 9.2.1 and 9.3.1, the following hypotheses were defined for each game.

9.3.2.1 Cautiousness Minigame

As someone cautious is prudent and avoids unnecessary risks, the following hypotheses were thought:

H1 – A more cautious person will avoid hard paths, despite knowing she can get more rewards.

H2 – A more cautious person will avoid entering the traps, even knowing he can get more coins.

H3 – If a more cautious person enters a hard path and dies, after respawning, she will choose the easy path instead.

H4 – A more cautious person will be less prone to explore hidden paths on the map.

Building on the fact that a cautious person is deliberate in the decisions and makes careful plans, the following hypothesis was thought:

H5 – A more cautious person will take more time to complete a hard path than a less cautious one.

9.3.2.2 Achievement-Striving Minigame

As achievers are driven by the desire to attain excellence and success, and are persistent and ambitious, the following hypotheses arose:

H6 – A more ambitious person will try to complete the game as fast as possible.

H7 – A more ambitious person will try to catch all the diamonds and hard coins.

H8 – A more ambitious person will try to beat the high scores.

Building on the opposite, low achievement-striving individuals are less ambitious and persistent, putting in low effort, so:

H9 – A less ambitious person will not explore the long and tedious paths.

9.3.3 Pilot Study

During the development, the minigames were incrementally tested by some friends and familiars of different age groups and play skill, providing important feedback related to the gameplay, such as game controls and obstacles difficulty.

After the development, a pilot study was conducted to test the minigames for potential bugs and gameplay. An email was sent to scholars and students at the Superior Institute of Engineering of Porto (ISEP), asking to participate in the pilot. Members of the Research Group on Intelligent Engi-

neering and Computing for Advanced Innovation and Development (GECAD) were also invited to participate. A total of n = 21 valid participants were gathered for the pilot, providing relevant feedback to the improvement of the minigames.

9.3.4 Participants

A real use case scenario (Figure 9.7) was tested to determine if the minigames were measuring the participants' cautiousness and achievement-striving personality traits, and confirm or refute the proposed hypotheses. The only restriction was participants had to be 18 years old or more. To gather a wider and more heterogeneous sample, besides asking participants from the pilot to participate, 3 waves of emails were sent to scholars and general employees of several schools of Polytechnic of Porto and University of Minho (UMinho). Posters inviting participants were also placed in busier places at the same institutions. Through acquaintances, experiments with collaborators were also conducted at three more institutions. An Android mobile phone was lent to those who did not have one. In both phases, participants were compensated with 2 gifts at their choice. 131 individuals registered for the experiments, but only 104 (79%) participated.



Figure 9.7. Two participants playing the personality minigames.

9.3.5 Experimentation Setup

The experiments were conducted in June and July of 2023, in the cities of Vila Nova de Gaia, Porto and Braga, in Portugal.

The participants were instructed on how to use the game commands, manipulate Berry, to inspect the game HUD, and to play as if they were relaxed at home on the sofa, and that they could play Time Travel as many times as they wanted. On the contrary, the Which Way game could only be played once, to avoid introducing bias from a second attempt, as the participants would already know the map and consequently avoid certain paths, eliminating the surprise element. They were

told the WW game had bifurcations, leading to an easy or hard path, and that after choosing a path, the other path would get blocked. The exit key, checkpoints and life regeneration were also explained. The players were considered to make a complete attempt only if they reached the end of the game. Before starting the experiments, the participants were given a minute to familiarize themselves with each game.

All the participants had to fill a pre-questionnaire, created using Microsoft Forms, composed of 9 questions related to their demographics and 3 related to videogames playing frequency and platforms; a post-questionnaire for each minigame, to gather their feedback on the games played, including gameplay and tasks performed; followed by the IPIP-NEO-120 personality questionnaire (Johnson, 2014) to explicitly gather their personality traits and compare to the collected results. This personality questionnaire is composed of 120 questions, using a 5-point Likert scale, to assess an individual in the 30 traits of the Big Five dimensions of personality of Lewis R Goldberg (1990). This questionnaire is a shorter version of the IPIP-NEO (300-item), which is proven to be reliable and valid to determine the five personality dimensions and the corresponding 30 traits (Johnson, 2014). The experiment tasks order was the following: 1) fill pre-questionnaire, 2) play TT, 3) fill TT post-questionnaire, 4) play WW, 5) fill WW post-questionnaire, 6) fill IPIP-NEO-120 personality questionnaire.

Paper sheets with QR codes were given to the participants to download the games APK and access the questionnaires.

9.3.6 Measurements

The following data was collected in the WW game:

- Attempt ID;
- Attempts the player made in a monitoring section;
- The type of path (easy or hard) chosen on each attempt;
- Number of coins collected on each path attempt;
- Life lost on each path attempt;
- Time taken to complete each path;
- Traps risked visiting and if died or not;
- Coins caught on each visited trap.

The TT game collected the following data, for each attempt:

- Attempt number;
- ID of the hard coins caught;
- Total coins caught;
- ID of the diamonds caught;
- Time taken in the attempt;
- Final score and corresponding trophy.

Using Microsoft Excel 365, the gathered variables were then normalized and/or categorized to be comparable. The following metrics were calculated for the Which Way game:

- *ExploredMS1* (0 - no, 1 - yes) = if the player went back in the initial scene to explore monitoring sections 1 and/or 2;
- *TotalHardPaths* (hard paths/total hard paths) = ratio of hard paths the player tried to go at least once, from a total of 8 hard paths [0, 1];
- *InsistedHardPath* (0, 1 or 2) = 0, if the player only went through easy paths in all bifurcations; 1, if tried hard path at least once in only one bifurcation, gave up and went through the easy path the rest of the game; 2, if tried hard path one or more times, at least in two bifurcations, gave up and went through the easy path, or always tried several times the hard path until succeeding;
- *TotalTrapsRisked* (traps risked/total traps) = ratio of traps the player risked going, from a total of 5 traps [0, 1];
- *Traps2xAttempts* (0 - no, 1 - yes) = traps the player took the chance to go more than once, going to at least two different traps.

For the Time Travel game, the following normalized or categorized variables were calculated:

- *HardCoins* (hard coins/total coins) = ratio of hard coins the player caught [0, 1];
- *TotalCoins* (caught coins/total coins) = ratio of total coins caught (hard + easy) [0, 1];
- *Diamonds* = number of diamonds caught (0, 1, 2, or 3);
- *Time* = time taken to complete the game, in seconds;
- *Score* = $(diamonds \times 10 + coins) \times (10 \times reward)$, where $diamonds$ represent the number of diamonds caught, $coins$ the number of coins, and $reward$ the extra reward assigned to the time taken to complete the game (1 if game completed in ≤ 400 seconds, 0.9 if 400s < time ≤ 450s, 0.8 if 450s < time ≤ 500s, 0.7 if time > 500s);
- *Trophies* = 3 is Gold: ≤ 400 seconds to end game & caught all coins and diamonds. 2 is Silver: ≤ 450 seconds & caught ≥ 2 diamonds. 1 is Bronze: ≤ 500 seconds & caught ≥ 1 diamond. 0 the remaining situations.

Using IBM SPSS Statistics 26, a correlation analysis between all personality traits and the referred metrics was performed on the samples (Pearson for normal personality traits distributions, Spearman for non-normal). Also, parametric (independent samples t-test) and non-parametric tests (Mann-Whitney for 2 groups and Kruskal-Wallis for 3 or more groups), for normal (or n>30) and

non-normal distributions of the personality traits, respectively, were performed to compare the personality traits distribution across certain groups. The results and respective analysis can be found in Section 9.4.

9.4 Results and Analysis

9.4.1 Participants Characterization

Regarding the gathered sample, four individuals had to be removed, two due to data files that were not retrieved from the participants' device for both games, and two that did not fill the personality questionnaire, resulting in a final sample of n = 100.

As can be observed in Table 9.2, the participants ranged from 18 to 58 years old. The gender was equilibrated, with 51% female and 49% male participants. 87% of participants had higher education, almost half (49%) from the Engineering & Technology areas, albeit several other areas were also present. 61% of participants were employed and 48% were still studying. As for mobile games playing frequency, about half the participants played (53%), 36% used to play but did not play anymore, and 11% never played, which means the majority (89%) had some sort of experience in playing. Mobile devices were the top played platforms (68%), followed by laptop/desktop (42%) almost *ex aequo* with gaming consoles (38%). Adventure/Action were the majority preferred videogame genres (60%), almost *ex aequo* with multiplayer/RPG/MMORPG (58%), followed by strategy (53%), and puzzles (44%).

The participants personality revealed the same type of distribution as in the previous studies, which used the BFI (44-items) and had more participants (Alves, Martins, et al., 2024; Alves, Martins, Saraiva, et al., 2023) (see Figure 9.8 for some relevant traits, and respective variability and location measures), having responses above the mid-point for traits perceivably related to self-praising. These traits revealed a negative skewness, i.e., participants situated themselves more between "3- Neither agree nor disagree" and "5-Agree strongly", reflecting the same social desirability bias common in self-reporting questionnaires (Pedregon et al., 2012), like for example, the desire of being modest (modesty trait), ambitious (achievement-striving trait), cautious (cautiousness trait), and radiating joy (cheerfulness trait).

Table 9.2. Participants most relevant descriptive statistics (n=100).

		n, %
Age	Min = 18, Max = 58, Mean = 32.5 (SD=1.21)	
Gender	Female	51
	Male	49
Educational level	High school	13
	Bachelor	4
	Degree	47
	Master	22
	Ph.D.	13
	Other	1
Formation area	Engineering & Technology	49
	Exact Sciences	10
	Medical & Health Sciences	4
	Humanities	11
	Natural Sciences	6
	Social Sciences	6
	Other	13
	None	1
Professional situation	Employed	49
	Student	36
	Working student	12
	Unemployed	2
	Other	1
Mobile devices playing frequency	Several times a day	10
	Once a day	7
	Once a week	8
	Several times a week	23
	Used to play, but not anymore	36
	Never	11
	Another frequency	5
Most frequently played platforms	Gaming consoles (Xbox, PlayStation, etc.)	23
	Laptop/desktop	42
	Portable consoles (Nintendo Switch, etc.)	15
	Mobile devices (smartphone, tablet, etc.)	68
	Don't play	18
	Another	3

Some percentages do not match 100% because the question allowed multiple answers.

As can also be seen in Figure 9.8, and confirmed by the 1.5xIQR rule – boxplot rule (Vinutha, Poornima, & Sagar, 2018), one value for achievement-striving, and two for cheerfulness and excitement seeking are outliers. However, we decided to keep them, as these values represent a true response and reflect important individual differences. Also, we found that its removal would not alter the distributions' location measures. According to the Shapiro-Wilk normality test, except for excitement seeking and adventurousness, none of the represented traits have a normal distribution.

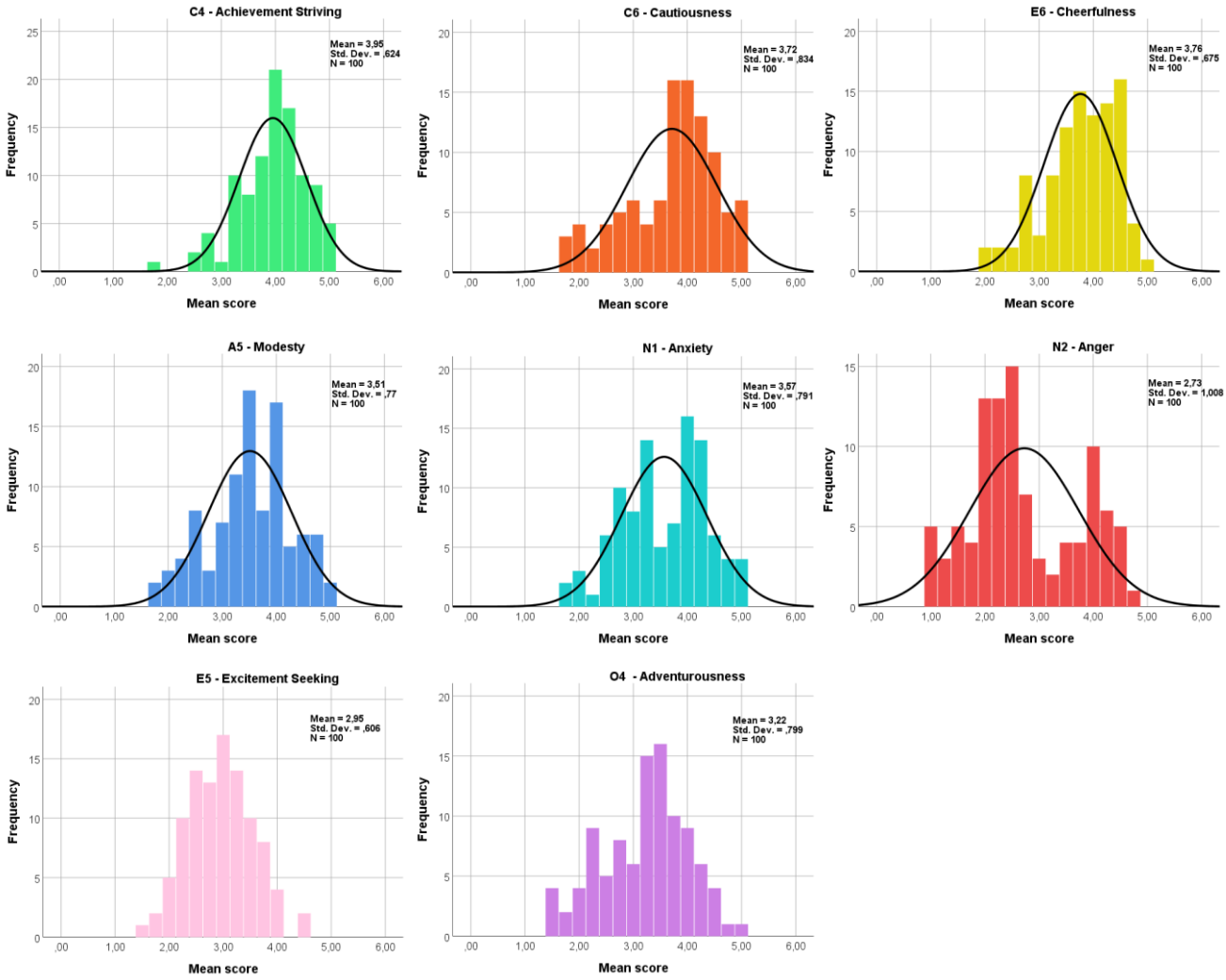


Figure 9.8. Participants' mean scores for some personality traits in the IPIP-NEO-120 questionnaire (n = 100).

The average personality scores were calculated for comparison, resulting in continuous variables, for interpretation we considered scores ≤ 2.49 as negative (low), between 2.50 and 3.49 as neutral, and ≥ 3.50 as positive (high). The participants' anger falls into a bimodal distribution, where 43% of the participants consider they do not get angry easily and 30% easily lose their temper (median = 2.50). As for anxiety (median = 3.75), 56% are anxious individuals, 38% are neutral about how they feel, and only 6% do not consider stressing out easily. For the cheerfulness trait, most participants (75%) consider themselves to be positive individuals, loving life, and radiating joy (median = 3.75), with only 4% thinking the opposite. The last one clearly seems to correspond to the social desirability bias associated with self-reporting questionnaires. The same can be said for

cautiousness, where 72% individuals consider they do not make rash decisions or act without thinking (median = 3.88), modesty, where 62% consider to be humble persons (median = 3.50), and achievement-striving, with 82% considering working hard and do more than the expected (median = 4.00).

9.4.2 Experiments Results and Discussion

In the post-questionnaires, 68% and 69% considered TT and WW fun to play, but only 9% and 6% did not find it fun, respectively. 44% said TT was “more or less easy to play”, and WW 26%. 64% of participants said TT made them lose their patience. 65% and 66% considered to feel immersed, with only 14% and 18% not feeling immersed, in TT and WW, respectively. To some extent, the difficulty inherent to both games seemed to hinder immersiveness and fun, but we cannot forget that not everyone likes to play the same sort of games, which was not the focus in this study. Some participants played with low music volume or no volume, which might also have affected immersiveness. In the WW game, only 12% of the participants said to go through easy paths because they were afraid of trying the hardest ones. Most participants, 60%, went through the path they just felt like at the time.

Some participants gave some suggestions, like the game controls in WW should be more fluid. Others suggested there should be a sound effect in TT when hitting an enemy, and when catching coins, and that the enemies should be improved to match the scenery style. Also, some said TT’s final boss should be removed, as it implied more skill to pass through it, leading to several players dying at the very end of the game and starting all over again just because they could not understand how to pass the boss. We agree with all this, which is also being considered in the minigames currently in development. Several players suggested the TT game should have checkpoints, so they didn’t need to start the game all over again every time they lost. However, this was intentional to test their persistence. Interesting suggestions to put visible walls in the monitoring sections of WW, instead of the invisible, were also mentioned, which makes more sense and would have improved the gameplay. Although manually registered, we also think the TT minigame should have automatically recorded the metrics even if the player did not finish the game, as this could have been an indicator of non-achievers.

The pilot study helped solve some bugs and adjust the gameplay, like augmenting some platforms that were too small or hard to land on and improve the controls sensitivity. Even with those improvements, several participants in the experiments had difficulties playing, asking for our help to overcome certain obstacles or even play the whole game for them. This resulted in 13 participants (13%) needing us to play for them in both minigames, and 17 in the TT minigame. In an attempt to avoid bias related to choices, the participants gave us instructions on how we should play and what items to catch ("go up", "jump to the elevator", "catch the 3 coins", etc.), i.e., we only did what they asked us to. This showed the WW was easier to play than the TT game, although the WW game controls were not so fluid. This was due to the fact the players could choose to go only through the easy paths, which were straight forward, finishing the WW game faster than those who adventured through hard paths and traps, as the game was not intended to measure achievement-striving. However, consulting Table 9.3, we can see there is a clear bias in the times taken, with the helped participants generally taking less time to complete the games. Therefore, and because we could not determine if helped players were somehow influenced to act differently due to our intervention, we decided to exclude them from the games' behavior analysis. This resulted in a sample of n = 86 valid participants for the WW game behavior analysis[51], and n = 70 for TT.

Table 9.3. Time taken by participants, in minutes, to complete the games when helped and not helped.

Game		n	min	max	mean	median
WW	Helped	13	0.88	2.55	1.53	1.34
	Not helped	86	0.38	4.35	1.88	1.70
TT	Helped	30	1.65	10.9	4.30	3.88
	Not helped	70	1.63	14.6	4.18	3.90

For the TT game, only the time taken for the first complete attempt is considered.

9.4.2.1 Cautiousness Acquisition

Consulting Figure 9.9, Table 9.4, and Appendix E Table E-A.1, Table E-A.2, Table E-A.3, and Table E-A.6, 10.5% of participants only went through easy paths (*TotalHardPaths* metric), 46.5% of participants went at least once through one to two hard paths, meaning most participants chose easiest paths. The median was 0.25, therefore 2 hard paths. As for the *TotalTrapsRisked* metric, 36.0% of the participants did not risk going to a trap, 47.7% went only to one trap, 14.0% to only 2, and 2.3% to 3 traps. Regarding *ExploredMS1* metric, 64% of participants did not explore monitoring

[51] The CSV file was not retrieved for a participant in the WW game.

sections 1 and/or 2, and 36% did. The time taken to complete the game varied from 23s to 261s, with a median of 102s.

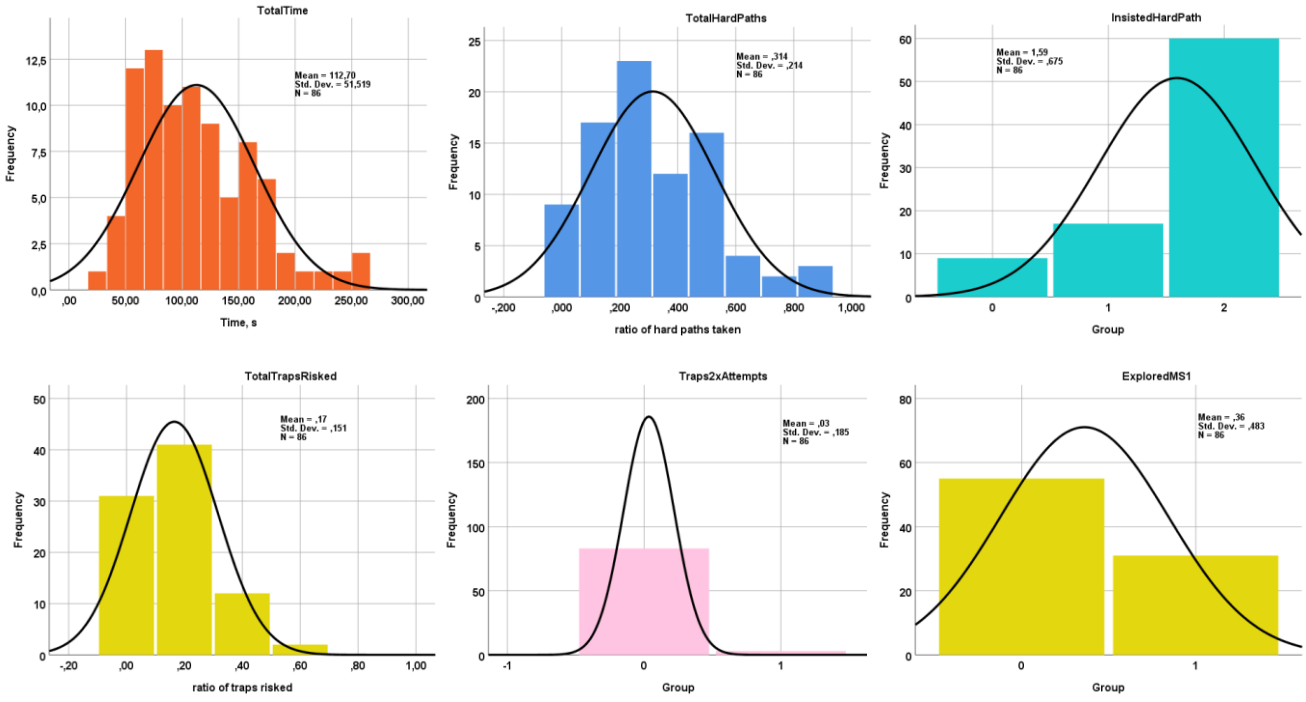


Figure 9.9. Histograms for the metrics measured in the Which Way minigame (n=86).

Next are presented the correlations and independent samples tests results for the WW game and proposed hypotheses.

H1 - A more cautious person will avoid hard paths, despite knowing she can get more rewards

No statistically significant correlations were found between cautiousness and the number of hard paths taken. However, statistically significant correlations between *TotalHardPaths* and anger, modesty, and cheerfulness, were found (Table 9.4). This shows participants who seek harder paths are individuals who get angry less easily and are therefore more patient, are less modest and tend to consider themselves better than others, and like to have fun.

To determine if the participants' cautiousness was different between those who preferred mostly easy paths (at most 2 hard paths), and those who tried more hard paths, the variable was split into two groups, where G_0 < 3 hard paths and G_1 ≥ 3 hard paths, and an independent-samples Mann-Whitney's test was performed (Figure 9.10a). The means of cautiousness were not statistically

different across the two groups (p = 0.709), nor across all the eight possible *TotalHardPath* values (p = 0.736) (Figure 9.10b). Therefore, hypothesis H1 could not be supported.

Table 9.4. Correlation coefficients between the WW game measured variables and relevant personality traits (n = 86).

Trait	Normality (Shapiro-Wilk)	Time	TotalHard Paths	Insisted Hard Path	TotalTraps Risked	Traps2xAttempts	Explored MS1
O3-Emotionality	No	0.025	-0.033	-0.049	-0.042	-0.071	-0.189
C6-Cautiousness	No	0.129	-0.018	-0.050	-0.060	-0.145	0.046
E6-Cheerfulness	No	0.176	**0.219***	**0.242***	0.047	-0.099	0.154
A1-Trust	No	-0.100	0.130	0.193	0.036	0.014	-0.007
A5-Modesty	*Yes*	*-0.076*	***-0.211****	*-0.195*	*-0.137*	*-0.033*	*-0.162*
N1-Anxiety	No	**-0.222***	-0.057	-0.043	-0.070	0.005	-0.123
N2-Anger	No	-0.197	**-0.224***	-0.109	-0.095	-0.050	-0.097
N6-Vulnerability	No	-0.178	-0.155	-0.092	-0.207	0.021	-0.025

Statistically significant values are in bold [*Correlation is significant at the 0.05 level (2-tailed)]. Underlined values have a p-value close to 0.05. A Pearson correlation was calculated for the personality normal distributions (in italics). A Spearman correlation was calculated for non-normal distributions.

H2 – A more cautious person will avoid entering the traps, even knowing he can get more coins

No statistically significant correlations were found between cautiousness and entering a trap (*TotalTrapsRisked*), nor different cautiousness' means between the participants who did not enter a trap, G_0, and the ones who entered at least one trap, G_1 (Appendix E Table E-A.7). Therefore, hypothesis H2 could not be supported.

Regarding other personality traits, different means across the referred two groups were found. The participants who avoided entering the traps had an average lower self-discipline, having more difficulty in starting tasks; were more vulnerable, panicking more easily; less assertive, waiting for others to take the lead; and more modest.

As only 3 participants risked going to at least two different traps more than once (*Traps2xAttempts*, Appendix E Table E-A.4), the metric did not have sufficient data to be related to the cautiousness trait or other personality traits.

H3 – If a more cautious person enters a hard path and dies, after respawning, she will choose the easy path instead

Regarding the persistence to try a hard path (*InsistedHardPath*, Figure 9.9 and Appendix E Table E-A.5), 10.5% only went through easy paths in all bifurcations (G_0), 19.8% tried the hard path at least once in only one bifurcation, gave up and went through the easy path the rest of the game (G_1), 69.8% tried the hard path one or more times, at least in two bifurcations, gave up and went

through the easy path, or always tried several times the hard path until succeeding (G_2). Are the participants who gave up after dying in a hard path (G_1) more cautious than those who insisted more on hard paths (G_2)? Comparing the two groups (Figure 9.10c), the means of cautiousness are the same across the two groups (p = 0.792), therefore, the participants who gave up hard paths, going through easy paths instead, are not more cautious than those who insisted on hard paths. And G_1's participants are more cautious than G_0's? No, as can be seen in the same graphic. The same result happens if we compare the means across all the eight possible *TotalHardPath* values (p = 0.736) (Figure 9.10b), and if we join G_0 with G_1 (renamed G_0 for simplicity) and compare with G_2 (Figure 9.10d). Furthermore, no statistically significant correlations were found between cautiousness and the persistence to take hard paths. Therefore, hypothesis H3 could not be supported.

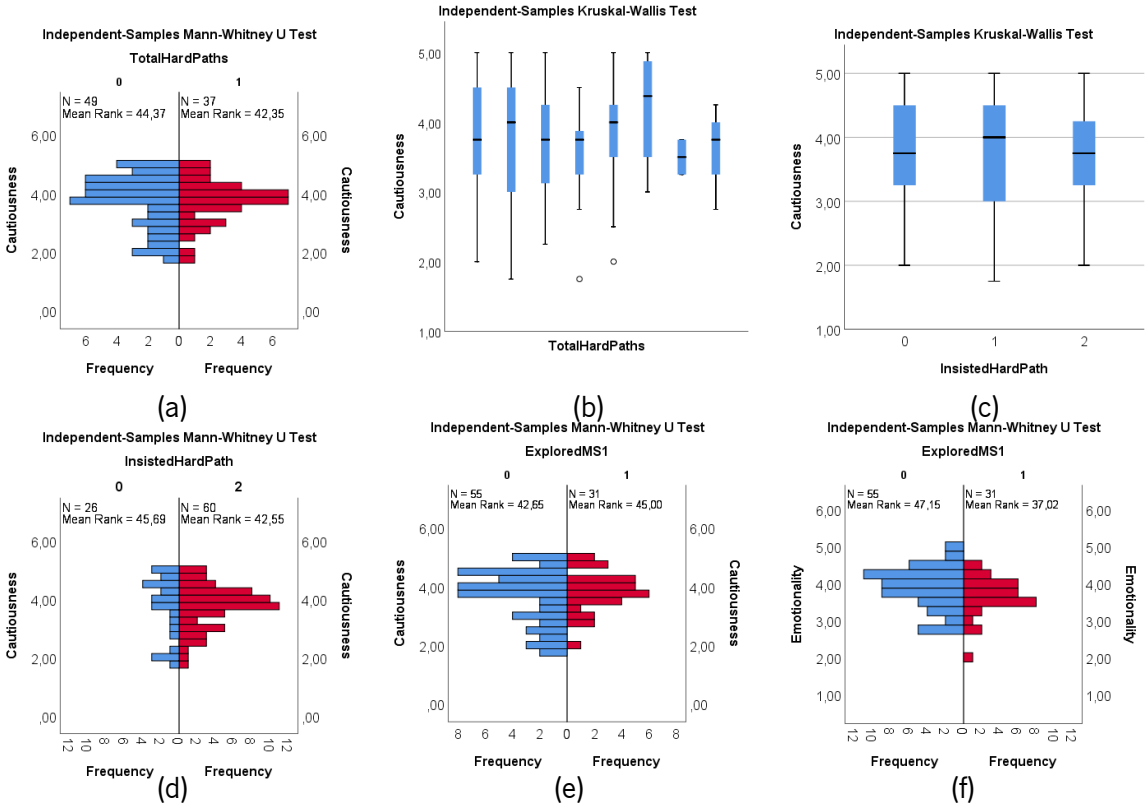


Figure 9.10. Independent-samples tests for the cautiousness distribution across different groups of the WW metrics (n=86).

However, statistically significant correlations between *InsistedHardPath* and cheerfulness, and nearly significant with trust and modesty were found (Table 9.4), where individuals who enjoy having a good time, are less modest and easily trust others, insist more in taking hard paths.

H4 – A more cautious person will be less prone to explore hidden paths on the map

Again, no statistically significant correlation was found between cautiousness and the exploration of hidden paths. Yet, a quasi-statistically significant negative correlation (p=0.068) between *ExploredMS1* and emotionality was found (Table 9.4), suggesting that individuals who explore the unknown are less emotional, experiencing less their and the others' emotions. Also, no correlation with intellectually curious individuals was found. Except for emotionality (Figure 9.10f), no statistically significant difference was found between the cautiousness' means across the participants who did not explore MS1/MS2 and those who did (Figure 9.10e and Appendix E Table E-A.8), not allowing to confirm H4.

H5 – A more cautious person will take more time to complete a hard path than a less cautious one

No statistically significant correlation was found between cautiousness and the time taken to complete the game, not supporting H5, but a statistically significant negative one was found for anxiety (Table 9.4) and nearly statistically significant negative for anger ($p = 0.069$), i.e., anxious and who easily get angry individuals finish WW game faster. Considering the *TotalHardPaths* groups defined in Section 0, G_0 and G_1, and the time taken, an independent samples t-test was performed (Appendix E Table E-A.9). The test revealed there is a statistically significant difference in the average time taken across the two groups ($p = 0.001$), where the participants who went through 0 to 2 hard paths took in average less time than the ones who went through 3 or more hard paths (avg = 97.12s and 133.34s, respectively), but, as already stated before, there is no difference in the cautiousness' means across them. Therefore, the time taken cannot be associated with cautiousness.

Final Remarks

The *TotalHardPaths* metric is statistically significantly positively correlated with all the other metrics. The same can be said for all the other game's metrics (*Time*, *InsistedHardPath*, *TotalTrapsRisked*, *Traps2xAttempts, and ExploredMS1*), showing they are related to the same behavior.

While the cautiousness correlation to the WW metrics could not be statistically significant, the WW game revealed to be capable of measuring other personality traits. Following hard paths is pursued by more patient (low anger), modest and joyful individuals. The ones who insist on pursuing hard paths not only are more cheerful and modest, but also easily trust others. Entering a trap is pursued by highly self-disciplined, highly assertive, less vulnerable, and less modest individuals. Exploring hidden sections is sought by low emotionality persons. Anxious and impatient (high anger) individuals finish the game faster.

Although cautiousness could not be successfully measured, we could measure nine personality traits with a simple minigame, with an average duration of less than 2 minutes playtime.

For curiosity, if we had considered the original 100 participants, a significant correlation with cautiousness would have been found (p=0.034), where those who insisted more in going through the hard paths, not giving up so easily, were less cautious, and the ones who went through the easy paths, more cautious. This means that with a larger sample, statistically significant correlations could have been obtained between cautiousness and the WW metrics, which is a situation that needs to be adequately analyzed in future works, as the game could actually be measuring cautiousness.

9.4.2.2 Achievement-Striving Acquisition

Looking at Figure 9.11 and Appendix E Table E-B.1, and considering the first completed attempt, almost all participants (98.6%) managed to end the game before 500s (ca. 8 minutes). Of the 70 viable participants, 64.3% managed to finish the game in less than 5 minutes (300s), 34.3% took between 5 and 7.5 minutes, and one participant took more than 14 minutes. The median was 4.03 minutes (242s). Only 10% managed to end the game before 2 minutes.

45.7% of participants did not catch any diamond, 15.7% only caught 1 diamond, 25.7% 2 diamonds, and 12.9% 3 diamonds, resulting in a median of 1 diamond per participant, showing only

few participants managed to catch all diamonds in the complete attempt (Appendix E Table E-B.2). Regarding the hard and total coins caught, the data distribution is clearly bimodal for both cases. The same can be said for the final score, as the formula depends on the items caught. 22.9% of the participants caught all hard coins, and 20.0% caught all coins. 47.1% of participants did not manage to get a trophy, 17.1% and 25.7% of participants got bronze and silver trophies, respectively, and only 10.0% got a gold trophy (Appendix E Table E-B.3). That is, only 7 players managed to get all the diamonds and coins in 400s or less.

18.6% of the participants repeated at least twice the full game to obtain all items or a better score (Appendix E Table E-B.4), but only 2 players insisted hardly on getting the best possible score, playing dozens of times (more than 1 hour of gameplay).

Comparing the in-game results with some relevant post-questionnaire answers, 41.4% of participants said to try to catch all coins, and 44.3% intentionally tried to catch all diamonds. This shows that although these participants' intention was to get all the collectables, not all managed to get them. Of the 37 participants who got a trophy, 13 did not understand what trophies were for, that they even existed, or how to obtain them.

The correlations and independent samples tests results for the TT game and proposed hypotheses are presented next.

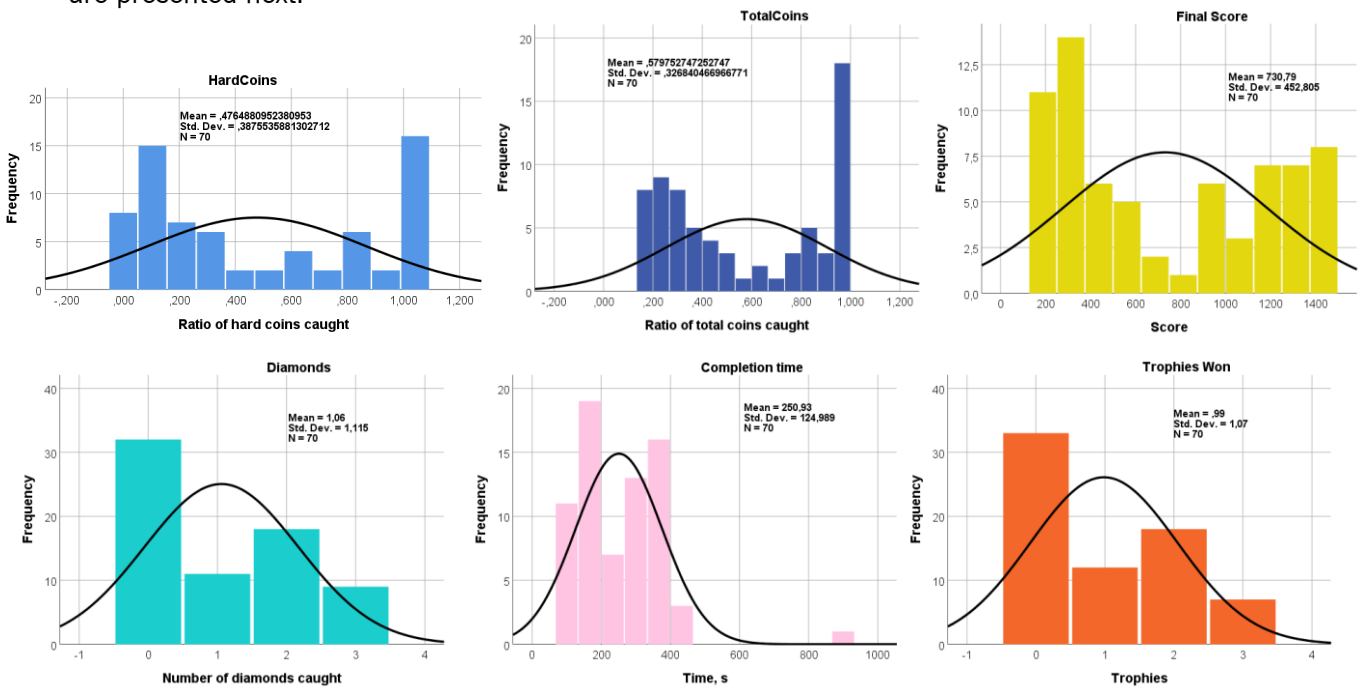


Figure 9.11. Histograms for metrics measured in the Time Travel minigame (n=70) in the first complete attempt.

H6 – A more ambitious person will try to complete the game as fast as possible

A statistically significant positive correlation was found between adventurousness and the time to complete the TT game, indicating adventurous individuals spend more time exploring the game, but none related to achievement-striving (Table 9.5). However, contrary to the expected, if we divide the participants' completion time into two groups, G_1<300s and G_2≥300s (less than 5min and 5min or more, respectively), and perform an independent samples t-test (Appendix E Table E-B.5 and Table E-B.6), we can see the average achievement-striving is nearly statistically significantly higher for G_2 than for G_1 (p=0.074), where individuals who take more time to complete the game have a higher achievement score in average. This may be related to the fact that those participants explored the game to retrieve all coins and diamonds, taking more time. Therefore, H6 is not supported, but its opposite is, i.e., ambitious individuals take more time to complete TT game because they want to get all the collectables. Also, participants in G_2 are more adventurous (p=0.008), intellectual (p=0.055), and liberal (p=0.064) than participants in G_1.

H7 – A more ambitious person will try to catch all the diamonds and hard coins

No significant correlation between achievement-striving and the items caught was found. However, statistically significant correlations were found between other personality traits and the hard and total coins. Catching hard/all coins is positively related to imaginative, adventurous, excitement-seeking, cheerful, and with higher intellect individuals. On the contrary, individuals who catch hard/all coins do not get angry easily, being more patient, which is in line with the anger findings for the WW game, and are less self-conscious, which indicates they are not bothered by difficult (social) situations. Curiously, individuals who care to catch hard/all coins are more cautious. This can be related to the paths they had to take to catch the hard coins, implying more prudence and planning.

Statistically significant correlations were also found between several personality traits and the diamonds caught. Similarly to the coins caught, individuals who strive to catch all diamonds love excitement and seeking adventures, prefer variety to routine, have a high intellect, are cautious, make friends easily, are cheerful people, and are not easily annoyed. They are also not bothered by difficult (social) situations, and are less vulnerable, remaining calm under pressure.

Considering the time taken to complete the game and the groups defined in Section 0, G_1 and G_2, the average hard coins caught is very high for G_2 compared to G_1 (mean = 0.85, SD = 0.20 vs. mean = 0.27, SD = 0.30, respectively, see Appendix E Table E-B.6). The same can be observed for the total coins (mean = 0.89, SD = 0.16 vs. mean = 0.40, SD = 0.26, respectively), and the diamonds caught (mean = 0.53, SD = 0.97 vs. mean = 2.00, SD = 0.65, respectively). The trophy won and average final score is also significantly higher for G_2.This suggests two groups of players, the ones who only catch the items along the easiest path and the ones who strive to catch all of them. These groups seem to correspond to the non-achievers and achievers mentioned by Bartle (1996), respectively, which is in line with the independent samples t-test previously performed for the two groups (Appendix E Table E-B.5), where the achievement-striving trait is nearly statistically significantly higher for G_2 than for G_1 (p=0.074), supporting hypothesis H7.

No significant differences for the achievement trait were found between the participants who won one of the trophies (bronze, silver or gold) and the ones who did not win any (Appendix E Table E-B.7), nor a statistically significant difference between achievement-striving and any of the trophies won (Appendix E Table E-B.8). Therefore, trophies do not contribute to hypothesis H7, which is clearly related to the time needed to complete the game, as the formula to give a trophy depends on the time taken, and, to get a better trophy, the players need to complete the game in less time, which was not the case of the ambitious players (see Section 0).

Table 9.5. Correlation coefficients between the TT game measured variables and relevant personality traits (n = 70)

Personality Trait	Normality (Shapiro-Wilk)	HardCoins	TotalCoins	Diamonds	Time	Score	Trophies
O1-Imagination	No	**0.267***	**0.270***	0.184	0.056	0.228	0.150
O4-Adventurousness	*Yes*	***0.323****	***0.338****	***0.382****	***0.265****	***0.350****	***0.378****
O5-Intellect	No	0.201	0.221	**0.243***	0.068	0.224	0.218
C4-Achievement-Striving	No	-0.014	-0.055	-0.035	-0.040	-0.085	-0.068
C6-Cautiousness	No	**0.268***	**0.254***	0.211	0.187	**0.242***	0.193
E1-Friendliness	*Yes*	*0.181*	*0.161*	***0.259****	*0.023*	*0.198*	***0.259****
E5-Excitement Seeking	*Yes*	***0.258****	***0.264****	***0.312****	*0.043*	***0.281****	***0.304****
E6-Cheerfulness	No	**0.258***	**0.262***	**0.348****	0.144	**0.275***	**0.324****
N2-Anger	No	-0.232	-0.214	**-0.329****	-0.181	**-0.243***	**-0.342****
N4-Self-conscientiousness	*Yes*	*-0.210*	***-0.236****	***-0.266****	*-0.084*	***-0.261****	***-0.249****
N6-Vulnerability	*Yes*	*-0.195*	*-0.164*	***-0.240****	*-0.177*	*-0.194*	***-0.245****

Statistically significant values are in bold [*correlation is significant at p < 0.05 (2-tailed), ** correlation is significant at p < 0.01 (2-tailed)]. Underlined values have a p-value close to 0.05. A Pearson correlation was calculated for the personality normal distributions (in italics). A Spearman correlation was calculated for non-normal distributions.

H8 – A more ambitious person will try to beat the high scores

No statistically significant correlation was found between the score or the number of attempts to achieve a better score and achievement-striving. Nonetheless, as expected due to the dependence on the score formula, statistically significant correlations were found between the obtained score and the same traits related to the total coins caught (*vide* Table 9.5 and Section 0). A larger sample of game attempts by the same player was needed to determine if a correlation with achievement-striving existed.

Again, considering the time taken to complete the game and the groups defined in Section 0, G_1 and G_2, G_2's final average game score is statistically significantly higher than G_1's (Appendix E Table E-B.6), which represent the more ambitious participants, supporting hypothesis H8.

H9 – A less ambitious person will not explore the long and tedious paths

The players who caught the three diamonds and hard coins (or said that tried to) are the ones who had to explore long and tedious paths, corresponding to 42.9% of the participants in the TT post-questionnaire. No significant differences in the means of achievement-striving were found between them and the participants who did not go to the longest paths. But analyzing the in-game behaviors, the participants who managed to collect more hard coins and diamonds, and therefore, to complete the tedious paths, are more ambitious than the others, as stated previously, and vice-versa, supporting H9.

Final Remarks

The number of coins caught is strongly and positively correlated with the other metrics, as well as the other TT metrics between themselves, which validates the scoring equation. Interesting correlations between the 30 personality traits were also found.

All TT's hypotheses could be supported. Statistically significant correlations were found for achievement-striving, where players who strive to get all collectables and better scores are more ambitious than the others, taking more time to explore the game (contrary to the expected). An interesting positive correlation between cautiousness and catching diamonds and hard coins was found, corresponding to the participants who went through the long and tedious paths.

A curious positive relationship as well was observed between friendliness and the diamonds caught, meaning individuals who gain more trophies thought of themselves as being able to make friends easily and feel comfortable around others. Possibly, the participants with high self-reported extraversion (friendliness) intentionally wanted more to engage in this study, thus showing more disposition to accomplish the given tasks and therefore meet the game objectives, and consequently the researchers' expectations, which ultimately is a way of seeking social interaction. In this regard, extraversion works in a way that would more often be attributable to Agreeableness, but that in this specific gaming context, both dimensions disambiguation cannot be assured.

An (obvious) relationship with excitement seeking and adventurousness was encountered, being positively correlated with all considered metrics (except time for excitement). Individuals who like to feel excitement and adventure are the ones who strive more to get all the collectables and better scores in the game. This is in line with Teng and Chen (2009) results, who found excitement seeking and achievement were positively related to challenge. Gimmon, Rob, Farja, and Golan (2023) discovered that experienced escape room players played for the excitement and the less experienced for achievement. Being cheerful and positive is positively related to getting more coins, diamonds, higher scores, and better trophies.

No significant correlation between excitement seeking and achievement-striving was found, meaning they might not be correlated as initially expected. If we look closely at the traits' definition, someone who is perfectionist and works hard is not necessarily the same as a person who seeks adventure. In fact, excitement seeking is more connected to less conscientious individuals and achievement to more conscientious ones (Alves, Martins, Saraiva, et al., 2023).

And adventure? Is it positively related to achievement-striving? Costa Jr et al. (1995) consider someone positive in the openness to actions trait (O4) is an individual who needs variety and gets bored by routine, corresponding to the adventurousness trait considered by Johnson (2014) in the IPIP-NEO-120 scale. Someone positive in achievement-striving is an ambitious individual who endeavors for excellence, having high standards, according to Costa Jr et al. (1995), and works hard doing more than the expected (Johnson, 2014). A sort of association with both traits seems evident, which is supported by their positive correlation.

All these results show the TT game can be used to determine achievement-striving and other personality traits. This is a great advance to start improving and refining personality games to implicitly detect personality traits, which we are already working on[52].

9.5 Conclusions and Future Work

Personality is a strong influence on the users' choices in a variety of domains, such as tourism, music, movies, etc. However, to focus only on the five dimensions of personality, and not on the thirty traits and on the correlations between them, may limit the preferences prediction. For example, a person considered extraverted may not be a risk taker or like adrenaline activities. It would not be very good if a RS suggested a roller coaster to the tourist. Also, to acquire someone's personality is complex and a challenge, as the explicit techniques, such as self-reporting questionnaires, are subject to the social desirability bias and fake responses, they are boring and time-consuming to fill, and subject to wrong interpretations; the implicit ones need a great amount of users' interactions to make the predictions, use complex and/or not so accurate games, are mostly only for desktop computers, and/or only predict the broader five personality dimensions. Also, to the best of our knowledge, there are no short-duration mobile games that can accurately predict personality.

To try to overcome those limitations, we developed two mobile minigames, "Time Travel Mania" and "Which Way", as concept proof for implicitly detecting two of the Big Five personality more granular traits, achievement-striving and cautiousness, respectively, in a short playing time (< 5 min) and at a first interaction. Contrary to F. Y. Wu et al. (2022) study, TT game proved to be capable of measuring achievement-striving, easily identifying the achievers and non-achievers as suggested by Bartle (1996), supporting hypotheses H6 to H9, showing with the right kind of games it may be possible to accurately measure those traits. However, the WW game could not successfully measure cautiousness, not supporting hypotheses H1 to H5, suggesting that more participants were needed to obtain significant correlations (at least larger on the lower scores of the trait), which should be considered in future studies.

[52] Other results could be analyzed in the obtained data, but only the most relevant were presented.

Thus, we think the main limitation of this study was not the games concept themselves, but the sample size to gather ground truth data for the Openness to Experience, Conscientiousness, and Agreeableness personality dimensions, as also verified, for example, by T. T. Nguyen et al. (2018) and Alves, Martins, Saraiva, et al. (2023), and consequently for some of their corresponding traits, such as the ones studied. These are definitely the hardest dimensions to measure, and we are currently working on ways of trying to overcome that.

An unexpected finding was that TT was measuring cautiousness, which was related to the players who went to long and deadly paths to collect hard coins and diamonds. So, cautiousness is more related to being prudent and thoughtful (Costa Jr et al., 1995) than to being fearful, which might be difficult to measure separately in a game. This difference needs to be further studied in the future, so cautiousness can be accurately measured.

We also found some participants had difficulty playing both games, or just TT game. Although designed to imply less skill, the games needed to be even easier to play, so any type of person could play it, as well as more immersive (such as having sound effects in certain events, as suggested by some participants, and forcing participants to hear the game music with headphones), to foster participants' enjoyment and involvement. This could also have been a limiting factor for the results obtained, especially for the cautiousness game, where a more immersive environment could foster more prudence and alertness in the players. We also think the best accomplishment for each collectible in TT game should have been recorded, and that the participants shouldn't have been obliged to finish the game, as it could have revealed stronger correlations to achievement-striving.

Interestingly, we also found statistically significant correlations to other traits. Participants who get angry less easily and are less modest chose the most challenging paths in the WW game. Also, in the TT game, the participants who get less angry are the ones who got more collectables and better scores. The same can be said for excitement seeking, cheerfulness, and adventurousness. These findings make sense and are in line with the results obtained by Teng and Chen (2009) for excitement seeking and achievement, and with the observations made at the end of Section 9.2.2, as several personality traits can be related to each other and may not be possible to be measured separately. These findings are an interesting subject for future studies in the area.

With this work, to the best of our knowledge, we could measure more granular personality traits and with a much smaller duration playtime and interactions than the games found in literature. We believe this is a great advance in the area, because, beside removing the social desirability bias in a few minutes with simple minigames, the users will be more engaged and amused while their detailed personality traits are acquired, which is not the case of filling explicit questionnaires.

We can therefore affirm we are on the right path to develop short-duration serious mobile games to implicitly acquire an individual's more granular personality traits, without the need for ML techniques. With the right design and metrics, this kind of games can be integrated into personality-based systems to help gather the users' personality and solve the limitations found in the area, as well as be used in other areas, such as to assess and select job interviewees for example.

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Ethics statement

This work involved human subjects in its research. Approval of all ethical and experimental procedures and protocols was granted by the Polytechnic of Porto Data Protection Office, and performed in line with the institution requirements. The used questionnaires were anonymous and confidential, and the collected data was analyzed in aggregated form. All participants signed an informed

consent to participate in the study, ensuring confidentiality, anonymity, and informing the aims of the research and where the data was stored.

Supplemental online material

The questionnaires used in the experiments can be consulted in the folder “Questionnaires” of the supplementary material (in Portuguese). The complete collected responses and respective statistics, as well as the collected games’ metrics (dataset used), can be found in folder “Responses” of the supplementary material.

Supplementary games’ statistics and the complete Pearson and Spearman’s correlations tables can be found in the supplementary material main folder.

The games APK can be downloaded in the supplementary material (APK folder). Please accept the warnings in order to install.

Part III

IN CONCLUSION

"Logic will get you from A to B. Imagination will take you everywhere."

Albert Einstein

10

CONCLUSIONS

This doctoral work proposed to address several current main challenges of Group Recommender Systems, some pertaining to the tourism area, namely:

1. The cold-start problem;
2. The group's members' heterogeneous and conflicting preferences;
3. Show concern for the individual users' needs;
4. The intrusiveness to build the users' initial profile;
5. Sparsity issues;
6. How the users' preferences can be aggregated so all members can be satisfied with the recommendations;
7. How the group can be aided in reaching the final choice without the emotional contagion phenomenon;
8. How to promote the sense of community and companionship in excursion groups.

Based on the evidence found in literature, all these challenges led to many individual and group brainstorming sessions on how such problems could be addressed. Several versions of a GRS prototype were idealized until the final version was finally conceptualized.

In a first concept, the whole process from the planning to the excursion itself was being considered, including the use of an AR avatar to represent the tourist, and dialogue games between agents to facilitate the recommendations negotiation process, which is reflected in Paper 1 (Chapter 3). But the ideas were still fresh, and due to the defined timeline, it was recognized that not everything could be considered in the doctoral work. So, as the research progressed, the engineered ideas shifted to a more cohesive and higher quality solution directed to solve the identified problems mostly in the phase of the excursion planning.

The importance of personality in predicting the users' preferences in a variety of domains was acknowledged and it could be the missing leverage in the project, as was seen in Papers 2 and 3 (Chapter 4 and Chapter 5, respectively). A large-scale study with real participants was conducted, showing it was possible to predict tourist preferences, motivations and travel-related preferences & concerns based on the raw personality dimensions of a person instead of using tourist typologies like most of the existing works, which answered to research questions "RQ1.1 - Does personality predict preferences for tourist attractions, travel motivations, and personal preferences & concerns when travelling?" and "RQ1.2 - If so, which personality dimensions or traits are antecedents of which tourist attractions, travel motivations, and personal preferences & concerns when travelling?". This resulted in three models that were used as the basis for predicting the tourists' preferences in the GRS prototype, being the first, to the best of our knowledge, to propose such models, solving the cold-start problem, as there was no need to data mine a great number of users' data or interactions to make the initial recommendations. The developed personality models allowed to predict the tourists' preferences in eleven tourism categories, five travelling motivations, and four travel-related preferences & concerns, only by knowing their raw personality, using the most used and recognized personality model, the Big Five.

The first working GRS prototype was demonstrated in Paper 4 (Chapter 6). The use of a micro-services-based architecture, including a Multi-Agent Microservice with agents modeled with the tourists' characteristics, were the core features of the demonstration. This architecture was thought up to make the GRS modular, independent, scalable, easily maintainable, so it could be used by any HTTP client, benefiting from the agents being exposed as resources that could be easily accessed, and a more efficient interoperability, providing faster recommendations. By using the developed personality models, personalized and satisfactory recommendations could be generated, not just for excursion groups, but also for individuals, showing concern for the individual tourists needs (such as their physical limitations, fears/phobias, and travel-related preferences & concerns), as demonstrated in a real use case scenario (Paper 5, Chapter 7). The initial recommendations are solely based on the users' personality, without needing to data mine large amounts of data and users' interactions, also solving the cold-start problem. All this answers to research questions "RQ2 – Is it possible to generate personalized and relevant recommendations

based on the tourists' personality?" and "RQ3 - Can the cold-start problem be solved just by using the tourists' personality?".

To solve the heterogeinity and conflicting preferences in excursion groups, especially in larger ones, the idea of dividing the main group into subgroups emerged. As it was found that personality is strongly related to tourist preferences, if similar personality tourists could be grouped together, instead of being mixed in the main group, the heterogeinity and conflicting preferences problem could be tackled. So, the idea of creating clusters of similar personality tourists by the MAMS emerged (demographic filtering). These clusters needed to have a restriction, or the problem would continue. So, it was decided to include only tourists with 0.80 ∈ [0,1] or more similarity in a cluster, which was shown to be the ideal value in the experiments performed (see Paper 5, Chapter 7). Also, to better and faster assign the tourists into a cluster, that process is automatically performed at the tourist's registration in the application, meaning when a tourist registers in the GRS, if a similarity to the centroid of 0.80 or more is found, she is immediately assigned to a cluster, otherwise, she generates a new cluster, becoming the centroid. The clusters are created in real-time as the tourists register. This led to a new dynamic clustering algorithm, d-means, based in a modified version of k–means, that does not need to know and initialize the number of initial clusters *a priori*, and, to the best of our knowledge, is a novelty in GRS. The implemented clustering algorithm outperformed k–means and k-means++ in scalability and clustering quality, and significantly surpassed k-means++ in the time needed to create clusters in bulk. d-means avoids wasting time on cluster initialization or performing clustering during offline and online phases. Instead, clusters are created dynamically when needed, or the new user is directly added to an existing cluster, with its centroid being updated accordingly. d-means ensures that there are no outliers or large distances between cluster members by assigning tourists to an existing cluster only if their similarity to the cluster's centroid is at least 0.80 (configurable). This approach makes the clustering process more precise and faster, as it is run in the MAMS. Tourists who do not meet this criterion are placed in a new cluster, which can later accommodate other similar tourists as more users register in the app, helping to mitigate sparsity issues and tackling the dynamic shifts in the group's composition without affecting the recommendations quality.

d-means allows to divide excursion groups into subgroups of also similar personality tourists (and therefore interests), so it becomes more beneficial to them than to stay in the main and heterogeneous group. Therefore, the tourists in the clusters and subgroups have similar tourist preferences, which mitigates the heterogeneity and conflicting preferences, and the alienation by minority, giving voice to all the group's members without disproportionally favoring one over another, resolving research question "RQ4 - How can tourists in an excursion be "separated" into subgroups of other tourists with similar interests/personality so it becomes more beneficial to them than to stay in the main and heterogeneous group?". This new algorithm can be adapted to various contexts by incorporating different attributes beyond personality, such the users' age range, formation area, etc., i.e., any attribute that can be used to predict a certain preference. Additionally, a key benefit is that the users' personality assessment only needs to be conducted once and can be utilized across multiple research domains.

To help refine the initial recommendations, the Apriori algorithm was implemented in the MAMS to find possible positive or negative association rules in the clusters, namely related to demographic data, personality, physical impairments, fears/phobias, weather preferences, and ratings given to (un)visited POI. The weather conditions in the excursion's destination are also considered, to determine if indoor or outdoor POI are more suitable for the recommendations. The recommendation of different POI from the top-3 preferred tourism categories, according to the tourists' preference scores, allows for diversity in the recommendations. The suggestion of never visited POI is prioritized against already visited ones, even if only one member of a group has visited that POI, ensuring novelty in the recommendations. This last version of the GRS prototype is demonstrated in Paper 6 (Chapter 8).

To determine the users' personality, when they register in the GRS prototype, they need to fill in a personality questionnaire. As self-reporting personality questionnaires are prone to social desirability bias and false responses, we tried to determine the users' personality implicitly, without the influence of the self-response. As it was also found that the use of the broader dimensions of personality is not so accurate, as, for instance, someone that scores high in Openness to Experience may not be a thrill seeker, we decided to determine the personality's more granular traits. The idea of using short-duration serious games to unobtrusively determine more granular personality traits

emerged as a proof of concept, as is described in Paper 7 (Chapter 9). The minigames revealed to be a viable way of implicitly determining, in five minutes or less, someone's granular personality traits in a fun and motivating way, answering to research question "RQ1 - Is it possible to effectively learn the users' personality in a non-intrusive and less time-consuming way by using serious games?", and that with only one game more than one trait can be assessed, as some traits are related to others, and their existence as independent traits seems to be improbable. The short-duration serious games are also a great alternative to other implicit techniques, as they do not need a great number of users' interactions to determine the personality traits. This showed to be the right path to unobtrusively determine someone's granular personality traits without the need for ML techniques. This type of games can be incorporated into RS to collect users' personality data and address existing limitations in the field. They can also be applied in other domains, such as evaluating and selecting job candidates.

The findings and results of the doctoral work are all intertwined by the seven papers written, successfully answering to the proposed objectives and research questions (see Figure 10.1).

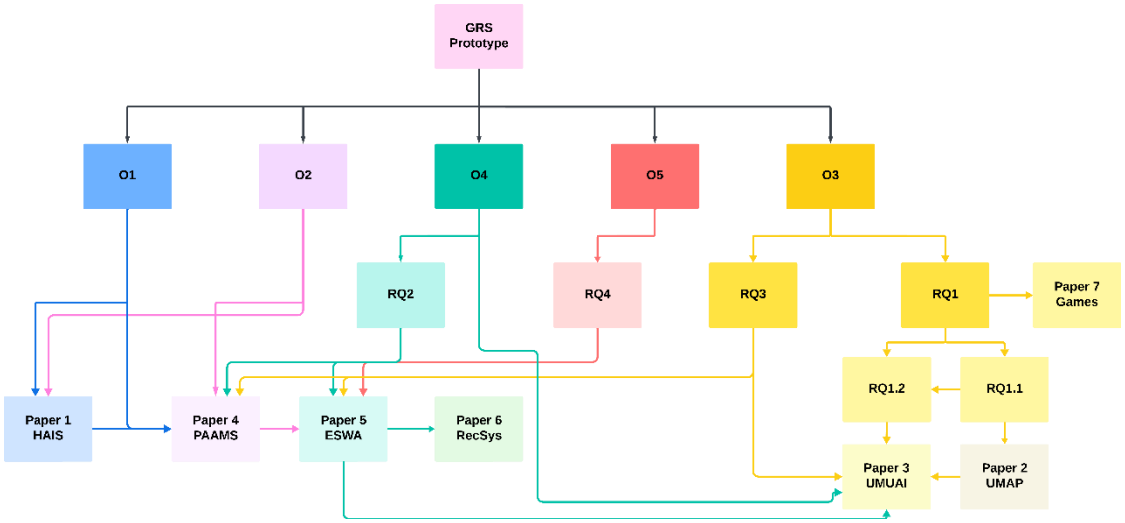


Figure 10.1. Diagram representing the relationship between the proposed objectives, research questions, and the seven papers written.

10.1 Limitations

During the doctoral work, some limitations were found and discussed in the papers. Although the sample used to predict the tourist preferences based on personality and to create the correspond-

ing models was large (n=1035), due to the number of observable variables, a larger and more heterogeneous one was needed to obtain better models' fits, and consequently a higher accuracy, such as more cases per each personality type, gender, proposed attraction types, travel-related preferences & concerns, etc. This could have increased the predicted average preference for the tourism categories and the travel-related preferences & concerns in the experiments performed in Paper 5 (Chapter 7), as well as improved the travel-related preferences & concerns model to consider other relevant aspects, such as health-related risks, loss of luggage, etc. (described in detail in Paper 3, Chapter 5).

It was also observed and confirmed in the studies presented in Papers 2 and 3 (Chapter 4 and Chapter 5, respectively), that using only the five personality dimensions instead of the more granular 30 traits could also be limiting the models predictions and accuracy. An extraverted individual may not be a reckless person. Or an aggregable person may not blindly trust in others. Therefore, future studies should consider the more granular 30 traits instead of the broader five personality dimensions.

As also mentioned, the study was conducted with a Portuguese sample, so the relationships found may not be the same for other cultures. Other studies with different cultures would be needed to compare those relationships, although the results found in literature for some cultures seemed to be similar (*vide* Paper 3, Chapter 5).

The social desirability bias was confirmed in all the studies performed, reinforcing the need for implicit ways of acquiring the users' personality. The use of short-duration serious games can be the solution, as proven in the last paper (Paper 7, Chapter 9), where correlations to several personality traits were found. In fact, other personality games were developed in the meantime, and it was found that morality, cooperation, and orderliness, among other traits, could also be predicted, supporting the results obtained.

10.2 Future Directions

Although personality traits could be correlated to the users' behavior in less than five minutes in the short-duration mobile serious games, it would be interesting to improve the developed games and determine the accuracy of the personality traits measured, by performing an A/B test for ex-

ample, and with a much larger sample. The Marlowe-Crowne Social Desirability Bias Scale (Crowne & Marlowe, 1960), or similar, could be used to assess the participants' tendency to respond in social desirable ways, enabling more informed adjustments to the interpretation of results. Also, the games could have a range of difficulty levels adapted to the players' skill, ensuring that the games are challenging and that can adapt to individual capabilities. These games can be a shift in the way personality data can be acquired, and to include those minigames in the GRS prototype to determine the users' personality, instead of using the BFI, would be an interesting experience for future works.

Although the GRS was tested for accuracy and the participants' satisfaction confirmed in a real use case scenario, simulating an excursion, it would be interesting, like Netflix suggests (Bansal & Sharma, 2024), to do an A/B test with real excursion groups, to determine if the excursion members get more satisfied and how the members interaction and compatibility is affected by dividing or not the main group into subgroups.

An experiment should also be performed to determine the association rules effectiveness in improving the initial recommendations. Also, when rules are not found in a cluster, the Apriori algorithm should be improved to search in the closest cluster, and so on, instead of searching for rules in all the other clusters. In this way, the rules will more closely align with the tourists' profile in the nearest cluster, making them more accurate. Similarly, instead of association rules, other algorithms/techniques could be experimented, like deep neural networks, or generative artificial intelligence models, and compare the recommendations.

Similarly to the POI history functionality in the GRS prototype, the recommendation lists should also allow tourists to indicate if they already visited the suggested POI and if they want to visit them again, which would improve the recommendation diversity and novelty. A representative photograph of the suggested POI should also be presented in the recommendation lists, as during the experiments several participants had difficulties in recognizing certain POI by the name.

In the developed Tourism Categories model, some tourism categories combine different types of attractions, such as "Museums, Boat Trips & Viewpoints" or "Party, Music & Nightlife." In these cases, the recommendation engine should suggest two or more POI from each type to offer a greater recommendation diversity, as tourists may have preferences for one type over another. For

instance, a tourist might prefer to go to a live concert but not want to attend a night bar or disco. Furthermore, serendipitous suggestions should be added to surprise the tourist. Additionally, the user should be able to reorder the predicted tourism categories in their profile to enhance the accuracy of the recommended POI.

As for further functionalities and following the first conceptualization for the GRS in Paper 1 (Chapter 3), the GRS prototype should be gamified by adding gaming components, like experience points, user's level, rewards, trophies, leaderboards, etc., to motivate the use of the application. Also, the GRS prototype should be extended to the post-recommendation process, like accompanying the tourists during the excursion's itinerary by using a virtual pet, and use more context data to provide other relevant recommendations on-site, such as notifications of interesting POI nearby the tourist according to her top-k preferences, provided by the virtual pet.

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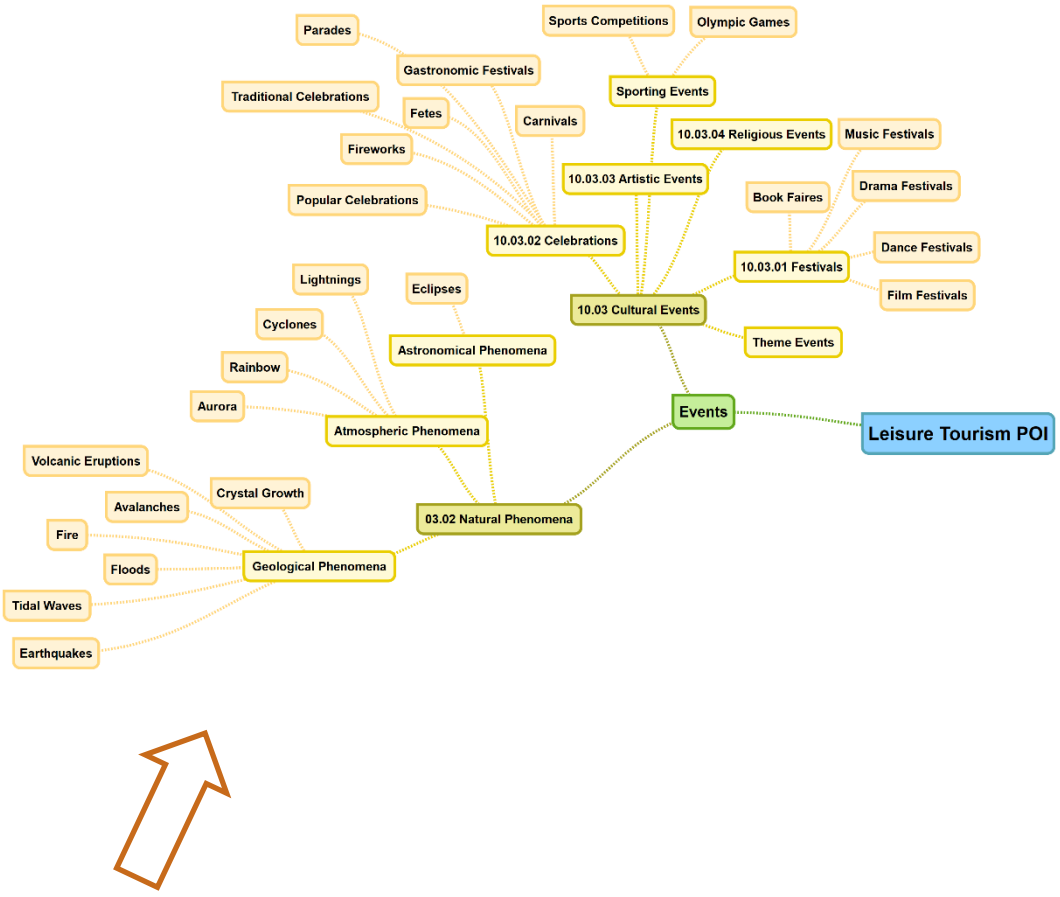
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APPENDICES

Appendix A: Mind map for the most relevant terms for tourist attractions



Figure A.1. Mind map for the most relevant terms for tourist attractions related to Tourism Heritage, zoomed out from the global mind map. Content adapted from UNWTO (2001).



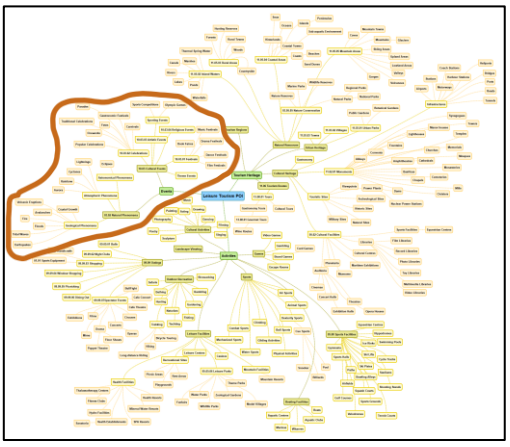


Figure A.2. Mind map for the most relevant terms for tourist attractions related to Events, zoomed out from the global mind map. Content adapted from UNWTO (2001).

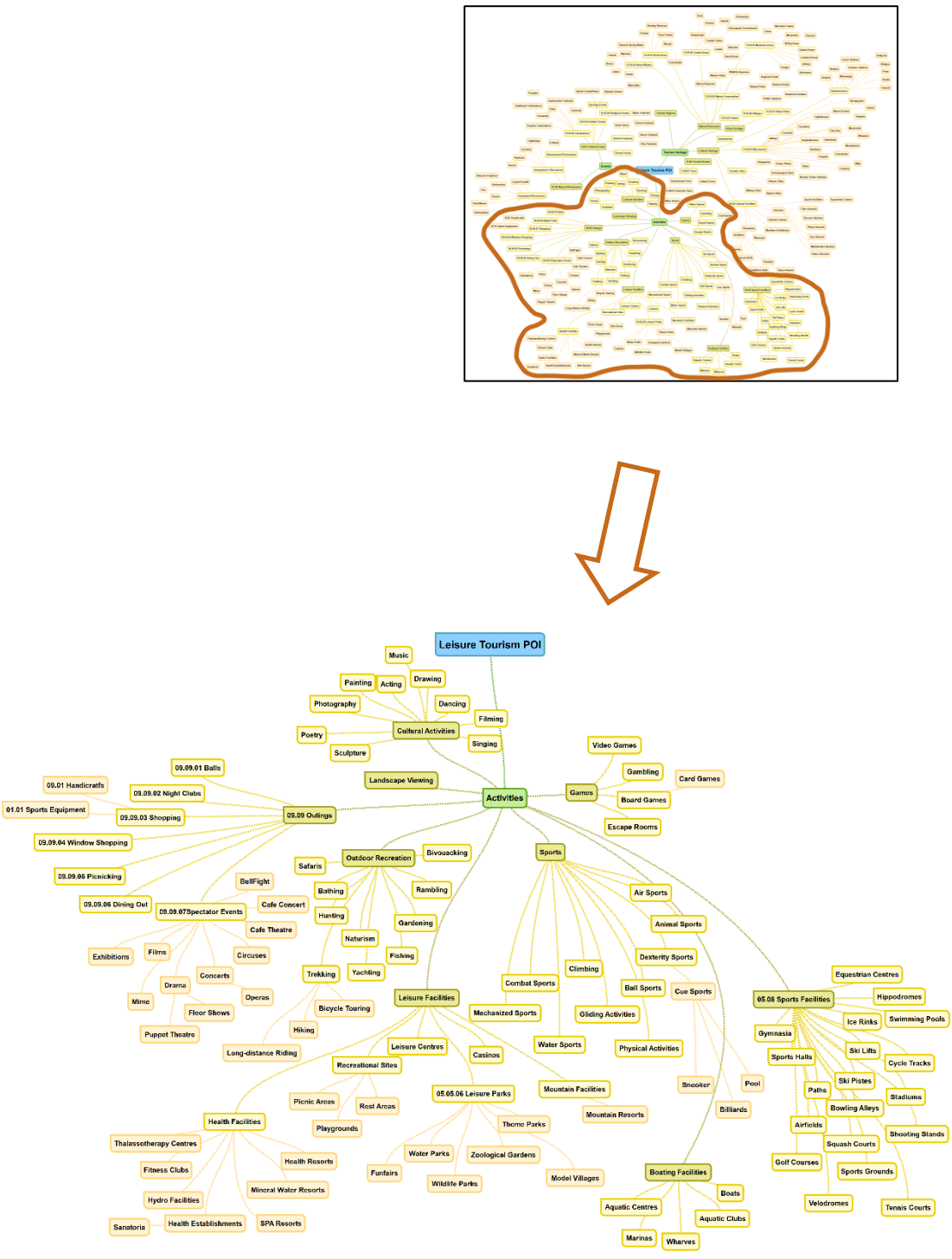


Figure A.5. Mind map for the most relevant terms for tourist attractions related to Activities, zoomed out from the global mind map. Content adapted from UNWTO (2001).

Appendix B: The Big Five Inventory

The Big Five Inventory (BFI)

Here are a number of characteristics that may or may not apply to you. For example, do you agree that you are someone who likes to spend time with others? Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement.

Disagree strongly	Disagree a little	Neither agree nor disagree	Agree a little	Agree Strongly
1	2	3	4	5

I see Myself as Someone Who...

____1. Is talkative

____2. Tends to find fault with others

____3. Does a thorough job

____4. Is depressed, blue

____5. Is original, comes up with new ideas

____6. Is reserved

____7. Is helpful and unselfish with others

____8. Can be somewhat careless

____9. Is relaxed, handles stress well

____10. Is curious about many different things

____11. Is full of energy

____12. Starts quarrels with others

____13. Is a reliable worker

____14. Can be tense

____15. Is ingenious, a deep thinker

____16. Generates a lot of enthusiasm

____17. Has a forgiving nature

____18. Tends to be disorganized

____19. Worries a lot

____20. Has an active imagination

____21. Tends to be quiet

____22. Is generally trusting

____23. Tends to be lazy

____24. Is emotionally stable, not easily upset

____25. Is inventive

____26. Has an assertive personality

____27. Can be cold and aloof

____28. Perseveres until the task is finished

____29. Can be moody

____30. Values artistic, aesthetic experiences

____31. Is sometimes shy, inhibited

____32. Is considerate and kind to almost everyone

____33. Does things efficiently

____34. Remains calm in tense situations

____35. Prefers work that is routine

____36. Is outgoing, sociable

____37. Is sometimes rude to others

____38. Makes plans and follows through with them

____39. Gets nervous easily

____40. Likes to reflect, play with ideas

____41. Has few artistic interests

____42. Likes to cooperate with others

____43. Is easily distracted

____44. Is sophisticated in art, music, or literature

Scoring:

BFI scale scoring ("R" denotes reverse-scored items):

Extraversion: 1, 6R, 11, 16, 21R, 26, 31R, 36
Agreeableness: 2R, 7, 12R, 17, 22, 27R, 32, 37R, 42
Conscientiousness: 3, 8R, 13, 18R, 23R, 28, 33, 38, 43R
Neuroticism: 4, 9R, 14, 19, 24R, 29, 34R, 39
Openness: 5, 10, 15, 20, 25, 30, 35R, 40, 41R, 44

Figure B.1. The Big Five Inventory (BFI), adapted from John and Srivastava (1999).

Appendix C: Poster presented at RecSys'23

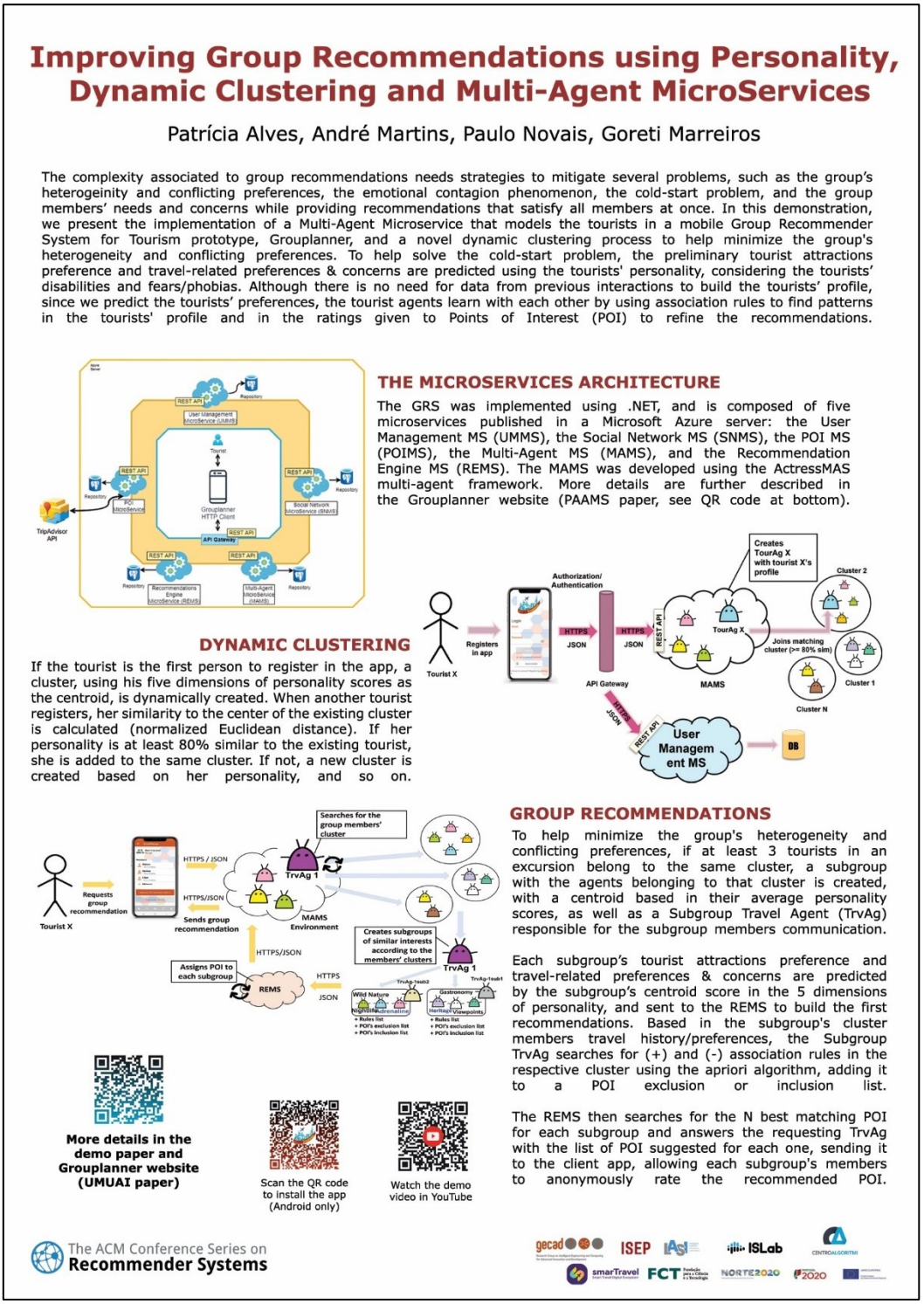


Figure C.1. Poster presented at RecSys'23 conference.

Appendix D: Paper 5 Appendices

Appendix D-A. Clustering statistics

Table D-A.1. Clustering statistics for the simulation with real participants' formed subgroups (n=35).

Subgroup	Number of members	α	Closest Cluster, β	Silhouette, s
$C_{14}Sg$	7	0,013479	0,07860	0,828509
$C_{15}Sg$	3	0,006909	0,05109	0,864767
$C_{3}g$	6	0,004258	0,05109	0,916656
$C_{7}Sg$	3	0,006531	0,07860	0,916910
$C_{5}Sg$	5	0,006450	0,09477	0,931943
$C_{9}Sg$	7	0,0073889	0,12614	0,941428
$C_{11}Sg$	4	0,0031304	0,08381	0,962647

Table D-A.2. Clustering statistics for d-means, n=50.

Members per Cluster	α	β	Silhouette
2	0,0059	0,0741	0,9207
4	0,0069	0,0587	0,8817
3	0,0123	0,0830	0,8520
2	0,0151	0,0984	0,8469
2	0,0115	0,0623	0,8148
3	0,0118	0,0544	0,7827
4	0,0211	0,0902	0,7664
7	0,0144	0,0527	0,7267
38	0,0164	0,0640	0,7258
3	0,0223	0,0544	0,5899
8	0,0259	0,0527	0,5080
Average	**0,0147**	**0,0681**	**0,7690**

Table D-A.3. Clustering statistics for k-means when the optimal number of clusters was determined, n=50.

Members per Cluster	α	β	Silhouette
33	0,0824	0,1619	0,4910
17	0,0974	0,1619	0,3986
Average	**0,0899**	**0,1619**	**0,4448**

Table D-A.4. Clustering statistics for k-means++ when the optimal number of clusters was determined, n=50.

Members per Cluster	α	β	Silhouette
17	0,0974	0,1619	0,3986
33	0,0824	0,1619	0,4910
Average	**0,0899**	**0,1619**	**0,4448**

Table D-A.5. Clustering statistics for d-means, n=150.

Members per Cluster	α	β	Silhouette
2	0,0059	0,0767	0,9235
2	0,0102	0,0898	0,8861
2	0,0051	0,0435	0,8832
2	0,0130	0,0951	0,8634
5	0,0146	0,0990	0,8522
2	0,0116	0,0760	0,8474
2	0,0112	0,0682	0,8354
5	0,0116	0,0682	0,8306
4	0,0132	0,0679	0,8058
4	0,0136	0,0697	0,8053
3	0,0159	0,0792	0,7995
4	0,0145	0,0692	0,7903
6	0,0129	0,0609	0,7886
2	0,0150	0,0683	0,7802
3	0,0118	0,0536	0,7795
3	0,0119	0,0536	0,7773
7	0,0187	0,0793	0,7646
4	0,0297	0,1188	0,7500
3	0,0138	0,0493	0,7201
8	0,0182	0,0623	0,7086
9	0,0158	0,0534	0,7039
3	0,0229	0,0683	0,6647
13	0,0156	0,0453	0,6551
3	0,0152	0,0435	0,6504
7	0,0238	0,0657	0,6373
5	0,0241	0,0623	0,6141
4	0,0233	0,0510	0,5429
11	0,0211	0,0453	0,5345
Average	**0,0155**	**0,0673**	**0,7569**

Table D-A.6. Clustering statistics for k-means when the optimal number of clusters was determined, n=150.

Members per Cluster	α	β	Silhouette
86	0,0991	0,1467	0,3243
64	0,1167	0,1467	0,2045
Average	**0,1079**	**0,1467**	**0,2644**

Table D-A.7. Clustering statistics for k-means++ when the optimal number of clusters was determined, n=150.

Members per Cluster	α	β	Silhouette
100	0,1034	0,1628	0,3648
50	0,1121	0,1628	0,3113
Average	**0,1078**	**0,1628**	**0,3381**

Appendix D-B. Participants' real ratings

Table D-B.1. Real ratings (from 1 to 5 starts) given by each participant, in the subgroups formed, to the tourism categories and travel-related preferences & concerns, the average rating for each subgroup (full mean) and the average rating only for the members of the same cluster (cluster mean).

Cluster #	User #	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	FP1	FP2	FP3	FP4
C21	1	1	3	3	5	4	4	5	1	3	4	4	5	4	5	2
C11	**4**	4	4	4	4	4	4	3	4	4	3	4	4	4	4	2
C11	**8**	2	5	4	4	3	3	3	4	4	3	4	4	4	3	3
C11	**13**	4	5	3	5	5	3	4	2	4	5	5	3	4	4	2
	Cluster mean	3	5	4	4	4	3	3	3	4	4	4	4	4	4	2
	Full mean	3	4	4	5	4	4	4	3	4	4	4	4	4	4	2

Cluster #	User #	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	FP1	FP2	FP3	FP4
C4	26	2	5	5	5	3	4	5	3	4	4	5	3	3	4	4
C7	**28**	4	4	4	5	4	5	4	1	3	3	3	3	5	5	2
C7	**34**	5	5	5	5	4	5	4	1	4	4	4	4	5	5	2
	Cluster mean	5	5	5	5	4	5	4	1	4	4	4	4	5	5	2
	Full mean	4	5	5	5	4	5	4	2	4	4	4	3	4	5	3

Cluster #	User #	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	FP1	FP2	FP3	FP4
C3	**5**	4	4	5	5	4	4	3	2	4	4	4	5	4	4	2
C3	**6**	4	4	3	5	2	2	3	3	1	2	3	2	3	5	5
C17	7	2	3	4	5	3	3	4	1	5	4	2	4	3	5	3
C3	**14**	5	5	5	5	5	3	3	4	3	4	4	4	4	3	4
C3	**22**	4	4	4	5	4	4	4	3	4	4	3	4	4	5	2
C6	25	3	4	4	5	5	5	5	3	5	1	5	5	4	5	3
	Cluster mean	4	4	4	5	4	3	3	3	3	4	4	4	4	4	3
	Full mean	4	4	4	5	4	4	4	3	4	3	4	4	4	5	3

Cluster #	User #	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	FP1	FP2	FP3	FP4
C10	2	3	5	2	5	5	2	5	4	5	4	5	3	4	5	1
C1	3	5	4	4	5	2	4	4	5	4	3	4	2	4	5	2
C8	9	4	4	4	3	3	4	4	5	5	3	3	2	4	4	3
C17	23	1	4	4	3	3	4	4	3	3	2	2	5	4	3	4
C14	**31**	4	5	4	5	3	4	4	3	3	3	4	3	3	4	4
C14	**35**	3	4	3	5	4	4	4	5	5	5	4	5	5	5	5

Cluster #	User #	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	FP1	FP2	FP3	FP4
C16	36	2	5	5	5	5	4	5	1	3	4	3	4	5	5	2
	Cluster mean	4	5	4	5	4	4	4	4	4	4	4	4	4	5	5
	Full mean	3	4	4	4	4	4	4	4	4	3	4	3	4	4	3

Cluster #	User #	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	FP1	FP2	FP3	FP4
C9	**11**	2	5	1	1	3	4	5	1	3	2	5	3	5	5	3
C9	**15**	2	4	4	4	4	5	5	4	5	3	4	4	3	4	3
C9	**19**	4	5	3	5	4	4	5	3	3	3	3	5	4	5	5
C19	20	2	4	2	4	4	4	5	2	3	4	5	5	5	4	4
C18	29	2	5	3	5	3	4	4	2	4	5	4	3	3	4	2
C9	**32**	3	2	4	3	4	4	4	4	3	3	3	2	5	3	4
C9	**33**	2	1	4	5	3	3	4	3	4	5	2	3	4	3	5
	Cluster mean	3	3	3	4	4	4	5	3	4	3	3	3	4	4	4
	Full mean	2	4	3	4	4	4	5	3	4	4	4	4	4	4	4

Cluster #	User #	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	FP1	FP2	FP3	FP4
C12	10	2	5	3	4	3	5	4	5	3	2	5	4	3	4	2
C15	**12**	3	4	3	5	5	4	4	2	4	4	5	4	4	5	2
C15	**17**	1	4	2	5	3	4	3	2	2	2	4	4	5	5	4
	Cluster mean	2	4	3	5	4	4	4	2	3	3	5	4	5	5	3
	Full mean	2	4	3	5	4	4	4	3	3	3	5	4	4	5	3

Cluster #	User #	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	FP1	FP2	FP3	FP4
C5	**16**	3	4	3	5	5	4	5	5	3	2	3	5	4	5	4
C13	18	2	5	1	3	4	3	5	1	4	3	3	3	5	4	3
C2	21	2	5	3	4	5	5	5	4	3	2	4	3	5	4	4
C20	24	2	3	3	4	3	2	4	4	4	2	2	4	3	3	4
C5	**30**	2	3	4	4	3	4	5	4	5	3	3	4	4	4	4
	Cluster mean	3	4	4	5	4	4	5	5	4	3	3	5	4	5	4
	Full mean	2	4	3	4	4	4	5	4	4	2	3	4	4	4	4

Users belonging to the same cluster in a subgroup are in bold.

Table D-B.2. Individual ratings (from 1 to 5 stars) given by each participant to the suggested POI in the respective subgroup's recommendation list.

User #	Subgroup	POI ID	POI name	Rating/Interest
4	$C_{11}Sg$	652	Palácio da Bolsa	4
4	$C_{11}Sg$	885	Sé Catedral do Porto	3
4	$C_{11}Sg$	382	Igreja de São Francisco	3
4	$C_{11}Sg$	170	Centro Histórico de Guimarães	4
4	$C_{11}Sg$	135	Castelo de Guimarães	4
4	$C_{11}Sg$	606	Museu Serralves	5
4	$C_{11}Sg$	588	Museu FC Porto	4
4	$C_{11}Sg$	624	O Navio Gil Eannes	5
4	$C_{11}Sg$	174	Centro Português de Fotografia	4
4	$C_{11}Sg$	580	Museu do Douro	4
3	$C_{14}Sg$	652	Palácio da Bolsa	3
3	$C_{14}Sg$	885	Sé Catedral do Porto	4
3	$C_{14}Sg$	382	Igreja de São Francisco	1
3	$C_{14}Sg$	170	Centro Histórico de Guimarães	5
3	$C_{14}Sg$	683	Passadiços do Paiva	5
3	$C_{14}Sg$	486	Mata Nacional do Buçaco	4
3	$C_{14}Sg$	33	Arouca Geopark	3
3	$C_{14}Sg$	690	Pateira de Fermentelos	3
3	$C_{14}Sg$	708	Poço Negro	4
3	$C_{14}Sg$	692	Pedra Bolideira	4
7	$C_{3}Sg$	652	Palácio da Bolsa	5
7	$C_{3}Sg$	885	Sé Catedral do Porto	5
7	$C_{3}Sg$	382	Igreja de São Francisco	4
7	$C_{3}Sg$	170	Centro Histórico de Guimarães	5
7	$C_{3}Sg$	588	Museu FC Porto	1
7	$C_{3}Sg$	624	O Navio Gil Eannes	1
7	$C_{3}Sg$	174	Centro Português de Fotografia	1
7	$C_{3}Sg$	486	Mata Nacional do Buçaco	3
7	$C_{3}Sg$	519	Montanha- Parque da Penha	3
7	$C_{3}Sg$	33	Arouca Geopark	3
30	$C_{5}Sg$	652	Palácio da Bolsa	4
30	$C_{5}Sg$	885	Sé Catedral do Porto	5
30	$C_{5}Sg$	382	Igreja de São Francisco	4
30	$C_{5}Sg$	170	Centro Histórico de Guimarães	5
30	$C_{5}Sg$	588	Museu FC Porto	2
30	$C_{5}Sg$	624	O Navio Gil Eannes	4
30	$C_{5}Sg$	174	Centro Português de Fotografia	3
30	$C_{5}Sg$	690	Pateira de Fermentelos	4
30	$C_{5}Sg$	708	Poço Negro	4
30	$C_{5}Sg$	692	Pedra Bolideira	2
11	$C_{9}Sg$	652	Palácio da Bolsa	5

User #	Subgroup	POI ID	POI name	Rating/Interest
11	C_9Sg	885	Sé Catedral do Porto	5
11	C_9Sg	382	Igreja de São Francisco	4
11	C_9Sg	170	Centro Histórico de Guimarães	5
11	C_9Sg	588	Museu FC Porto	1
11	C_9Sg	624	O Navio Gil Eannes	5
11	C_9Sg	174	Centro Português de Fotografia	4
11	C_9Sg	683	Passadiços do Paiva	5
11	C_9Sg	486	Mata Nacional do Buçaco	5
11	C_9Sg	33	Arouca Geopark	5
8	$C_{11}Sg$	652	Palácio da Bolsa	4
8	$C_{11}Sg$	885	Sé Catedral do Porto	4
8	$C_{11}Sg$	382	Igreja de São Francisco	2
8	$C_{11}Sg$	170	Centro Histórico de Guimarães	3
8	$C_{11}Sg$	135	Castelo de Guimarães	2
8	$C_{11}Sg$	606	Museu Serralves	4
8	$C_{11}Sg$	588	Museu FC Porto	4
8	$C_{11}Sg$	624	O Navio Gil Eannes	2
8	$C_{11}Sg$	174	Centro Português de Fotografia	3
8	$C_{11}Sg$	580	Museu do Douro	3
6	C_3Sg	652	Palácio da Bolsa	3
6	C_3Sg	885	Sé Catedral do Porto	3
6	C_3Sg	382	Igreja de São Francisco	2
6	C_3Sg	170	Centro Histórico de Guimarães	1
6	C_3Sg	588	Museu FC Porto	5
6	C_3Sg	624	O Navio Gil Eannes	4
6	C_3Sg	174	Centro Português de Fotografia	5
6	C_3Sg	486	Mata Nacional do Buçaco	4
6	C_3Sg	519	Montanha- Parque da Penha	4
6	C_3Sg	33	Arouca Geopark	4
29	C_9Sg	652	Palácio da Bolsa	2
29	C_9Sg	885	Sé Catedral do Porto	4
29	C_9Sg	382	Igreja de São Francisco	3
29	C_9Sg	170	Centro Histórico de Guimarães	4
29	C_9Sg	588	Museu FC Porto	2
29	C_9Sg	624	O Navio Gil Eannes	4
29	C_9Sg	174	Centro Português de Fotografia	2
29	C_9Sg	683	Passadiços do Paiva	5
29	C_9Sg	486	Mata Nacional do Buçaco	5
29	C_9Sg	33	Arouca Geopark	5
5	C_3Sg	652	Palácio da Bolsa	3
5	C_3Sg	885	Sé Catedral do Porto	4
5	C_3Sg	382	Igreja de São Francisco	2
5	C_3Sg	170	Centro Histórico de Guimarães	4

User #	Subgroup	POI ID	POI name	Rating/Interest
5	C_3Sg	588	Museu FC Porto	3
5	C_3Sg	624	O Navio Gil Eannes	5
5	C_3Sg	174	Centro Português de Fotografia	3
5	C_3Sg	486	Mata Nacional do Buçaco	3
5	C_3Sg	519	Montanha- Parque da Penha	4
5	C_3Sg	33	Arouca Geopark	3
35	$C_{14}Sg$	652	Palácio da Bolsa	4
35	$C_{14}Sg$	885	Sé Catedral do Porto	3
35	$C_{14}Sg$	382	Igreja de São Francisco	3
35	$C_{14}Sg$	170	Centro Histórico de Guimarães	5
35	$C_{14}Sg$	683	Passadiços do Paiva	5
35	$C_{14}Sg$	486	Mata Nacional do Buçaco	5
35	$C_{14}Sg$	33	Arouca Geopark	4
35	$C_{14}Sg$	690	Pateira de Fermentelos	4
35	$C_{14}Sg$	708	Poço Negro	4
35	$C_{14}Sg$	692	Pedra Bolideira	1
10	$C_{15}Sg$	588	Museu FC Porto	1
10	$C_{15}Sg$	624	O Navio Gil Eannes	3
10	$C_{15}Sg$	174	Centro Português de Fotografia	2
10	$C_{15}Sg$	580	Museu do Douro	3
10	$C_{15}Sg$	885	Sé Catedral do Porto	3
10	$C_{15}Sg$	382	Igreja de São Francisco	3
10	$C_{15}Sg$	170	Centro Histórico de Guimarães	4
10	$C_{15}Sg$	690	Pateira de Fermentelos	5
10	$C_{15}Sg$	457	Lagoas Naturais Fafião	5
36	$C_{14}Sg$	652	Palácio da Bolsa	5
36	$C_{14}Sg$	885	Sé Catedral do Porto	4
36	$C_{14}Sg$	382	Igreja de São Francisco	3
36	$C_{14}Sg$	170	Centro Histórico de Guimarães	5
36	$C_{14}Sg$	683	Passadiços do Paiva	5
36	$C_{14}Sg$	486	Mata Nacional do Buçaco	3
36	$C_{14}Sg$	33	Arouca Geopark	5
36	$C_{14}Sg$	690	Pateira de Fermentelos	3
36	$C_{14}Sg$	708	Poço Negro	2
36	$C_{14}Sg$	692	Pedra Bolideira	3
32	C_9Sg	652	Palácio da Bolsa	4
32	C_9Sg	885	Sé Catedral do Porto	3
32	C_9Sg	382	Igreja de São Francisco	2
32	C_9Sg	170	Centro Histórico de Guimarães	4
32	C_9Sg	588	Museu FC Porto	1
32	C_9Sg	624	O Navio Gil Eannes	4
32	C_9Sg	174	Centro Português de Fotografia	3
32	C_9Sg	683	Passadiços do Paiva	4

User #	Subgroup	POI ID	POI name	Rating/Interest
32	C_9Sg	486	Mata Nacional do Buçaco	4
32	C_9Sg	33	Arouca Geopark	4
23	$C_{14}Sg$	652	Palácio da Bolsa	4
23	$C_{14}Sg$	885	Sé Catedral do Porto	2
23	$C_{14}Sg$	382	Igreja de São Francisco	3
23	$C_{14}Sg$	170	Centro Histórico de Guimarães	5
23	$C_{14}Sg$	683	Passadiços do Paiva	5
23	$C_{14}Sg$	486	Mata Nacional do Buçaco	5
23	$C_{14}Sg$	33	Arouca Geopark	5
23	$C_{14}Sg$	690	Pateira de Fermentelos	4
23	$C_{14}Sg$	708	Poço Negro	5
23	$C_{14}Sg$	692	Pedra Bolideira	3
22	C_3Sg	652	Palácio da Bolsa	5
22	C_3Sg	885	Sé Catedral do Porto	5
22	C_3Sg	382	Igreja de São Francisco	4
22	C_3Sg	170	Centro Histórico de Guimarães	4
22	C_3Sg	588	Museu FC Porto	3
22	C_3Sg	624	O Navio Gil Eannes	4
22	C_3Sg	174	Centro Português de Fotografia	4
22	C_3Sg	486	Mata Nacional do Buçaco	4
22	C_3Sg	519	Montanha- Parque da Penha	4
22	C_3Sg	33	Arouca Geopark	3
21	C_5Sg	652	Palácio da Bolsa	5
21	C_5Sg	885	Sé Catedral do Porto	5
21	C_5Sg	382	Igreja de São Francisco	5
21	C_5Sg	170	Centro Histórico de Guimarães	4
21	C_5Sg	588	Museu FC Porto	5
21	C_5Sg	624	O Navio Gil Eannes	4
21	C_5Sg	174	Centro Português de Fotografia	2
21	C_5Sg	690	Pateira de Fermentelos	4
21	C_5Sg	708	Poço Negro	5
21	C_5Sg	692	Pedra Bolideira	3
1	$C_{11}Sg$	652	Palácio da Bolsa	3
1	$C_{11}Sg$	885	Sé Catedral do Porto	4
1	$C_{11}Sg$	382	Igreja de São Francisco	5
1	$C_{11}Sg$	170	Centro Histórico de Guimarães	4
1	$C_{11}Sg$	135	Castelo de Guimarães	5
1	$C_{11}Sg$	606	Museu Serralves	3
1	$C_{11}Sg$	588	Museu FC Porto	2
1	$C_{11}Sg$	624	O Navio Gil Eannes	2
1	$C_{11}Sg$	174	Centro Português de Fotografia	3
1	$C_{11}Sg$	580	Museu do Douro	2
13	$C_{11}Sg$	652	Palácio da Bolsa	4

User #	Subgroup	POI ID	POI name	Rating/Interest
13	$C_{11}Sg$	885	Sé Catedral do Porto	4
13	$C_{11}Sg$	382	Igreja de São Francisco	5
13	$C_{11}Sg$	170	Centro Histórico de Guimarães	5
13	$C_{11}Sg$	135	Castelo de Guimarães	4
13	$C_{11}Sg$	606	Museu Serralves	5
13	$C_{11}Sg$	588	Museu FC Porto	2
13	$C_{11}Sg$	624	O Navio Gil Eannes	3
13	$C_{11}Sg$	174	Centro Português de Fotografia	5
13	$C_{11}Sg$	580	Museu do Douro	4
15	C_9Sg	652	Palácio da Bolsa	4
15	C_9Sg	885	Sé Catedral do Porto	3
15	C_9Sg	382	Igreja de São Francisco	2
15	C_9Sg	170	Centro Histórico de Guimarães	5
15	C_9Sg	588	Museu FC Porto	4
15	C_9Sg	624	O Navio Gil Eannes	5
15	C_9Sg	174	Centro Português de Fotografia	3
15	C_9Sg	683	Passadiços do Paiva	5
15	C_9Sg	486	Mata Nacional do Buçaco	3
15	C_9Sg	33	Arouca Geopark	4
31	$C_{14}Sg$	652	Palácio da Bolsa	5
31	$C_{14}Sg$	885	Sé Catedral do Porto	4
31	$C_{14}Sg$	382	Igreja de São Francisco	3
31	$C_{14}Sg$	170	Centro Histórico de Guimarães	4
31	$C_{14}Sg$	683	Passadiços do Paiva	5
31	$C_{14}Sg$	486	Mata Nacional do Buçaco	5
31	$C_{14}Sg$	33	Arouca Geopark	5
31	$C_{14}Sg$	690	Pateira de Fermentelos	5
31	$C_{14}Sg$	708	Poço Negro	5
31	$C_{14}Sg$	692	Pedra Bolideira	3
9	$C_{14}Sg$	652	Palácio da Bolsa	3
9	$C_{14}Sg$	885	Sé Catedral do Porto	2
9	$C_{14}Sg$	382	Igreja de São Francisco	2
9	$C_{14}Sg$	170	Centro Histórico de Guimarães	4
9	$C_{14}Sg$	683	Passadiços do Paiva	4
9	$C_{14}Sg$	486	Mata Nacional do Buçaco	4
9	$C_{14}Sg$	33	Arouca Geopark	4
9	$C_{14}Sg$	690	Pateira de Fermentelos	3
9	$C_{14}Sg$	708	Poço Negro	4
9	$C_{14}Sg$	692	Pedra Bolideira	3
33	C_9Sg	652	Palácio da Bolsa	5
33	C_9Sg	885	Sé Catedral do Porto	3
33	C_9Sg	382	Igreja de São Francisco	3
33	C_9Sg	170	Centro Histórico de Guimarães	5

User #	Subgroup	POI ID	POI name	Rating/Interest
33	C_9Sg	588	Museu FC Porto	2
33	C_9Sg	624	O Navio Gil Eannes	4
33	C_9Sg	174	Centro Português de Fotografia	3
33	C_9Sg	683	Passadiços do Paiva	1
33	C_9Sg	486	Mata Nacional do Buçaco	3
33	C_9Sg	33	Arouca Geopark	3
28	C_7Sg	57	Bom Jesus do Monte	5
28	C_7Sg	652	Palácio da Bolsa	5
28	C_7Sg	885	Sé Catedral do Porto	4
28	C_7Sg	382	Igreja de São Francisco	5
28	C_7Sg	486	Mata Nacional do Buçaco	3
28	C_7Sg	519	Montanha- Parque da Penha	3
28	C_7Sg	283	Excursão de meio dia ao Palácio Bussaco, jardins e floresta	4
28	C_7Sg	588	Museu FC Porto	5
28	C_7Sg	624	O Navio Gil Eannes	4
28	C_7Sg	174	Centro Português de Fotografia	3
18	C_5Sg	652	Palácio da Bolsa	4
18	C_5Sg	885	Sé Catedral do Porto	5
18	C_5Sg	382	Igreja de São Francisco	4
18	C_5Sg	170	Centro Histórico de Guimarães	5
18	C_5Sg	588	Museu FC Porto	2
18	C_5Sg	624	O Navio Gil Eannes	5
18	C_5Sg	174	Centro Português de Fotografia	4
18	C_5Sg	690	Pateira de Fermentelos	5
18	C_5Sg	708	Poço Negro	5
18	C_5Sg	692	Pedra Bolideira	4
17	$C_{15}Sg$	588	Museu FC Porto	1
17	$C_{15}Sg$	624	O Navio Gil Eannes	4
17	$C_{15}Sg$	174	Centro Português de Fotografia	4
17	$C_{15}Sg$	580	Museu do Douro	4
17	$C_{15}Sg$	885	Sé Catedral do Porto	4
17	$C_{15}Sg$	382	Igreja de São Francisco	4
17	$C_{15}Sg$	170	Centro Histórico de Guimarães	2
17	$C_{15}Sg$	690	Pateira de Fermentelos	4
17	$C_{15}Sg$	457	Lagoas Naturais Fafião	4
34	C_7Sg	57	Bom Jesus do Monte	5
34	C_7Sg	652	Palácio da Bolsa	5
34	C_7Sg	885	Sé Catedral do Porto	4
34	C_7Sg	382	Igreja de São Francisco	5
34	C_7Sg	486	Mata Nacional do Buçaco	5
34	C_7Sg	519	Montanha- Parque da Penha	5
34	C_7Sg	283	Excursão de meio dia ao Palácio Bussaco, jardins e floresta	5
34	C_7Sg	588	Museu FC Porto	4

User #	Subgroup	POI ID	POI name	Rating/Interest
34	C_7Sg	624	O Navio Gil Eannes	4
34	C_7Sg	174	Centro Português de Fotografia	3
20	C_9Sg	652	Palácio da Bolsa	5
20	C_9Sg	885	Sé Catedral do Porto	5
20	C_9Sg	382	Igreja de São Francisco	4
20	C_9Sg	170	Centro Histórico de Guimarães	5
20	C_9Sg	588	Museu FC Porto	3
20	C_9Sg	624	O Navio Gil Eannes	5
20	C_9Sg	174	Centro Português de Fotografia	5
20	C_9Sg	683	Passadiços do Paiva	5
20	C_9Sg	486	Mata Nacional do Buçaco	5
20	C_9Sg	33	Arouca Geopark	5
2	$C_{14}Sg$	652	Palácio da Bolsa	4
2	$C_{14}Sg$	885	Sé Catedral do Porto	4
2	$C_{14}Sg$	382	Igreja de São Francisco	5
2	$C_{14}Sg$	170	Centro Histórico de Guimarães	3
2	$C_{14}Sg$	683	Passadiços do Paiva	5
2	$C_{14}Sg$	486	Mata Nacional do Buçaco	5
2	$C_{14}Sg$	33	Arouca Geopark	5
2	$C_{14}Sg$	690	Pateira de Fermentelos	4
2	$C_{14}Sg$	708	Poço Negro	3
2	$C_{14}Sg$	692	Pedra Bolideira	3
25	C_3Sg	652	Palácio da Bolsa	5
25	C_3Sg	885	Sé Catedral do Porto	4
25	C_3Sg	382	Igreja de São Francisco	3
25	C_3Sg	170	Centro Histórico de Guimarães	5
25	C_3Sg	588	Museu FC Porto	3
25	C_3Sg	624	O Navio Gil Eannes	5
25	C_3Sg	174	Centro Português de Fotografia	5
25	C_3Sg	486	Mata Nacional do Buçaco	4
25	C_3Sg	519	Montanha- Parque da Penha	5
25	C_3Sg	33	Arouca Geopark	5
16	C_5Sg	652	Palácio da Bolsa	3
16	C_5Sg	885	Sé Catedral do Porto	2
16	C_5Sg	382	Igreja de São Francisco	3
16	C_5Sg	170	Centro Histórico de Guimarães	5
16	C_5Sg	588	Museu FC Porto	4
16	C_5Sg	624	O Navio Gil Eannes	4
16	C_5Sg	174	Centro Português de Fotografia	4
16	C_5Sg	690	Pateira de Fermentelos	5
16	C_5Sg	708	Poço Negro	5
16	C_5Sg	692	Pedra Bolideira	3
12	$C_{15}Sg$	588	Museu FC Porto	3

User #	Subgroup	POI ID	POI name	Rating/Interest
12	$C_{15}Sg$	624	O Navio Gil Eannes	2
12	$C_{15}Sg$	174	Centro Português de Fotografia	4
12	$C_{15}Sg$	580	Museu do Douro	4
12	$C_{15}Sg$	885	Sé Catedral do Porto	4
12	$C_{15}Sg$	382	Igreja de São Francisco	3
12	$C_{15}Sg$	170	Centro Histórico de Guimarães	5
12	$C_{15}Sg$	690	Pateira de Fermentelos	5
12	$C_{15}Sg$	457	Lagoas Naturais Fafião	5
14	$C_{3}Sg$	652	Palácio da Bolsa	4
14	$C_{3}Sg$	885	Sé Catedral do Porto	4
14	$C_{3}Sg$	382	Igreja de São Francisco	3
14	$C_{3}Sg$	170	Centro Histórico de Guimarães	3
14	$C_{3}Sg$	588	Museu FC Porto	4
14	$C_{3}Sg$	624	O Navio Gil Eannes	4
14	$C_{3}Sg$	174	Centro Português de Fotografia	4
14	$C_{3}Sg$	486	Mata Nacional do Buçaco	4
14	$C_{3}Sg$	519	Montanha- Parque da Penha	4
14	$C_{3}Sg$	33	Arouca Geopark	3
19	$C_{9}Sg$	652	Palácio da Bolsa	3
19	$C_{9}Sg$	885	Sé Catedral do Porto	4
19	$C_{9}Sg$	382	Igreja de São Francisco	5
19	$C_{9}Sg$	170	Centro Histórico de Guimarães	4
19	$C_{9}Sg$	588	Museu FC Porto	2
19	$C_{9}Sg$	624	O Navio Gil Eannes	4
19	$C_{9}Sg$	174	Centro Português de Fotografia	3
19	$C_{9}Sg$	683	Passadiços do Paiva	5
19	$C_{9}Sg$	486	Mata Nacional do Buçaco	3
19	$C_{9}Sg$	33	Arouca Geopark	4
26	$C_{7}Sg$	57	Bom Jesus do Monte	5
26	$C_{7}Sg$	652	Palácio da Bolsa	5
26	$C_{7}Sg$	885	Sé Catedral do Porto	5
26	$C_{7}Sg$	382	Igreja de São Francisco	2
26	$C_{7}Sg$	486	Mata Nacional do Buçaco	3
26	$C_{7}Sg$	519	Montanha- Parque da Penha	5
26	$C_{7}Sg$	283	Excursão de meio dia ao Palácio Bussaco, jardins e floresta	4
26	$C_{7}Sg$	588	Museu FC Porto	3
26	$C_{7}Sg$	624	O Navio Gil Eannes	5
26	$C_{7}Sg$	174	Centro Português de Fotografia	4
24	$C_{5}Sg$	652	Palácio da Bolsa	4
24	$C_{5}Sg$	885	Sé Catedral do Porto	4
24	$C_{5}Sg$	382	Igreja de São Francisco	4
24	$C_{5}Sg$	170	Centro Histórico de Guimarães	4
24	$C_{5}Sg$	588	Museu FC Porto	5

User #	Subgroup	POI ID	POI name	Rating/Interest
24	C_5Sg	624	O Navio Gil Eannes	2
24	C_5Sg	174	Centro Português de Fotografia	2
24	C_5Sg	690	Pateira de Fermentelos	4
24	C_5Sg	708	Poço Negro	4
24	C_5Sg	692	Pedra Bolideira	1

The POI names are in Portuguese.

Appendix D-C. Tourist attraction types

Table D-C.1. Tourist attraction types considered for each tourism category.

Attraction type		Tourism category
A12	Practice aquatic sports (e.g., sailing, canoeing, diving, jet skiing)	Adrenaline activities
A24	Ride a bike	Adrenaline activities
A29	Do motorsports (e.g., karting, motocross)	Adrenaline activities
A37	Observe sub-aquatic environments / marine life (e.g., snorkeling, submarine)	Adrenaline activities
A46	Practice climbing or bungee jumping	Adrenaline activities
A63	Do air sports (e.g., parachute jump, skydiving, gliding)	Adrenaline activities
A68	Ski	Adrenaline activities
A3	Watch a religious celebration	Cultural heritage
A4	Visit the historic cities/villages of the destination	Cultural heritage
A7	Visit archaeological sites / ruins	Cultural heritage
A20	Visit monuments (e.g. churches, cathedrals, castles, fortresses, monasteries, palaces, etc.)	Cultural heritage
A23	To enjoy / buy local handicrafts	Cultural heritage
A38	Visit large man-made constructions (e.g., bridges, tunnels, mines)	Cultural heritage
A18	Taste typical local dishes	Gastronomy events
A40	Participate in a gastronomy tour (typical and/or gourmet dishes, wine tasting)	Gastronomy events
A14	Undergo health and wellness treatments (e.g., hydrotherapy centers, mineral water resorts)	Health & well-being
A26	Attend gyms / fitness centers	Health & well-being
A28	Go to a SPA / beauty center	Health & well-being
A32	Visit museums of historical themes	Museums, boat trips & viewpoints
A33	Visit museums of scientific themes (e.g., planetarium, paleontology)	Museums, boat trips & viewpoints
A34	Visit viewpoints of natural landscape	Museums, boat trips & viewpoints
A35	Visit viewpoints of urban landscape	Museums, boat trips & viewpoints
A49	Take boat trips to know the destination's coast	Museums, boat trips & viewpoints
A50	Take boat trips for the historical value of the route	Museums, boat trips & viewpoints
A51	Take boat trips for the pleasure of boating	Museums, boat trips & viewpoints
A2	Watch a natural phenomenon (e.g., volcanic eruption or northern lights)	Natural phenomena
A6	Visit caves/caverns/volcanoes	Natural phenomena
A8	Attend cultural activities / artistic performances	Party, Music & Nightlife
A9	Go to the disco/nightclub	Party, Music & Nightlife
A16	Attend a typical celebration of the destination (e.g., popular celebrations, carnivals, fireworks)	Party, Music & Nightlife

Attraction type		Tourism category
A17	Go to a film festival	Party, Music & Nightlife
A39	Go to a thematic parade (e.g., military, electronic music)	Party, Music & Nightlife
A43	Go to a music festival/concert	Party, Music & Nightlife
A44	Go to a dance/ballet festival	Party, Music & Nightlife
A45	Go to balls (dancing)	Party, Music & Nightlife
A48	Go to a live music bar/place	Party, Music & Nightlife
A67	Assist an opera/theater	Party, Music & Nightlife
A53	Play ball sports (e.g., football, handball, volleyball, tennis)	Sports & Games
A55	Play at the casino	Sports & Games
A56	Assist to a sporting competition (e.g., watch a football game from a club of that country)	Sports & Games
A58	Hunt / fish	Sports & Games
A59	Participate in an escape game	Sports & Games
A60	Watch a bullfight	Sports & Games
A61	Go to the circus	Sports & Games
A22	Go to the beach (sunbathing/ swimming)	Sun, water & sand
A62	Go on a cruise	Sun, water & sand
A64	Go to the swimming pool to swim/dive	Sun, water & sand
A65	Go to the swimming pool to relax	Sun, water & sand
A66	Have vacation on an island	Sun, water & sand
A5	Visit an oceanarium	Theme & animal parks
A13	Go to a theme park (e.g., Disneyland Paris)	Theme & animal parks
A15	Go to a Zoo	Theme & animal parks
A19	Visit a botanical garden	Theme & animal parks
A25	Go to a funfair (e.g., amusements such as Ferris wheel, bumper cars, etc.)	Theme & animal parks
A27	Go to a water park	Theme & animal parks
A10	Appreciate natural landscapes	Wild nature activities
A11	Do hiking / mountaineering	Wild nature activities
A21	Visit a beach for its natural beauty	Wild nature activities
A36	Visit nature or wildlife reserves	Wild nature activities
A41	Walk in the forest / woods	Wild nature activities
A42	Take a walk along the river / sea coast	Wild nature activities
A47	Visit mountain areas / gorges	Wild nature activities
A54	Do a safari	Wild nature activities
A57	Ride a horse	Wild nature activities

Table D-C.2. Default d-means algorithm and application configuration parameters.

Parameter	Default value
Minimum tourists' similarity	0.80
Apriori rules Confidence	95%
Apriori rules Support	95%
Rules check frequency	every 24h
Minimum tourists to divide main excursion	6

Parameter	Default value
Minimum tourists in a subgroup	3
Minimum tourists in a cluster to search rules	50
Minimum tourists in a subgroup to match a rule for POI inclusion/exclusion	50%
Minimum POI to recommend in a list	10
Minimum rating to exclude a POI	≤ 2
Threshold to consider a category as the Top-3	0.49
Minimum travel preference value to consider that preference	≥ 0.50
Minimum travel concern value to consider that concern	≥0.50
Weather API check frequency	every 24h

Appendix D-D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eswa.2024.124812.

Appendix E: Paper 7 Appendices

Appendix E-A: Which Way game's relevant statistics

Table E-A.1. Which Way minigame's metrics statistics

		TotalTime	TotalHardPaths	InsistedHardPath	TotalTrapsRisked	Traps2x Attempts	ExploredMS1
N	Valid	86	86	86	86	86	86
	Missing	0	0	0	0	0	0
Mean		112.7001	.31395	1.59	.1651	.03	.36
Std. Error of Mean		5.55549	.023093	.073	.01627	.020	.052
Median		101.9990	.25000	2.00	.2000	.00	.00
Mode		23.00[a]	.250	2	.20	0	0
Std. Deviation		51.51946	.214154	.675	.15089	.185	.483
Variance		2654.255	.046	.456	.023	.034	.233
Skewness		.809	.641	-1.404	.639	5.160	.592
Std. Error of Skewness		.260	.260	.260	.260	.260	.260
Kurtosis		.287	.107	.639	.085	25.214	-1.690
Std. Error of Kurtosis		.514	.514	.514	.514	.514	.514
Range		237.94	.875	2	.60	1	1
Minimum		23.00	.000	0	.00	0	0
Maximum		260.94	.875	2	.60	1	1
Sum		9692.21	27.000	137	14.20	3	31

Table E-A.2. WW game *TotalHardPaths* metric's frequency table

		Frequency	Percent	Valid percent	Cumulative percent
Valid	.000	9	10.5	10.5	10.5
	.125	17	19.8	19.8	30.2
	.250	23	26.7	26.7	57.0
	.375	12	14.0	14.0	70.9
	.500	16	18.6	18.6	89.5
	.625	4	4.7	4.7	94.2
	.750	2	2.3	2.3	96.5
	.875	3	3.5	3.5	100.0
	Total	86	100.0	100.0	

Table E-A.3. WW game *TotalTrapsRisked* metric's frequency table

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	31	36.0	36.0	36.0
	.20	41	47.7	47.7	83.7
	.40	12	14.0	14.0	97.7
	.60	2	2.3	2.3	100.0
	Total	86	100.0	100.0	

Table E-A.4. WW game *Traps2xAttempts* metric's frequency table

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	83	96.5	96.5	96.5
	1	3	3.5	3.5	100.0
	Total	86	100.0	100.0	

Table E-A.5. WW game *InsistedHardPath* metric's frequency table

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	9	10.5	10.5	10.5
	1	17	19.8	19.8	30.2
	2	60	69.8	69.8	100.0
	Total	86	100.0	100.0	

Table E-A.6. WW game *ExploredMS1* metric's frequency table

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	55	64.0	64.0	64.0
	1	31	36.0	36.0	100.0
	Total	86	100.0	100.0	

Table E-A.7. WW game *TotalTrapsRisked* independent-samples Mann-Whitney U Test comparing groups 0 and 1 (participants who did not enter a trap and the ones who did, respectively)

	Null Hypothesis	Sig.	Decision
1	The distribution of C1_SelfEfficacy is the same across categories of *TotalTrapsRisked*.	.074	Retain the null hypothesis.
2	The distribution of C2_Order is the same across categories of *TotalTrapsRisked*.	.591	Retain the null hypothesis.
3	The distribution of C3_Dutifulness is the same across categories of *TotalTrapsRisked*.	.837	Retain the null hypothesis.
4	The distribution of C4_Achievement is the same across categories of *TotalTrapsRisked*.	.454	Retain the null hypothesis.
5	**The distribution of C5_SelfDiscipline is the same across categories of *TotalTrapsRisked*.**	**.038**	**Reject the null hypothesis. G_0(avg)=3.03 G_1(avg)=3.33**
6	The distribution of C6_Cautiousness is the same across categories of *TotalTrapsRisked*.	.654	Retain the null hypothesis.
7	The distribution of N1_Anxiety is the same across categories of *TotalTrapsRisked*.	.250	Retain the null hypothesis.
8	The distribution of N2_Anger is the same across categories of *TotalTrapsRisked*.	.217	Retain the null hypothesis.
9	The distribution of N3_Depression is the same across categories of *TotalTrapsRisked*.	.176	Retain the null hypothesis.
10	The distribution of N4_SelfConsc is the same across categories of *TotalTrapsRisked*.	.272	Retain the null hypothesis.
11	The distribution of N5_Immoderation is the same across categories of *TotalTrapsRisked*.	.088	Retain the null hypothesis.
12	**The distribution of N6_Vulnerability is the same across categories of *TotalTrapsRisked*.**	**.012**	**Reject the null hypothesis. G_0(avg)=2.88 G_1(avg)=2.43**
13	The distribution of E1_Friendliness is the same across categories of *TotalTrapsRisked*.	.084	Retain the null hypothesis.
14	The distribution of E2_Gregarious is the same across categories of *TotalTrapsRisked*.	.209	Retain the null hypothesis.
15	**The distribution of E3_Assertiveness is the same across categories of *TotalTrapsRisked*.**	**.043**	**Reject the null hypothesis. G_0(avg)=3.13 G_1(avg)=3.45**
16	The distribution of E4_Activity is the same across categories of *TotalTrapsRisked*.	.156	Retain the null hypothesis.
17	The distribution of E5_ExcitementSeek is the same across categories of *TotalTrapsRisked*.	.200	Retain the null hypothesis.
18	The distribution of E6_Cheerfulness is the same across categories of *TotalTrapsRisked*.	.147	Retain the null hypothesis.
19	The distribution of O1_Imagination is the same across categories of *TotalTrapsRisked*.	.463	Retain the null hypothesis.
20	The distribution of O2_ArtisticInterests is the same across categories of *TotalTrapsRisked*.	.479	Retain the null hypothesis.
21	The distribution of O3_Emotionality is the same across categories of *TotalTrapsRisked*.	.803	Retain the null hypothesis.
22	The distribution of O4_Adventurous is the same across categories of *TotalTrapsRisked*.	.204	Retain the null hypothesis.
23	The distribution of O5_Intellect is the same across categories of *TotalTrapsRisked*.	.515	Retain the null hypothesis.
24	The distribution of O6_Liberalism is the same across categories of *TotalTrapsRisked*.	.620	Retain the null hypothesis.
25	The distribution of A1_Trust is the same across categories of *TotalTrapsRisked*.	.496	Retain the null hypothesis.
26	The distribution of A2_Morality is the same across categories of *TotalTrapsRisked*.	.583	Retain the null hypothesis.
27	The distribution of A3_Altruism is the same across categories of *TotalTrapsRisked*.	.982	Retain the null hypothesis.
28	The distribution of A4_Cooperation is the same across categories of *TotalTrapsRisked*.	.662	Retain the null hypothesis.
29	**The distribution of A5_Modesty is the same across categories of *TotalTrapsRisked*.**	**.043**	**Reject the null hypothesis. G_0(avg)=3.71 G_1(avg)=3.33**
30	The distribution of A6_Sympathy is the same across categories of *TotalTrapsRisked*.	.593	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is 0.05. Statistically significant different distributions across the groups are in bold.

Table E-A.8. WW game *ExploredMS1* independent-samples Mann-Whitney U Test comparing groups 0 and 1 (participants who did not explore hidden sections 1 and 2 and the ones who did, respectively)

	Null Hypothesis	Sig.	Decision
1	The distribution of C1_SelfEfficacy is the same across categories of ExploredMS1.	.442	Retain the null hypothesis.
2	The distribution of C2_Order is the same across categories of ExploredMS1.	.473	Retain the null hypothesis.
3	The distribution of C3_Dutifulness is the same across categories of ExploredMS1.	.373	Retain the null hypothesis.
4	The distribution of C4_Achievement is the same across categories of ExploredMS1.	.758	Retain the null hypothesis.
5	The distribution of C5_SelfDiscipline is the same across categories of ExploredMS1.	.561	Retain the null hypothesis.
6	The distribution of C6_Cautiousness is the same across categories of ExploredMS1.	.674	Retain the null hypothesis.
7	The distribution of N1_Anxiety is the same across categories of ExploredMS1.	.258	Retain the null hypothesis.
8	The distribution of N2_Anger is the same across categories of ExploredMS1.	.373	Retain the null hypothesis.
9	The distribution of N3_Depression is the same across categories of ExploredMS1.	.807	Retain the null hypothesis.
10	The distribution of N4_SelfConsc is the same across categories of ExploredMS1.	.741	Retain the null hypothesis.
11	The distribution of N5_Immoderation is the same across categories of ExploredMS1.	.845	Retain the null hypothesis.
12	The distribution of N6_Vulnerability is the same across categories of ExploredMS1.	.821	Retain the null hypothesis.
13	The distribution of E1_Friendliness is the same across categories of ExploredMS1.	.660	Retain the null hypothesis.
14	The distribution of E2_Gregarious is the same across categories of ExploredMS1.	.481	Retain the null hypothesis.
15	The distribution of E3_Assertiveness is the same across categories of ExploredMS1.	.762	Retain the null hypothesis.
16	The distribution of E4_Activity is the same across categories of ExploredMS1.	.703	Retain the null hypothesis.
17	The distribution of E5_ExcitementSeek is the same across categories of ExploredMS1.	.382	Retain the null hypothesis.
18	The distribution of E6_Cheerfulness is the same across categories of ExploredMS1.	.156	Retain the null hypothesis.
19	The distribution of O1_Imagination is the same across categories of ExploredMS1.	.856	Retain the null hypothesis.
20	The distribution of O2_ArtisticInterests is the same across categories of ExploredMS1.	.677	Retain the null hypothesis.
21	**The distribution of O3_Emotionality is the same across categories of ExploredMS1.**	**.068**	**Retain the null hypothesis.**
22	The distribution of O4_Adventurous is the same across categories of ExploredMS1.	.832	Retain the null hypothesis.
23	The distribution of O5_Intellect is the same across categories of ExploredMS1.	.581	Retain the null hypothesis.
24	The distribution of O6_Liberalism is the same across categories of ExploredMS1.	.964	Retain the null hypothesis.
25	The distribution of A1_Trust is the same across categories of ExploredMS1.	.946	Retain the null hypothesis.
26	The distribution of A2_Morality is the same across categories of ExploredMS1.	.098	Retain the null hypothesis.
27	The distribution of A3_Altruism is the same across categories of ExploredMS1.	.412	Retain the null hypothesis.
28	The distribution of A4_Cooperation is the same across categories of ExploredMS1.	.261	Retain the null hypothesis.
29	The distribution of A5_Modesty is the same across categories of ExploredMS1.	.112	Retain the null hypothesis.
30	The distribution of A6_Sympathy is the same across categories of ExploredMS1.	.312	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is 0.05. Nearly statistically significant different distributions across the groups are in bold.

Table E-A.9. WW game *TotalHardPaths* metric's independent samples t-test comparing groups 0 and 1 (0 – 0 to 2 hard paths; 1- 3 or more hard paths) personality and time taken to complete the game

		Levene's Test for Equality of Variances		**t-test for Equality of Means**						
		F	**Sig.**	**t**	**df**	**Sig. (2-tailed)**	**Mean Difference**	**Std. Error Difference**	**95% Confidence Interval of the Difference**	
									Lower	**Upper**
WWTotal-Time	**Equal variances assumed**	**.639**	**.426**	**-3.426**	**84**	**.001*** **	**-36.224**	**10.572**	**-57.24909**	**-15.19899**
	Equal variances not assumed			-3.370	72.5	.001	-36.224	10.748	-57.64729	-14.80079
C1_SelfEfficacy	Equal variances assumed	1.406	.239	-.932	84	.354	-.128	.138	-.40221	.14545
	Equal variances not assumed			-.963	83.8	.338	-.128	.133	-.39341	.13665
C2_Order	Equal variances assumed	.729	.396	-.158	84	.875	-.031	.195	-.41841	.35691
	Equal variances not assumed			-.155	71.7	.877	-.031	.199	-.42673	.36523
C3_Dutifulness	Equal variances assumed	2.446	.122	1.439	84	.154	.142	.099	-.05439	.33928
	Equal variances not assumed			1.378	63.0	.173	.142	.103	-.06417	.34905
C4_Achievement	Equal variances assumed	1.344	.250	-.427	84	.671	-.060	.140	-.33795	.21853
	Equal variances not assumed			-.441	83.8	.661	-.060	.135	-.32912	.20970
C5_SelfDiscipline	Equal variances assumed	.000	.988	-.617	84	.539	-.087	.140	-.36575	.19255
	Equal variances not assumed			-.624	80.5	.535	-.087	.139	-.36295	.18976
C6_Cautiousness	Equal variances assumed	2.378	.127	-.019	84	.985	-.004	.184	-.36979	.36262
	Equal variances not assumed			-.020	83.2	.984	-.004	.179	-.36047	.35330

Statistically significant different distributions across groups are in bold [***correlation is significant at the 0.001 level (2 tailed)].

Appendix E-B: Time Travel Mania game's relevant statistics (complete attempt)

Table E-B.1. Time Travel minigame metrics statistics (n=70)

		HardCoins	TotalCoins	Diamonds	Time	Score	Trophies
N	Valid	70	70	70	70	70	70
	Missing	0	0	0	0	0	0
Mean		.476	.580	1.06	250.93	730.79	.99
Std. Error of Mean		.046	.039	.133	14.939	54.121	.128
Median		.333	.495	1.00	242.00	570.00	1.00
Mode		1.000	1.000	0	100[a]	1300[a]	0
Std. Deviation		.388	.327	1.115	124.989	452.805	1.070
Variance		.150	.107	1.243	15622.328	205032.142	1.145
Skewness		.258	.141	.466	1.816	.232	.541
Std. Error of Skewness		.287	.287	.287	.287	.287	.287
Kurtosis		-1.632	-1.693	-1.269	7.386	-1.610	-1.139
Std. Error of Kurtosis		.566	.566	.566	.566	.566	.566
Range		1.000	.864	3	776	1250	3
Minimum		.000	.136	0	98	150	0
Maximum		1.000	1.000	3	874	1400	3

a. Multiple modes exist, the smallest value is shown

Table E-B.2. TT game *Diamonds* metric's frequency table (0 to 3 diamonds caught)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	32	45.7	45.7	45.7
	1	11	15.7	15.7	61.4
	2	18	25.7	25.7	87.1
	3	9	12.9	12.9	100.0
	Total	70	100.0	100.0	

Table E-B.3. TT game *Trophies* metric's frequency table

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	33	47.1	47.1	47.1
	1	12	17.1	17.1	64.3
	2	18	25.7	25.7	90.0
	3	7	10.0	10.0	100.0
	Total	70	100.0	100.0	

Table E-B.4. TT game 2 or more complete attempts frequency table (0- 1 completed attempt; 1- 2 or more)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	57	81.4	81.4	81.4
	1	13	18.6	18.6	100.0
	Total	70	100.0	100.0	

Table E-B.5. Independent samples t-test comparing the personality traits' scores across the completion time of groups 1 (<5min) and 2 (≥5min) in the TT game.

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
C1_SelfEfficacy	Equal variances assumed	.004	.951	-.597	68	.552	-.09333	.15626	-.40515	.21848
	Equal variances not assumed			-.614	53.963	.541	-.09333	.15190	-.39787	.21120
C2_Order	Equal variances assumed	1.075	.303	-.516	68	.607	-.11556	.22382	-.56218	.33107
	Equal variances not assumed			-.489	42.309	.628	-.11556	.23647	-.59267	.36155
C3_Dutifulness	Equal variances assumed	.544	.463	.058	68	.954	.00667	.11582	-.22445	.23778
	Equal variances not assumed			.058	51.088	.954	.00667	.11474	-.22368	.23701
C4_Achievement	Equal variances assumed	4.260	.043	-1.621	68	.110	-.25556	.15765	-.57014	.05903
	Equal variances not assumed			*-1.815*	*65.739*	*.074*	*-.25556*	*.14077*	*-.53663*	*.02552*
C5_SelfDiscipline	Equal variances assumed	.610	.438	.346	68	.730	.05222	.15085	-.24879	.35323
	Equal variances not assumed			.363	56.849	.718	.05222	.14390	-.23596	.34040
C6_Cautiousness	Equal variances assumed	2.234	.140	-1.467	68	.147	-.31111	.21200	-.73416	.11194
	Equal variances not assumed			-1.552	58.174	.126	-.31111	.20050	-.71242	.09020
N1_Anxiety	Equal variances assumed	2.555	.115	1.333	68	.187	.25889	.19419	-.12860	.64638
	Equal variances not assumed			1.230	39.393	.226	.25889	.21039	-.16654	.68432
N2_Anger	Equal variances assumed	2.361	.129	1.448	68	.152	.37889	.26171	-.14335	.90113
	Equal variances not assumed			1.506	55.650	.138	.37889	.25162	-.12524	.88302
N3_Depression	Equal variances assumed	.008	.927	.815	68	.418	.18667	.22916	-.27061	.64395
	Equal variances not assumed			.814	49.610	.420	.18667	.22931	-.27401	.64734
N4_SelfConsc	Equal variances assumed	.872	.354	.562	68	.576	.12111	.21550	-.30892	.55114
	Equal variances not assumed			.545	45.307	.589	.12111	.22239	-.32673	.56895
N5_Immoderation	Equal variances assumed	.156	.694	-.135	68	.893	-.02222	.16417	-.34981	.30536
	Equal variances not assumed			-.133	47.489	.895	-.02222	.16673	-.35754	.31310
N6_Vulnerability	Equal variances assumed	1.605	.209	1.410	68	.163	.29222	.20731	-.12146	.70590
	Equal variances not assumed			1.345	43.349	.185	.29222	.21720	-.14569	.73014
E1_Friendliness	Equal variances assumed	.242	.624	-.656	68	.514	-.11000	.16777	-.44478	.22478
	Equal variances not assumed			-.684	56.129	.497	-.11000	.16080	-.43210	.21210
E2_Gregarious	Equal variances assumed	.154	.696	-1.234	68	.221	-.25889	.20976	-.67746	.15968
	Equal variances not assumed			-1.237	50.008	.222	-.25889	.20933	-.67933	.16155

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
E3_Assertiveness	Equal variances assumed	1.253	.267	.071	68	.944	.01222	.17308	-.33315	.35759
	Equal variances not assumed			.067	43.156	.947	.01222	.18161	-.35399	.37844
E4_Activity	Equal variances assumed	.278	.599	-.792	68	.431	-.12778	.16135	-.44976	.19420
	Equal variances not assumed			-.802	51.520	.426	-.12778	.15939	-.44769	.19213
E5_ExcitementSeek	Equal variances assumed	2.187	.144	-.707	68	.482	-.11444	.16177	-.43726	.20837
	Equal variances not assumed			-.668	42.065	.508	-.11444	.17126	-.46005	.23116
E6_Cheerfulness	Equal variances assumed	.028	.867	-.945	68	.348	-.16222	.17175	-.50495	.18050
	Equal variances not assumed			-.964	52.682	.340	-.16222	.16836	-.49996	.17551
O1_Imagination	Equal variances assumed	.003	.958	-.928	68	.357	-.17889	.19281	-.56364	.20587
	Equal variances not assumed			-.940	51.653	.352	-.17889	.19030	-.56081	.20303
O2_ArtisticInterests	Equal variances assumed	1.406	.240	-1.670	68	.099	-.28778	.17228	-.63156	.05601
	Equal variances not assumed			-1.782	59.467	.080	-.28778	.16154	-.61096	.03540
O3_Emotionality	Equal variances assumed	.544	.463	1.065	68	.291	.15000	.14083	-.13102	.43102
	Equal variances not assumed			1.121	57.414	.267	.15000	.13385	-.11799	.41799
O4_Adventurous	**Equal variances assumed**	**.198**	**.657**	**-2.713**	**68**	**.008****	**-.52222**	**.19245**	**-.90626**	**-.13819**
	Equal variances not assumed			-2.663	47.044	.011	-.52222	.19608	-.91668	-.12776
O5_Intellect	**Equal variances assumed**	**.032**	**.859**	**-1.950**	**68**	**.055***	**-.37222**	**.19090**	**-.75316**	**.00872**
	Equal variances not assumed			-1.940	48.974	.058	-.37222	.19187	-.75780	.01336
O6_Liberalism	*Equal variances assumed*	*.415*	*.522*	*-1.883*	*68*	*.064*	*-.28000*	*.14870*	*-.57673*	*.01673*
	Equal variances not assumed			-1.947	54.777	.057	-.28000	.14378	-.56817	.00817
A1_Trust	Equal variances assumed	.193	.662	-.762	68	.449	-.14889	.19541	-.53882	.24104
	Equal variances not assumed			-.768	50.820	.446	-.14889	.19394	-.53826	.24049
A2_Morality	Equal variances assumed	.026	.872	-.816	68	.417	-.11667	.14293	-.40187	.16854
	Equal variances not assumed			-.834	52.983	.408	-.11667	.13983	-.39713	.16379
A3_Altruism	Equal variances assumed	.000	.995	.496	68	.621	.05667	.11423	-.17127	.28461
	Equal variances not assumed			.495	49.369	.623	.05667	.11449	-.17337	.28671
A4_Cooperation	Equal variances assumed	.279	.599	-.941	68	.350	-.16111	.17130	-.50294	.18072
	Equal variances not assumed			-.990	57.422	.327	-.16111	.16281	-.48707	.16485
A5_Modesty	Equal variances assumed	1.556	.216	-.981	68	.330	-.18889	.19255	-.57312	.19534
	Equal variances not assumed			-.919	41.085	.363	-.18889	.20554	-.60395	.22617

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
A6_Sympathy	Equal variances assumed	1.448	.233	1.244	68	.218	.20111	.16164	-.12144	.52366
	Equal variances not assumed			1.163	40.865	.251	.20111	.17287	-.14803	.55026

Statistically significant different distributions across groups are in bold [***correlation is significant at the 0.001 level (2 tailed); *correlation is significant at the 0.05 level (2 tailed)]. Nearly significant different distributions (p-value close to 0.05) are in italics and underlined.

Table E-B.6. Comparison statistics for groups 1 (<5 min) and 2 (≥5 min) across different metrics in the TT game.

	Group	N	Mean	Std. Deviation	Std. Error Mean
HardCoins	1	45	,269	,302	,045
	2	25	,850	,195	,039
TotalCoins	1	45	,405	,258	,038
	2	25	,895	,158	,032
Diamonds	1	45	,530	,968	,144
	2	25	2,00	,645	,129
Time	1	45	180,60	60,854	9,072
	2	25	377,52	110,263	22,053
Score	1	45	498,44	373,253	55,641
	2	25	1149,00	225,040	45,008
Trophies	1	45	,51	,920	,137
	2	25	1,84	,746	,149

Table E-B.7. Independent samples t-test comparing the personality traits' scores across groups 0 (no trophies won) and 1 (one of the trophies won) in the TT game.

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
C1_SelfEfficacy	Equal variances assumed	,005	,944	-0,439	68	0,662	-0,066	0,150	-0,366	0,234
	Equal variances not assumed			-0,437	66	0,663	-0,066	0,151	-0,367	0,235
C2_Order	Equal variances assumed	,036	,849	-0,394	68	0,695	-0,085	0,215	-0,514	0,344
	Equal variances not assumed			-0,394	67	0,695	-0,085	0,215	-0,514	0,345
C3_Dutifulness	Equal variances assumed	,201	,655	0,092	68	0,927	0,010	0,111	-0,212	0,232
	Equal variances not assumed			0,093	67	0,926	0,010	0,110	-0,209	0,229
C4_Achievement	Equal variances assumed	1,584	,212	-0,178	68	0,859	-0,027	0,154	-0,335	0,280
	Equal variances			-0,175	60	0,861	-0,027	0,157	-0,341	0,286

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
	not assumed									
C5_SelfDiscipline	Equal variances assumed	1,224	,273	0,568	68	0,572	0,082	0,145	-0,206	0,371
	Equal variances not assumed			0,561	62	0,577	0,082	0,146	-0,210	0,375
C6_Cautiousness	Equal variances assumed	,924	,340	-1,392	68	0,168	-0,284	0,204	-0,690	0,123
	Equal variances not assumed			-1,380	64	0,172	-0,284	0,206	-0,695	0,127
N1_Anxiety	**Equal variances assumed**	**1,345**	**,250**	**1,972**	**68**	**,053***	**0,362**	**0,184**	**-0,004**	**0,729**
	Equal variances not assumed			1,995	68	0,050	0,362	0,182	0,000	0,725
N2_Anger	**Equal variances assumed**	**2,898**	**,093**	**2,997**	**68**	**,004****	**0,718**	**0,240**	**0,240**	**1,197**
	Equal variances not assumed			2,979	65	0,004	0,718	0,241	0,237	1,200
N3_Depression	*Equal variances assumed*	*2,806*	*,099*	*1,889*	*68*	*0,063*	*0,407*	*0,215*	*-0,023*	*0,837*
	Equal variances not assumed			1,867	62	0,067	0,407	0,218	-0,029	0,843
N4_SelfConsc	Equal variances assumed	,158	,693	1,420	68	0,160	0,290	0,204	-0,118	0,698
	Equal variances not assumed			1,426	68	0,158	0,290	0,203	-0,116	0,696
N5_Immoderation	Equal variances assumed	,088	,767	0,500	68	0,619	0,079	0,157	-0,235	0,393
	Equal variances not assumed			0,497	65	0,621	0,079	0,158	-0,237	0,394
N6_Vulnerability	*Equal variances assumed*	*,178*	*,675*	*1,851*	*68*	*0,068*	*0,365*	*0,197*	*-0,028*	*0,758*
	Equal variances not assumed			1,857	68	0,068	0,365	0,196	-0,027	0,757
E1_Friendliness	Equal variances	,777	,381	-1,740	68	0,086	-0,275	0,158	-0,590	0,040

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
	assumed									
	Equal variances not assumed			-1,724	63	0,090	-0,275	0,159	-0,594	0,044
E2_Gregarious	Equal variances assumed	,715	,401	-0,940	68	0,350	-0,190	0,202	-0,594	0,213
	Equal variances not assumed			-0,934	65	0,354	-0,190	0,204	-0,597	0,216
E3_Assertiveness	Equal variances assumed	,786	,378	0,609	68	0,544	0,101	0,166	-0,230	0,432
	Equal variances not assumed			0,617	67	0,540	0,101	0,164	-0,226	0,428
E4_Activity	Equal variances assumed	,515	,475	0,262	68	0,794	0,041	0,156	-0,270	0,351
	Equal variances not assumed			0,260	65	0,795	0,041	0,156	-0,272	0,353
E5_Excitement Seek	Equal variances assumed	2,117	,150	-0,975	68	0,333	-0,151	0,155	-0,460	0,158
	Equal variances not assumed			-0,983	68	0,329	-0,151	0,153	-0,457	0,155
E6_Cheerfulness	**Equal variances assumed**	**,386**	**,536**	**-2,115**	**68**	**,038***	**-0,340**	**0,161**	**-0,661**	**-0,019**
	Equal variances not assumed			-2,099	64	0,040	-0,340	0,162	-0,663	-0,016
O1_Imagination	Equal variances assumed	,416	,521	-0,641	68	0,524	-0,119	0,186	-0,489	0,252
	Equal variances not assumed			-0,644	68	0,522	-0,119	0,185	-0,488	0,250
O2_ArtisticInterests	Equal variances assumed	,311	,579	-0,742	68	0,461	-0,125	0,168	-0,460	0,211
	Equal variances not assumed			-0,736	64	0,465	-0,125	0,169	-0,463	0,214
O3_Emotionality	Equal variances assumed	1,409	,239	1,263	68	0,211	0,170	0,135	-0,099	0,439
	Equal variances not assumed			1,244	60	0,219	0,170	0,137	-0,104	0,444

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
	med									
O4_Adventurous	**Equal variances assumed**	**,149**	**,701**	**-2,879**	**68**	**,005****	**-0,529**	**0,184**	**-0,895**	**-0,162**
	Equal variances not assumed			-2,887	68	0,005	-0,529	0,183	-0,894	-0,163
O5_Intellect	Equal variances assumed	,054	,817	-0,766	68	0,447	-0,144	0,187	-0,518	0,231
	Equal variances not assumed			-0,768	68	0,445	-0,144	0,187	-0,516	0,229
O6_Liberalism	Equal variances assumed	,201	,655	-0,510	68	0,612	-0,075	0,146	-0,366	0,217
	Equal variances not assumed			-0,511	68	0,611	-0,075	0,146	-0,366	0,217
A1_Trust	**Equal variances assumed**	**,195**	**,660**	**-1,995**	**68**	**,050***	**-0,365**	**0,183**	**-0,731**	**0,000**
	Equal variances not assumed			-1,993	67	0,050	-0,365	0,183	-0,731	0,001
A2_Morality	Equal variances assumed	,336	,564	-0,198	68	0,844	-0,027	0,138	-0,302	0,248
	Equal variances not assumed			-0,197	67	0,844	-0,027	0,138	-0,303	0,248
A3_Altruism	Equal variances assumed	,266	,608	-0,461	68	0,646	-0,051	0,110	-0,269	0,168
	Equal variances not assumed			-0,460	66	0,647	-0,051	0,110	-0,270	0,169
A4_Cooperation	Equal variances assumed	,484	,489	-1,765	68	0,082	-0,286	0,162	-0,609	0,037
	Equal variances not assumed			-1,740	60	0,087	-0,286	0,164	-0,614	0,043
A5_Modesty	Equal variances assumed	1,908	,172	0,682	68	0,497	0,127	0,186	-0,244	0,497
	Equal variances not assumed			0,691	67	0,492	0,127	0,183	-0,239	0,492
A6_Sympathy	Equal variances assumed	,361	,550	1,258	68	0,213	0,195	0,155	-0,114	0,505

	Levene's Test for Equality of Variances		t-test for Equality of Means						
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
Equal variances not assumed			1,266	68	0,210	0,195	0,154	-0,112	0,503

Statistically significant different distributions across groups are in bold [**correlation is significant at the 0.01 level (2 tailed); *correlation is significant at the 0.05 level (2 tailed)]. Nearly significant different distributions (p-value close to 0.05) are in italics and underlined.

Table E-B.8. TT game's Trophies independent-samples Kruskal-Wallis test comparing groups 0 and 1 (0 – no trophies won; 1 – one type of trophy won)

	Null Hypothesis	Sig.	Decision
1	The distribution of C1_SelfEfficacy is the same across categories of AT01_trophies.	,895	Retain the null hypothesis.
2	The distribution of C2_Order is the same across categories of AT01_trophies.	,936	Retain the null hypothesis.
3	The distribution of C3_Dutifulness is the same across categories of AT01_trophies.	,668	Retain the null hypothesis.
4	The distribution of C4_Achievement is the same across categories of AT01_trophies.	,376	Retain the null hypothesis.
5	The distribution of C5_SelfDiscipline is the same across categories of AT01_trophies.	,686	Retain the null hypothesis.
6	The distribution of C6_Cautiousness is the same across categories of AT01_trophies.	,294	Retain the null hypothesis.
7	The distribution of N1_Anxiety is the same across categories of AT01_trophies.	,309	Retain the null hypothesis.
8	**The distribution of N2_Anger is the same across categories of AT01_trophies.**	**,033***	**Reject the null hypothesis.**
9	The distribution of N3_Depression is the same across categories of AT01_trophies.	,430	Retain the null hypothesis.
10	The distribution of N4_SelfConsc is the same across categories of AT01_trophies.	,258	Retain the null hypothesis.
11	The distribution of N5_Immoderation is the same across categories of AT01_trophies.	,853	Retain the null hypothesis.
12	The distribution of N6_Vulnerability is the same across categories of AT01_trophies.	,253	Retain the null hypothesis.
13	The distribution of E1_Friendliness is the same across categories of AT01_trophies.	,276	Retain the null hypothesis.
14	The distribution of E2_Gregarious is the same across categories of AT01_trophies.	,279	Retain the null hypothesis.
15	The distribution of E3_Assertiveness is the same across categories of AT01_trophies.	,291	Retain the null hypothesis.
16	The distribution of E4_Activity is the same across categories of AT01_trophies.	,174	Retain the null hypothesis.
17	**The distribution of E5_ExcitementSeek is the same across categories of AT01_trophies.**	**,004****	**Reject the null hypothesis.**
18	**The distribution of E6_Cheerfulness is the same across categories of AT01_trophies.**	**,020***	**Reject the null hypothesis.**
19	The distribution of O1_Imagination is the same across categories of AT01_trophies.	,309	Retain the null hypothesis.
20	The distribution of O2_ArtisticInterests is the same across categories of AT01_trophies.	,954	Retain the null hypothesis.
21	The distribution of O3_Emotionality is the same across categories of AT01_trophies.	,464	Retain the null hypothesis.
22	**The distribution of O4_Adventurous is the same across categories of AT01_trophies.**	**,033***	**Reject the null hypothesis.**
23	The distribution of O5_Intellect is the same across categories of AT01_trophies.	,101	Retain the null hypothesis.
24	The distribution of O6_Liberalism is the same across categories of AT01_trophies.	,713	Retain the null hypothesis.
25	The distribution of A1_Trust is the same across categories of AT01_trophies.	,131	Retain the null hypothesis.
26	The distribution of A2_Morality is the same across categories of AT01_trophies.	,945	Retain the null hypothesis.
27	The distribution of A3_Altruism is the same across categories of AT01_trophies.	,962	Retain the null hypothesis.
28	The distribution of A4_Cooperation is the same across categories of AT01_trophies.	,380	Retain the null hypothesis.
29	The distribution of A5_Modesty is the same across categories of AT01_trophies.	,233	Retain the null hypothesis.
30	The distribution of A6_Sympathy is the same across categories of AT01_trophies.	,723	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is 0.05. Statistically significant different distributions across the groups are in bold [**correlation is significant at the 0.01 level (2 tailed); *correlation is significant at the 0.05 level (2 tailed)].