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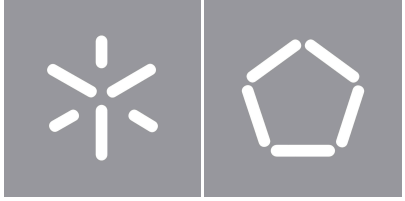
Human Well-being Monitoring: Intelligent Techniques application for improved Accuracy and Privacy

September, 2024

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UMinho | 2024



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Human Well-being Monitoring: Intelligent Techniques application for improved Accuracy and Privacy

Doctoral Thesis
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Work supervised by
Paulo Jorge Freitas de Oliveira Novais

September, 2024

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Statement of Integrity

I hereby declare having conducted this academic work with integrity.

I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration.

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University of Minho, Braga, september 2024

Filipe Manuel Carvalho Rodrigues Bravo Gonçalves

"Success is not the key to happiness. Happiness is the key to success. If you love what you are doing, you will be successful."

—Albert Schweitzer

Abstract

In today's society, there is a compelling need for innovative solutions to pressing issues, such as understanding performance fluctuations in individuals during complex and demanding tasks. In such situations, individuals face increasing performance demands, leading to constant pressure and consequently resulting in variations in their stress levels. As such, the capacity to monitor and manage an individual's psychological state is essential for maintaining well-being and optimising performance, particularly in high-stakes environments like education and workplace environments.

To address this challenge, this thesis explores academic stress monitoring through digital technologies and proposes a non-invasive performance monitoring framework that analyses behavioural biometric patterns from students' interactions with peripheral devices during online exams. Additionally, anonymisation methodologies are integrated to prevent the invasiveness of user-sensitive data and to comply with privacy, ethical and legal issues under general data protection regulations. The research uses data-driven approaches based on statistical analysis and Machine Learning techniques to analyse interaction data from students' use of peripheral devices. Applied in e-learning environments, the goal is to assess students' stress levels and provide timely and personalised stress-coping interventions to enhance their well-being and performance.

The research shows that stress significantly affects students' interaction patterns with computers during high-stakes exams. This insight supports the development of digital methods to assess and monitor mental stress in academic settings. Additionally, the study demonstrates the feasibility of implementing real-time prediction models for stress monitoring in e-learning platforms. The proposed framework also has potential applications in other domains, such as workplace environments, though further studies are required to address the unique characteristics of these settings.

Keywords Ambient Intelligence, Behavioural Biometrics, E-Learning, Mental Stress, Performance

Resumo

Na sociedade atual, existe uma necessidade urgente de soluções inovadoras para questões críticas, como a compreensão das flutuações de desempenho em indivíduos durante tarefas complexas. Nestas situações, os indivíduos enfrentam exigências crescentes de desempenho, levando a uma pressão constante e consequentemente a variações nos seus níveis de stress. Assim, a capacidade de monitorizar e gerir o estado psicológico de um indivíduo é essencial para manter o bem-estar e otimizar o seu desempenho.

Para abordar este desafio, esta tese explora a monitorização do stress académico através de tecnologias digitais e propõe um sistema de monitorização de desempenho não invasivo que analisa padrões biométricos comportamentais a partir das interações dos estudantes com dispositivos periféricos durante exames online. Adicionalmente, metodologias de anonimização são integradas para prevenir a invasividade de dados sensíveis dos utilizadores e garantir o cumprimento das questões de privacidade, éticas e legais ao abrigo do regulamento geral de proteção de dados. A investigação utiliza abordagens baseadas em dados, através de técnicas de análise estatística e aprendizagem automática para analisar os dados de interação proveniente do uso de dispositivos periféricos pelos estudantes. Aplicado em ambientes de ensino eletrónico, o objetivo passa por avaliar os níveis de stress dos estudantes e fornecer intervenções personalizadas e oportunas para lidar com o stress, melhorando o seu bem estar e desempenho.

A investigação revela que o stress afeta os padrões de interação dos estudantes com computadores em exames de alta pressão, apoiando o desenvolvimento de métodos digitais para monitorização do stress académico. O estudo também demonstra a viabilidade de modelos de previsão em tempo real em plataformas de ensino eletrónico, com possíveis aplicações em ambientes de trabalho, embora sejam necessários mais estudos.

Palavras-chave Biometria Comportamental, Ensino Eletrónico, Inteligência Ambiente, Performance, Stress Mental

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Acronyms

AAL Ambient Assisted Living

AI Artificial Intelligence

AmI Ambient Intelligence

ANS Autonomic Nervous System

APA American Psychological Association

APU Application Percentage Usage

BP Blood Pressure

CD Click Duration

CDMR Correct Decision-Making Ratio

CNN Convolutional Neural Network

CV Computer Vision

DBC Distance Between Clicks

DDC Duration Distance Clicks

DL Deep Learning

DMSL Distance of the Mouse to the Straight Line

DNN Deep Neural Network

DT Decision Tree

ECG Electrocardiogram

EDA Electro-dermal Activity

EDBC Excess of Distance Between Clicks

EEG Electroencephalogram

EMA Ecological Momentary Assessment

EMG Electromyography

fMRI Functional Magnetic Resonance Imaging

GDPR General Data Protection Regulation

GSR Galvanic Skin Response

GUI Graphical User Interface

HCI Human-Computer Interaction

HR Heart Rate

IEMOCAP Interactive Emotional Dyadic Motion Capture

IoT Internet of Things

ISLab Synthetic Intelligence Laboratory

IT Information Technology

ITS Intelligent Tutoring System

KDD Knowledge Discovery in Databases

KDT Key Down Time

KLT Kanade-Lucas-Tomasi

KNN K-Nearest Neighbour

LiDAR Light Detection and Ranging

LIWC Linguistic Inquiry and Word Count

LogR Logistic Regression

LR Linear Regression

LSTM Long Short-Term Memory

MA Mouse Acceleration

ML Machine Learning

MLP Multilayer Perceptron

MSE Mean Squared Error

MV Mouse Velocity

NB Naive Bayes

NLP Natural Language Processing

NN Neural Networks

NSE Natural Stress Emotion

OWL Ontology Web Language

PAD Pleasure, Arousal, and Dominance

PNS Parasympathetic Nervous System

PPG Photoplethysmography

PSQ Perceived Stress Questionnaire

PSS Perceived Stress Scale

RF Random Forest

RFID Radio Frequency Identification

RMSE Root Mean Squared Error

ROSE Random Oversampling Examples

RSSI Received Signal Strength Indicator

SMOTE Synthetic Minority Oversampling Tech.

SNS Sympathetic Nervous System

SRI Stress Response Inventory

SSP Social Signal Processing

SVM Support Vector Machine

TBD Time Between Decision

TBK Time Between Keys

TSST Trier Social Stress Test

UCD User-centred Design

VADER Valence Aware Dictionary and sEntiment Reasoner

WESAD Wearable Stress and Affective State Detection

XGB eXtreme Gradient Boosting

Chapter 1

Introduction

"Science knows no country, because knowledge belongs to humanity, and is the torch which illuminates the world."

—Louis Pasteur

In the rapidly evolving field of Computer Science, the intersection of technology and human well-being has become a major field of research. This thesis, entitled *Human Well-being Monitoring: Intelligent Techniques application for improved Accuracy and Privacy*, is a research project that aims to address the challenges of human well-being monitoring through non-invasive and non-intrusive means in e-learning environments. By leveraging **Artificial Intelligence (AI)** techniques and interdisciplinary approaches, this research contributes to the advancement of technologies that not only respect the privacy of its users but also provide insights into their psychological well-being, covering different domains of Computer Science such as Intelligent Systems, Software and Engineering, **Human-Computer Interaction (HCI)**, Affective Computing and Data Science.

This initial chapter introduces the basis for understanding the important role of assessing and monitoring human well-being, addressing its physiological and psychological aspects. It highlights the technological advancements in biometric and socially intelligent systems, which supports this research's motivation. The research's approach is also described, setting clear expectations for the study's scope and direction. Based on this information, a brief overview of the methodologies applied to tackle the research questions is provided, delivering an understanding of this research's proposed operational framework. Furthermore, the chapter assesses the potential impacts and contributions of the research, highlighting its importance and practical applications. Finally, the document's structure overview is presented, ensuring ease of navigation through the next chapters.

1.1 Context and Motivation

Intelligent sensing technologies are revolutionising how humans interact with machines, making biometric methods like facial recognition and fingerprint scanning the norm for tasks as routine as unlocking smartphones [1]. In healthcare, wearable devices use biometrics to monitor patient health metrics in real-time, facilitating personalised medical care [2]. Smart home systems employ voice and facial recognition to offer users a seamless and interactive experience, controlling devices based on the homeowner's preferences and commands [2]. For access control, biometric systems based on voice, fingerprint and iris scans secure entry to restricted zones, ensuring that only authorised individuals can enter sensitive or secured spaces [3]. In addition, highly populated countries are also developing vast national identity networks based on biometric data to improve public services, urban management and security [4].

The evolution of cognitive abilities and brain structures, influenced by the need for social interaction, emphasises the need for developing socially intelligent machines. This shift from computers being merely enhanced versions of old tools (*e.g.*, word processors replacing typewriters) to becoming integral social entities in everyday life emphasises the demand for **Social Signal Processing (SSP)**. **SSP** is instrumental in fostering social intelligence within machines, aiming to understand and mimic nonverbal signals such as facial expressions, gestures, and postures, which are necessary for engaging properly in social interactions [5]. From a social psychology perspective, social signals encompass behaviours intended to invite others into a collective activity, typically communication. These signals share informative cues that provide insights into social dynamics, such as social interactions, emotions, evaluations, attitudes, and relationships. By automating the recognition and generation of these nonverbal signals, **SSP** aims to equip machines with the capacity to interpret and express socially relevant information, fostering more natural and meaningful **HCI**s [5, 6].

The emphasis on understanding and responding to human emotions and social signals is particularly pertinent in managing stress. Stress is described as the physical and psychological reactions that occur to respond to a demanding challenge changing an organism's environment [7]. In today's high-pressure scenarios, where competitive societies engage in complex and high-risk tasks, assessing an individual's psychological stress levels is crucial for enhancing mental health and performance, especially in contexts where the boundaries of individual and team capabilities are continually being expanded [8]. The increasing demand for performance drives individuals to constant pressure, and prolonged exposure to stress-inducing factors can lead to emotional exhaustion (*e.g.*, burnout), mental disorders (*e.g.*, depression, chronic stress and subsequently chronic diseases) or even risk of suicide, with potential consequences

at the personal and professional lives, family relations, social interactions and economic status. Stressful settings are prevalent across various aspects of life, including workplace or academic environments [9, 10].

This research focuses on academic stress markers, highlighting how students perceive the vast amount of required knowledge and the lack of time to assimilate it, significantly contributing to heightened stress levels. According to Abouserie [11], *"students report experiencing academic stress at predictable times each semester with the greatest sources of stress resulting from taking and studying for exams, grade competition, and a large amount of content to master in a small amount of time"*. Consequently, this often causes a high occurrence of anxiety disorders among college students.

This growing concern emphasises the need for innovative approaches to stress monitoring that are both non-invasive and scalable. The proposed research aims to transcend traditional methods by leveraging technology to analyse behavioural biometric data, which can offer immediate, actionable insights without the drawbacks associated with more intrusive techniques. By focusing specifically on the academic environment, this project seeks to validate a prediction model that could be applied across various high stress professions. Ultimately, this thesis aims to enhance academic performance and well-being among students and to pioneer stress management techniques that could revolutionise how individuals manage stress in any high-demand environment, thereby improving overall quality of life.

1.2 Thesis Statement

The interest in developing non-invasive and non-intrusive systems that blend into our environments is growing within the **Ambient Intelligence (AmI)**, affective computing and **Intelligent Tutoring System (ITS)** domains. This aspiration is becoming increasingly achievable thanks to advancements in ubiquitous computing, communication, **Internet of Things (IoT)**, big data technologies, and smart user interfaces [12]. At the core of this progress lies the key role of intelligent systems, which contemplates a spectrum of **AI** strategies, tools, and principles, focusing on prioritising the adoption of data collection and predictive analytics methodologies to improve problem-solving, enhance user experience, ensure operational efficiency and maintain a commitment to user safety and data security [13].

The proposed research extends these principles into the specific domain of stress assessment and monitoring focusing on academic settings in a non-invasive and non-intrusive way. This study hypothesises that it's possible to determine and proactively address psychological stress by analysing behavioural biometric patterns, particularly through the interaction with standard peripheral devices like computer mice or key-

boards during online academic exams. To further elaborate, non-invasive approaches refer to methods that avoid interfering with the user's natural behaviour and use only non-sensitive data, ensuring the integrity of collected data, while non-intrusive approaches refer to methods that avoid extracting biomarker samples (*e.g.*, blood, saliva, urine, etc.) or cause discomfort to the user. Within this research, analysing how a student interacts with the computer standard devices during an online exam embodies both these characteristics. By examining behavioural variables such as cursor speed, click rates, the time between decisions, typing speed and interaction patterns, the system can infer mental stress levels without requiring any direct involvement or changes to the normal procedure.

This doctoral research highlights that informed decisions, enabled by an awareness of behavioural biometric and cognitive stress indicators, can result in more favourable outcomes for all individuals involved in the education domain. As such, this thesis attempts to validate the research hypothesis:

Research Hypothesis

Mental stress can be monitored by analysing changes in student's cognitive and behavioural patterns through non-invasive and non-intrusive methods, to improve online assessment processes.

This research hypothesis is derived from the research questions and aligned with its objectives and tasks, described in Chapter 3. Abstracting the research hypothesis into a straightforward statement that encapsulates this study's core argument produces the following thesis statement:

Thesis Statement

This research demonstrated that monitoring variations in students' behavioural biometric and cognitive engagement during online exams can serve as an early warning mechanism to assess mental stress, offering a non-invasive and non-intrusive approach for responsive and personalised stress-coping interventions.

Given the potential impact of mental stress on academic performance, this research aims to equip educators and students with a framework that supports better decision-making regarding when to intervene or adopt stress-coping strategies. The proposed framework's non-invasive and non-intrusive nature ensures that it respects the privacy and comfort of the users. It achieves this by analysing broad patterns of mouse

and keyboard usage and decision-making events within the e-learning platform, avoiding the analysis of personal or sensitive data.

1.3 Research Approach

As mentioned previously, the concept of stress refers to the physical and psychological responses that arise when an organism faces a challenging stimulus that alters its environment [14]. Understanding an individual's physiological stress level is an important factor for managing performance in today's high-pressure scenarios [15]. Prolonged exposure to stress, particularly in complex and highly demanding roles can lead to severe consequences such as emotional exhaustion and mental disorders. Furthermore, stressful environments are everywhere, from professional workplaces to academic settings [16, 17]. Within the academic environment, stress is significantly influenced by the student's perception of the vast amount of knowledge required and the insufficient time available to absorb this information, contributing to a high rate of anxiety disorders among them [11].

Current stress monitoring approaches often rely on expensive and complex equipment, making them difficult to scale and integrate into student environments without disrupting daily activities [14]. These methods face additional challenges, including low accuracy rates that may misinterpret stress levels, the obtrusive nature of tools like **Electroencephalogram (EEG)** headsets and body strap sensors, and the necessity of specialised personnel for data handling [15]. Moreover, their limited capability for real-time monitoring restricts the timely implementation of stress-mitigation strategies, complicating the assessment and intervention processes [18].

Following an action-research based methodology [19] (further discussed in Chapter 3), this thesis addresses these challenges by proposing a distributed system to monitor user's behaviour for stress assessment, with a particular focus on analysing students' computer interactions within the e-learning platform. It aims to explore how stress affects performance in demanding contexts, such as online exams, by assessing students' mouse and keyboard interaction efficiency and decision-making processes [20] (more details are presented in Chapter 4). This approach, which incorporates considerations for data privacy and ethical standards, seeks to offer a practical stress marker for widespread use among university students, thereby minimising disruptions to their daily routines. By understanding the impact of stress on each individual, this study intends to improve personalised teaching approaches and equip students with customised coping strategies, fostering the growth of better-trained professionals.

1.4 Significance of the Study

This research project pushes the boundaries of stress assessment by adopting non-invasive methodologies and technologies that respect user privacy while monitoring psychological states. By integrating behavioural biometrics with cognitive data analytics, this thesis presents an alternative approach to understanding and supporting students with high levels of mental stress.

Key to this research is the development of a scalable system that applies **AI** techniques to process and analyse large volumes of behavioural and cognitive data in real-time. Also, the system's capability for continuous stress monitoring enables the development of customised and quick interventions designed to mitigate stress and improve student performance.

The study also researches the use of behavioural biometrics beyond its conventional role in security, venturing into mental health monitoring and academic performance. This shift is significant as it leverages existing behavioural biometric data to assess stress levels without additional intrusive measures, thus maintaining user comfort and trust. By correlating these biometric indicators with academic performance, the research provides an understanding of how stress affects learning and offers a methodological framework for other educational institutions to implement similar stress assessment systems.

Moreover, the research's contribution to academic knowledge includes **AI** algorithms that predict stress levels and learning outcomes. These models are validated against established psychological scales (*e.g.*, **Perceived Stress Scale (PSS)** self-questionnaire) and physiological markers (*e.g.*, salivary cortisol levels), ensuring their reliability and significance. As these tools and methodologies are refined, they promise to revolutionise how educational systems understand and address the psychological needs of their students.

This thesis also delivers practical applications that can be directly implemented in educational settings worldwide. The potential for these methodologies to improve student engagement, reduce stress, and foster better educational outcomes reveals how educational institutions can support their students in increasingly digital and remote learning environments.

1.5 Document Structure

This section provides an overview of the chapters within this document, as a way to guide readers through the logical progression of the research. The document structure is composed of six chapters, each focusing on specific aspects of the research scope:

- **Chapter 1 "Introduction":** This chapter introduces the context and motivation driving the research, emphasising the importance of monitoring human well-being. It presents the research hypothesis and thesis statement, clarifies the methodology employed and discusses this work's contribution to the scientific community;

- **Chapter 2 "Background and Prior Art":** The chapter covers topics such as **AmI** and behavioural analysis, **HCI**, affective computing and explores the intersection between **AI** and mental stress monitoring, including the analysis of existing research projects. The chapter concludes by summarising the discussed themes;

- **Chapter 3 "Conceptualisation of the Research Problem":** The chapter presents the research framework for the doctoral programme, beginning with the definition of the problem statement and goals. It details the hypotheses and questions driving the research, breaks them down into objectives and tasks, and describes the strategic plan and roadmap for the research's execution. Additionally, it includes information on the research team and host institution and tasks undertaken during the doctoral programme. The last section summarises the main themes discussed throughout the chapter;

- **Chapter 4 "A Stress Monitoring Tool for E-learning Environments":** This chapter covers key aspects and perspectives concerning mental stress and its effects, evaluates existing stress assessment tools along with their limitations and explores established stress-coping mechanisms to manage high levels of stress. Furthermore, it proposes a stress assessment framework for e-learning environments by presenting its architecture, data workflow pipeline and database structure, providing details on data collection, anonymisation and preparation procedures. Additionally, the chapter describes the main behavioural biometric and cognitive features considered for this study;

- **Chapter 5 "Experiments Performed and Analysis of Results":** The chapter explores students' stress assessment within e-learning environments across different student demographics. It begins with analysing the collected and prepared datasets, followed by experiments to develop and evaluate stress assessment models that analyse behavioural biometric and cognitive patterns observed during e-exams. Building on this approach, the focus then shifts to assessing students' attentiveness, also based on behavioural biometric patterns and academic performance, where the effectiveness of e-learning systems is linked to student preferences and engagement strategies. The chapter concludes by summarising the key insights verified from these experiments and discusses their potential to enhance learning outcomes;

- **Chapter 6 “Conclusions”:** The final chapter summarises the main findings from this thesis. It highlights its key contributions, the dissemination of results and outlines potential future research directions in these domains;

Chapter 2

Background and Prior Art

"The important thing is not to stop questioning. Curiosity has its own reason for existing."

—Albert Einstein

This chapter explores the intersection between Education Systems, Digital Technologies, **AmI**, **HCI**, Affective Computing and **AI** in interpreting the user's affective and mental state. Furthermore, it analyses **AI**-based stress detection and monitoring systems, exploring state-of-the-art projects that address this challenge in a non-intrusive and non-invasive way, through various input modalities such as wearable sensors, mouse and keyboard inputs, and text analysis. The aim is to provide an overview of how these technologies improve user interaction, including an analysis of available public datasets, methods for data collection, annotation, preparation, **AI**-based prediction techniques, evaluation metrics and overall performance.
This study provides valuable knowledge for refining this thesis's proposed framework and methods by identifying the strengths and weaknesses of current state-of-the-art technologies.

2.1 Intersection of Ambient Intelligence, Education Systems and Affective Computing

The intersection of **AmI**, Education and Affective Computing represents an important advancement in the improvement of educational environments and in fostering student development [21–24]. **AmI** emerged from the convergence of ubiquitous computing, **AI** and sensor networks, where the concept gained momentum in the early 2000s, with the vision of creating environments that respond intelligently and adaptively to the presence and needs of users [12, 25].
As **AmI** evolved, its application in education became a natural progression, enabling the creation of re-

sponsive, personalised and context-aware learning environments [22, 23]. These technologies improve the educational experience by delivering adaptive content, providing real-time feedback and designing smart classrooms that support active learning and increase student engagement [22]. By monitoring and responding to students' emotional states, **AmI** promotes a supportive environment for mental and emotional well-being [12, 25].

In summary, the synergy between these domains offers transformative potential in shaping future educational paradigms. This section provides a background overview which is further elaborated, focusing on its definition, technological integration and the well-being benefits that these technologies can bring to our daily lives.

2.1.1 Education Systems and Digital Technologies

Education has been fundamental to civilisation since ancient times, evolving from informal oral traditions and apprenticeships to structured learning in schools and universities, continuously adapting to societal changes and needs, reflecting cultural, social and economic developments [21, 26, 27]. In the last decades, modern technologies have further advanced education through e-learning systems and intelligent tutoring tools, offering numerous advantages such as promoting personalised learning experiences, increasing student engagement and performance, and making educational content more accessible [22]. Furthermore, the global pandemic caused by the coronavirus (*i.e.*, COVID-19) and the response of several institutions around the world have reinforced the need to improve digital skills among teachers and students, thus demonstrating the relevance of technological tools and highlighting the advantages and limitations of each education system [23].

In this context, learning is defined as the process by which individuals acquire knowledge, skills, and values through experiences, studies, or teachings, involving cognitive, emotional and environmental factors [24, 28]. Learning includes the assimilation of information and the capacity to apply this knowledge across various contexts, leading to changes in an individual's behaviour and thought processes [29]. It is a flexible and continuous process that occurs formally in educational settings or informally through daily interactions, enhancing individuals' comprehension, retention, and practical application [24, 29]. Furthermore, learning outcomes are influenced by several factors, including attention, fatigue, anxiety, depression, emotions, and stress. These factors can significantly impact a student's ability to focus, retain information, and perform well academically [30–33]. More specifically, attention is essential as it affects the ability to concentrate and retain information [30], while fatigue can reduce cognitive functions and learning efficiency [33]. Anxiety can create barriers to learning by causing distractions and decreasing

cognitive resources [33]. Depression can lead to reduced motivation and concentration, and impaired cognitive functions, all of which interfere with academic performance [33]. Emotions are also important, with positive emotions improving engagement and information retention, whereas negative emotions can obstruct learning processes [31, 32]. Stress, if not managed properly, can negatively affect memory and cognitive functions, reducing academic performance [32].

It is necessary to recognise that traditional classroom learning and e-learning also impact learning outcomes differently, each offering unique benefits and drawbacks [34, 35]. For example, traditional classrooms offer structured environments that can reduce anxiety but increase fatigue due to long hours of attendance. They support social development and collaborative learning through face-to-face interactions and immediate feedback but are limited by location, fixed schedules, and a standardised pace that may not suit all students [36]. As for e-learning, this approach relies on digital technologies to offer flexibility and accessibility, allowing students to learn from any location at any time, accommodating different schedules and learning styles, and reducing stress from travel and fixed schedules [37]. These methods often include interactive elements like multimedia resources (*e.g.*, digital documents, websites, audio and video recordings) and virtual discussions (*e.g.*, forums, chat rooms, video conferences), improving students' engagement and understanding and supporting them on continuous assessment and feedback, helping track learning progress and identify areas for improvement [37]. However, e-learning can increase the sense of loneliness and unease due to less direct social interaction and may face challenges such as unequal access to technology (*e.g.*, high-speed internet access or specific software or hardware equipment) and differences in self-motivation, concentration and time management skills (*e.g.*, some students may procrastinate or find difficult to stay focused without a structured schedule) [32, 38]. Additionally, long periods of screen time may cause a decline in physical activity, increased sedentary behaviour and a diminished sense of community, making it harder for students to develop interpersonal skills and relationships with peers and teachers [38].

Considering the characteristics of each learning methodology, teacher-student interactions can be categorised into one of four types according to the dimensions of time (synchronous-asynchronous) and place (online-offline) [39], as shown in Figure 1. Online synchronous activities include live lectures and Q&A sessions, offering immediate feedback. Online asynchronous tasks, such as posting replies and assignments, provide flexible scheduling. Offline synchronous interactions involve face-to-face teaching and discussions, promoting direct engagement. Offline asynchronous tasks include independent work like material compilation and reviews. This classification shows how traditional classroom learning and e-learning each fit into these categories, addressing different educational needs and preferences.

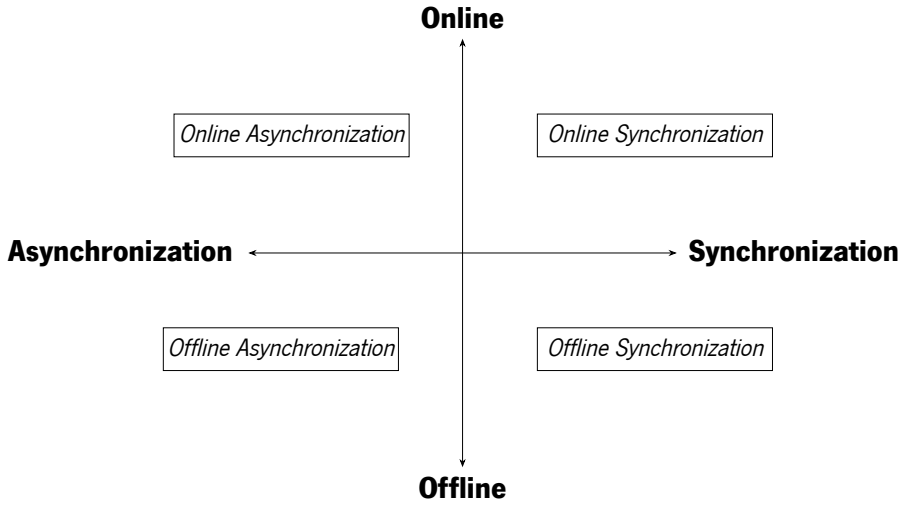


Figure 1: An overview of teacher-student interaction modalities. Based on: [39]

To improve students' learning outcomes, it is essential to address the limitations of both remote and traditional learning. For example, blended learning combines face-to-face classroom teaching with online digital media and interactive activities, integrating the strengths of both learning methodologies and offering flexibility, accessibility, and improved engagement [40, 41]. Another approach is the implementation of adaptive learning technologies, which uses data analytics and **AI** to personalise educational content to each student's needs and learning pace [42]. This personalised approach helps identify domains where students are struggling and provides targeted resources and support to address those gaps [43]. Additionally, promoting an online collaborative learning environment can greatly improve educational outcomes. Collaborative tools and platforms enable students to participate in group work, discussions, and projects, whether in a classroom or learning remotely, enhancing their understanding of academic content and developing teamwork and communication skills [44, 45].

In conclusion, considering the overall analysis of the evolution of educational approaches, the integration of digital technologies, and the advantages and disadvantages of each method, this study explored how these elements meet the needs of modern society. It identified the characteristics of traditional classroom learning and e-learning, noting their impacts on human health and learning outcomes. Another key aspect is the potential for digital technologies and **AI** to further enhance e-learning platforms by overcoming the challenges of today's educational approaches. This emphasises the need to implement adaptable and personalised educational strategies to create more effective and inclusive learning environments.

2.1.2 Ambient Intelligence and Behaviour Analysis

Computer science has experienced significant transformations since its birth, leading to technological advancements that enhance our interactions with our surroundings. Among the many areas of computer science, **AmI** stands out as notable in exploring this potential [25]. **AmI** represents a shift in computer science toward creating environments that are perceptive, adaptive, and reactive to meet the user's needs, powered by discreetly mobile devices and efficient user interfaces [12]. **AmI** merges **AI** and the **IoT** to enable a discreet interface between humans and machines, facilitating access to both assistive and predictive solutions that are interconnected with a wide array of sensor devices and networks (as represented in Figure 2). Notably, **AmI** applications capitalise on the intelligent use of context information obtained through sensors and engage with their surroundings using actuator devices [46]. Furthermore, considering the **AI** capabilities of accurately extracting contextual information from natural human behaviours (*e.g.*, voice, face or gesture sources), **AmI** can respond to explicit instructions and anticipate user needs by identifying patterns, allowing it to operate independently when necessary [47]. For instance, understanding and making decisions based on the user's actions require the system to analyse spatial and temporal contexts of events, offering insights into the users' daily activities.

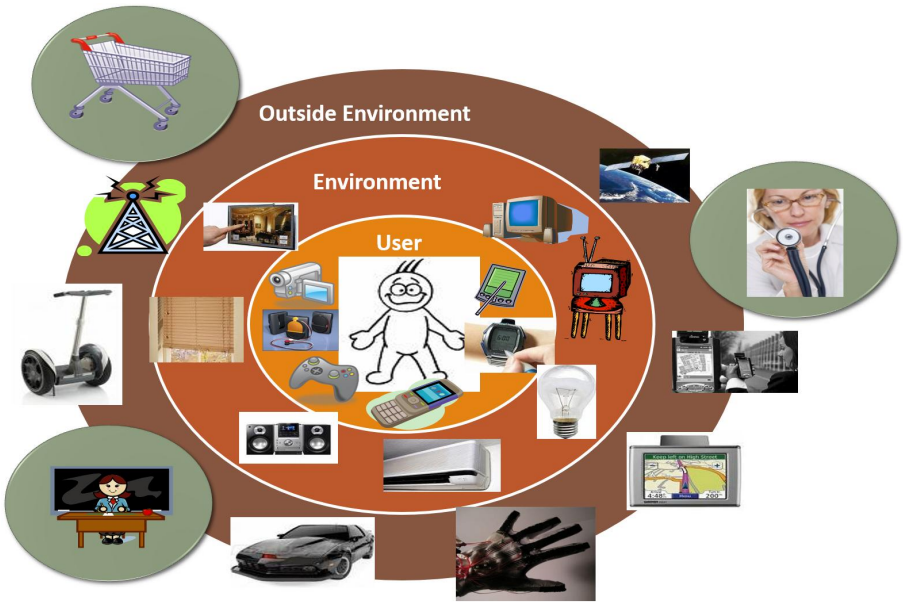


Figure 2: The multidisciplinary domain of ambient intelligence. Based on: [25]

According to Augusto et al. [48], an ideal **AmI** system must intelligently detect opportunities to assist, determine when its intervention is permissible, and customise its support to the specific needs and preferences of its users. It should fulfil its purpose effortlessly without requiring users to possess technical expertise and always safeguard their privacy and safety. Such a system must exhibit autonomy while op-

erating unobtrusively, without requiring changes to the environment or the daily routines of its inhabitants [48]. Central to its design is the principle that the user retains control, directing the technology rather than being directed by it.

AmI finds application across multiple sectors, improving user experience and operational efficiency. For example, in smart homes, **AmI** systems automatically regulate lighting, temperature or water heating, opening or closing windows and even play music based on the resident's preferences and current activities [49, 50]. In addition, smart homes can offer significant benefits to those needing extra care, such as the elderly or individuals with cognitive impairments. Within **Ambient Assisted Living (AAL)**'s framework, these intelligent systems focus on enhancing the health and safety of seniors [50]. By monitoring changes in health status, a smart home can promptly alert caregivers or medical professionals when necessary. A practical application includes using accelerometers to detect falls, enabling quick notification to emergency services or caregivers, thereby minimising response times and possibly saving lives [12]. In healthcare, wearable devices continuously monitor vital signs and detect irregularities, alerting healthcare professionals in real-time, thus facilitating rapid intervention [51]. Beyond wearable devices, **AmI** applications extend to smart hospital rooms equipped with sensors that track patient movements, sleep patterns and predict potential health risks, ensuring a proactive approach to care [52]. Retail environments have also been transformed through personalised shopping experiences, where customers receive targeted recommendations based on their shopping habits and preferences [53]. Another example is the smart fitting rooms equipped with interactive mirrors that offer customers personalised clothing recommendations and virtual try-ons, using **Radio Frequency Identification (RFID)** technology to identify items brought into the room [54]. Furthermore, in-store navigation systems use beacons to guide customers to products they search for online while in the store, improving the shopping experience through seamless integration of online and physical retail spaces [54]. In learning platforms, **AmI** can monitor the interaction of the students with the framework, such as engagement levels and emotional states, to provide real-time feedback and personalised learning styles [55]. **AmI** can also facilitate collaborative learning by analysing group dynamics and suggesting team compositions based on the strengths and weaknesses of students [55]. Furthermore, these systems can support accessibility by adjusting the interface and content delivery methods to suit individual learners' needs, including those with disabilities [56].

Current **AmI** systems face challenges related to ethical concerns, privacy considerations, and data security due to their continuous collection and analysis of vast amounts of personal data [12, 46, 48, 57]. This raises significant ethical and privacy issues, as sensitive information about individuals' habits, health, and preferences is at risk of unauthorised access or misuse. Ensuring data is collected, stored, and used in a

way that respects privacy requires robust encryption, secure data handling practices, and transparent user consent mechanisms [12, 48]. In addition, as **AmI** environments rely on interconnected devices and networks, they are vulnerable to cyber-attacks, which can lead to unauthorised access, system manipulation or sensitive data theft. Protecting these systems against such threats requires advanced security protocols, regular software updates, and the deployment of intrusion detection systems to safeguard against potential breaches [58]. Furthermore, **AmI** systems must be highly adaptable to respond to the needs of different individuals, including adapting to changes over time in users' preferences or physical environments. Creating systems that balance user independence with assistance and that can dynamically adjust to changing requirements is a complex challenge [46].

In summary, **AmI** offers applications across different sectors, integrating computational power into everyday environments. This approach enables the creation of computational spaces that operate transparently, enhancing user experiences without overt intrusion. Furthermore, **AmI** facilitates personalised interactions and adaptive services, significantly improving efficiency and convenience in various fields such as healthcare, commerce, education, smart homes, and urban management.

2.1.3 Artificial Intelligence and Data Analytics

The digital learning of prediction algorithms from empirical data is a fundamental theme in various research disciplines, ranging from classical statistics methods to the modern field of **AI** [59]. **AI** addresses the challenge of building computers that automatically improve through experience, blending computer science and mathematical statistics, and forming the core of intelligent systems [60–62].

Prediction model induction serves multiple purposes, including the prediction of future observations based on feature patterns verified in previous experiences and identifying the relevance of each feature that influences the prediction process within the domain under investigation, among other applications [63, 64]. Typically, the model induction process includes data acquisition and preparation, model development, model interpretation and evaluation, and model deployment [65].

Data-intensive analysis methods are utilised in various fields, such as healthcare, manufacturing, education, finance, law enforcement and marketing, to support evidence-based decision-making [66–68]. These methods handle different data types and problems by searching for optimal solutions using training data [69–73]. Each technique differs in how it represents solutions (*e.g.*, **Decision Tree (DT)** [74], which split data based on specific criteria, or mathematical modelling [75], which uses equations to model relationships) and how it searches for them (*e.g.*, optimisation techniques [76], which systematically improve a solution or evolutionary techniques [77], which generate and evaluate successive generations of solutions).

Similarly, the growing interest in data mining, also known as data analytics or **Knowledge Discovery in Databases (KDD)**, results from using historical data to identify relevant patterns and improve future decisions. These include the decreasing cost of data storage devices, the increasing accessibility of affordable high-performance computing hardware, advanced sensor technology and cloud services, the growing ease of data collection and sharing over the internet, the availability of increased parallel processing power to accelerate data processing and further develop advanced and complex **AI** algorithms, all of which enable the use of computationally intensive data analysis methods [59, 78, 79]. The data mining goal is not necessarily to create global models of the system under consideration, such as functional relationships between input and output variables, or to uncover an underlying data-generating process. Instead, it aims to discover local patterns of interest, such as very frequent (typical) or very rare (atypical) events. Data mining is more explanatory than predictive, concentrating on identifying descriptive patterns within a dataset. It emphasises the analysis of very large datasets, prioritising scalability and efficiency. In essence, data mining seeks to extract useful information from high data volumes [78, 79].

The field of **AI** and data mining has already produced practical applications in multiple areas. These include improving medical outcomes analysis [80], detecting and preventing credit card fraud [81], predicting customer purchase behaviour [82], optimising manufacturing workflows and personalising content for web users [82, 83].

Despite these advancements, these methodologies still face several limitations. More specifically, they require high data volumes and computing power, which can be resource-intensive and can reflect biases in their training data, leading to unfair results [84]. Moreover, they lack true understanding and common sense, rely solely on pattern detection and recognition, and are often hard to interpret, especially in complex architectures like **Deep Learning (DL)** models, which are seen as "black boxes" [85]. Also, **AI** algorithms can be compromised by adversarial attacks that can manipulate outputs, and there are significant ethical and legal concerns regarding data privacy and the potential misuse of these technologies [84, 86].

In summary, while **AI** and data mining technologies have revolutionised various fields by enabling the extraction of valuable insights from vast datasets, they are not without their challenges. It is vital to address these limitations for their continued advancement and responsible use. Future development should focus on overcoming these challenges to ensure that these technologies can be applied effectively and ethically, maximising their potential benefits while minimising risks.

2.1.4 Human-Computer Interaction and User Experience Design

The past decades have witnessed significant growth in the user interface and **HCI** technologies and methodologies, where initially **HCI** research mainly focused on graphical displays, keyboards and computer mice to interact with early command-line interfaces and **Graphical User Interface (GUI)**-based operating systems [87]. As technology evolved, **HCI** adapted to incorporate new interaction paradigms, devices, and interfaces, where technologies leveraging projection displays, context-aware devices and visual, auditory or tactile analysis enabled a richer interaction between men and machine [88, 89]. For instance, speech recognition technology is reducing the learning curve for newcomers and eliminating the challenges of using tiny keyboards on mobile devices, making these digital interactions particularly beneficial and more accessible for individuals with various levels of motor skills [90]. Similarly, interfaces based on gesture and motion recognition, which interpret different spatial movements associated with specific user intents, are increasingly becoming a natural choice for interacting with 3D virtual environments [91, 92]. Other **HCI** examples include eye-tracking technology, touch-based interfaces, augmented reality systems and haptic feedback systems [93].

Considering this information, **HCI** bridges the gap between cognitive science, engineering design, and technology. By understanding user behaviours and preferences, **HCI** seeks to create intuitive and effective systems that are accessible and user-friendly for its users [94]. The main purpose of interaction design is centred on minimising the user's negative experiences, such as irritation and frustration, while amplifying positive outcomes, like enjoyment and engagement. For designers to have insight into the users' needs, they must consider their skills and abilities [95].

User-centred Design (UCD) is a key principle within this research field, emphasising the importance of developing technology customised to the user's needs, goals, and preferences. This **HCI** principle involves iterative processes that engage users throughout the design life cycle [96]. Key principles include: understanding user behaviours, preferences, and pain points through methods such as surveys, interviews, and usability testing; creating interactive prototypes to gather user feedback and refining designs based on user input to ensure that the end product meets the needs of users; evaluating the usability of interfaces through real-user interactions helps identify usability issues and areas for improvement; consistent design patterns and simple, intuitive interfaces are essential to minimise cognitive load; designing interfaces that are contextually aware and adaptable to users' changing environments and tasks is essential [96, 97].

Successful **HCI** designs can be found in everyday applications. For example, smartphones have revolutionised user interaction through touchscreen interfaces, gesture controls, and intuitive application layouts, making technology more accessible [98, 99]. Similarly, intelligent voice assistants like *Amazon Alexa*,

Apple Siri, *Google Home* and *Microsoft Cortana* have introduced natural language interactions, offering users convenient assistance without requiring physical input [100, 101]. Digital social platforms, including *Facebook*, *Instagram*, *Twitter X*, *LinkedIn* and *Reddit*, have developed user-friendly interfaces that facilitate seamless content sharing and interactions among users [102, 103]. E-commerce websites, including *Amazon* and *eBay*, have enhanced shopping experiences by providing intuitive navigation and personalised recommendations [104]. Additionally, health and fitness apps utilise **HCI** guidelines to create easy-to-use interfaces that help users track physical activities, nutrition, and health goals efficiently [105, 106].

This field also faces various challenges that impact the design and usability of digital interfaces. For instance, managing a technical solution's complexity to balance functionality and features with simplicity is a must to avoid overwhelming users [107]. Furthermore, privacy and security are also crucial features in the design of a framework, as interfaces must safeguard user data while maintaining a seamless experience [108]. Also, designing interfaces that foster positive emotions and engage users emotionally can improve users' experience [109].

Regarding its future, **HCI** is set to introduce advancements that will reshape our technological interactions. Some examples include the adoption of virtual reality and augmented reality in sectors like education, entertainment, and healthcare, offering immersive experiences and the potential to create additional **HCI** methodologies (*e.g.*, remote surgeries) [110–112]. Enhancements in gesture and voice interfaces are anticipated to provide more natural and intuitive ways to interact with digital devices, significantly improving user experience and accessibility [113, 114]. **AI** technologies are also advancing, leading to improved virtual assistants and chatbots that promise personalised interactions and real-time support [100, 101]. Lastly, the evolution towards multi-modal interactions, which combine touch, voice, and gesture inputs, aims to make technology more accessible and user-friendly, especially for those with disabilities [110, 112, 114, 115].

2.1.5 Affective Computing

Affective computing is a prominent field that intersects various research domains including psychology, cognitive science, physiology, and computer science, aiming to equip computers with the ability to recognise, interpret and model human emotions [116, 117]. People express their emotions through various means, including facial expressions, body language, movements, gestures, voice patterns and physiological signals. By applying emotion recognition techniques, which incorporate both unimodal and multimodal affective recognition methodologies, affective computing aims to decode and understand emotional cues from these sources, enabling machines to gain insights into human affective states and adapt their re-

sponses to create more empathetic and intuitive interactions [116, 118–120].

Affective computing's growth is closely aligned with the evolution of the **IoT** and wearable and practical sensory devices, like fitness trackers and smartwatches, that facilitate the continuous monitoring of users' affective states [121, 122]. Unlike traditional computers, wearable devices offer a discreet approach to collecting physiological data (*e.g.*, **Heart Rate (HR)**, **Blood Pressure (BP)**, **Galvanic Skin Response (GSR)**, muscle activity, brain waves, sleep duration, breathing rhythm, sweating, and more) without the need of heavy or visible equipment. This less invasive approach minimises biases in data analysis and provides a robust reflection of the user's physiological state [122]. However, the challenge remains in managing the huge data volumes these devices generate, requiring intelligent systems to analyse and extract meaningful insights. Additionally, motion-induced artifacts are another challenge to be addressed to enhance the affect recognition accuracy [123].

To enable affective computing systems, affect measurements are necessary to gather individuals' subjective assessments of their emotions, feelings, and mood states at a specific time or over a period, providing insights into their emotional experiences [124]. Significant progress was accomplished during the last decades in this domain, with research broadly grouping these approaches into three main categories: physiological, which examines bodily responses; behavioural, which focuses on observable actions and reactions; and psychological, which delves into emotional and cognitive processes [125].

Physiological pattern recognition involves the analysis of patterns within physiological data to understand, diagnose and predict certain states or conditions of an individual, playing a major role in areas such as healthcare, entertainment, and **HCI** [126]. For example, depression, anxiety and chronic anger are proven to weaken the body's immune system, increasing susceptibility to infections and slowing recovery from surgery or illness. Using affective computing systems, healthcare assessment and performance can provide real-time emotional state monitoring, facilitating early detection of psychological issues and enabling personalised treatment plans [123].

Behaviour pattern recognition is an emerging field that analyses how users interact with technological devices such as computer mice and keyboards. Unlike traditional security measures that rely on possessions (*e.g.*, ID cards) or knowledge (*e.g.*, passwords), behaviour biometrics distinguish on the basis of their unique physiological and behavioural characteristics (*e.g.*, comparison between the user's previous keystroke patterns or mouse dynamics with the current one) [127, 128]. Beyond security, this approach is also applied to monitor the user's performance and health, assessing states such as distraction, fatigue and depression in environments like classrooms and workplaces [129–132] or targeted as an assisted living application concerning adverse event prediction or patient profiling [133, 134].

Psychological pattern recognition involves analysing and identifying specific patterns within emotional and cognitive processes associated with distinct affective states [135]. This approach often employs various self-assessment instruments, including questionnaires, rating scales, and semantic differentials, offering a systematic procedure to monitor an individual's affective qualities, including emotional and mood state [136]. Additionally, advanced computational methods such as **AI** algorithms and neuroimaging techniques are used to enhance the precision and depth of psychological pattern recognition, enabling the recognition of subtle and complex patterns that might not be evident through traditional assessment methods [137–139]. Examples of these approaches include using **Machine Learning (ML)** algorithms to classify text data from social media posts to detect patterns indicative of depression [137] or employing neuroimaging techniques like **Functional Magnetic Resonance Imaging (fMRI)** to identify brain activity patterns associated with anxiety and stress responses [139].

Embedding emotional intelligence into machinery holds great potential across multiple fields, including customer relations management, healthcare, education, and entertainment. For instance, in healthcare, emotion-aware virtual assistants could assist in mental health support by monitoring the patient's emotions, identifying distress, and providing customised interventions [140]. Similarly, in education, tutoring platforms which adapt to learners' emotional states could revolutionise teaching methods by customising content to maintain engagement and comprehension [141]. Customer service might be enhanced with chatbots that understand users' feelings, improving overall experiences [142]. Advancements in immersive technologies, such as virtual reality and augmented reality, could also benefit from integrating **AI** and emotion recognition, offering personalised and interactive experiences [141]. Anticipated advancements in neuroimaging and wearable technology are set to improve the emotion recognition systems's accuracy. By monitoring physiological reactions and brain signals, these technologies can refine the detection and interpretation of human emotions. Such improvements promise a more accurate and context-aware understanding of human emotions, enhancing the effectiveness of emotionally intelligent machines [143].

While affective computing holds the promise of enhancing **HCI** and user experience, it also presents several challenges and limitations, mainly due to the intricacy of human emotions. These include interpreting emotions across different cultures, genders, and contexts, and recognising subtle emotional cues, such as sarcasm or masked feelings, which leads to misinterpretation [144]. Additionally, analysing emotions and affective states often involves the use of personal data like physiological signals or facial expressions. Therefore, ethical considerations are crucial to ensure user consent is obtained, data usage transparency is maintained, privacy is strictly protected, and potential biases or discrimination in emotion recognition are actively avoided to uphold ethical standards [141, 145, 146]. Lastly, the integration of affective computing

requires robust validation, standardised protocols, and interdisciplinary research to ensure reliability and accuracy across diverse populations [147]. Overall, the success of affective computing depends on its ability to support users without compromising ethical principles or trust.

2.1.6 Psychological Dimensions of Affect, Emotion and Mood

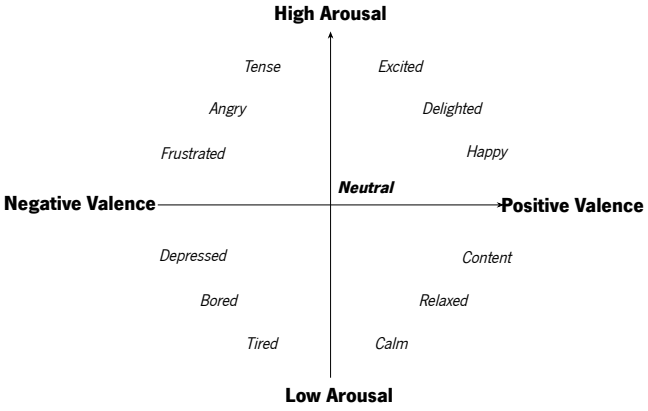
Understanding the concept of affect can be challenging due to the broad and occasionally overlapping terms that describe an individual's psychological state. Affect is a broad term that includes the experience of emotions and moods, whether positive, negative or neutral and shapes our interactions with the environment and processing of experiences [148]. Emotions, characterised by their intensity and short duration, are specific responses to particular events that often result in behaviour adjustments and physiological reactions (*e.g.*, joy, anger, fear, sadness and surprise) [149]. In contrast, moods are prolonged and diffuse states that subtly influence our overall view and attitude, even without a direct trigger (*e.g.*, happiness, gloominess, irritability and calmness) [149].

Scientific research has shown how affective states can influence human daily life, affecting communication, cognition, decision-making, and overall well-being, as well as reflecting and influencing psychological and physical conditions and contributing to shaping human behaviour and interactions [148–151]. Furthermore, external factors often cause variations in an individual's affective states, resulting in measurable alterations in physiological signals that offer relevant insights into their emotions. For example, **EEG** signals reveal brain activity linked to the functioning of cerebral neurons [152]. Similarly, **Electro-dermal Activity (EDA)** measures changes in the electrical properties of the skin [153]. **Electrocardiogram (ECG)** tracks the heart's electrical activity [154] and **Electromyography (EMG)** monitors the muscles' electrical activity [155]. Together, these physiological signals provide practical insights that can aid in indirectly assessing affect aspects that may have been triggered during an interaction.

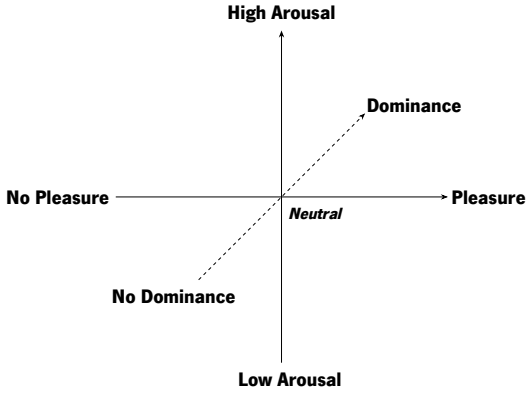
The dominant theory in affective neuroscience suggests that emotions can be categorised into independent categories, each with unique responses originating from the activation of different neural pathways in the central nervous system [156]. To study and describe affective states, various emotion dimensional models (considering one or more dimensions) have been proposed by researchers to conceptualise and explain the diverse spectrum of emotional experiences [157–159].

One well-established emotion dimensional model is the *Circumplex Model of Affect* proposed by Russell [157], a two-dimensional framework that considers that all affective states have their origin in two neurophysiological systems, namely valence (*i.e.*, the emotional value of an experience, ranging from positive to negative, indicating the degree of pleasure or displeasure) and arousal (*i.e.*, the intensity or level of

emotional activation within the body) [160, 161]. In this framework, emotions can be mapped on a co-ordinate system where the y-axis represents arousal levels and the x-axis measures the valence, ranging from negative to positive emotions, as illustrated in Subfigure 3a. While this model can distinguish core feelings, including joy, contentment, anger, fear, disgust or sadness, it struggles to distinguish emotions with similar valence and arousal levels (*e.g.*, anger and fear) [157]. To address this, Mehrabian [158] introduced a third dimension, leading to the proposal of the three-dimensional **Pleasure, Arousal, and Dominance (PAD)** model (as illustrated in Subfigure 3b). This addition improves the model's ability to distinguish between similar emotions by considering the aspect of dominance (*i.e.*, the extent of feeling in control in a given emotional state), along with pleasure and arousal. For example, despite both being negative emotions, anger is characterised by a sense of control (*i.e.*, dominant feeling) while fear is characterised by a feeling of vulnerability (*i.e.*, submissive feeling) [158].



(a) Russell [157] proposed circumplex model of affect.



(b) Mehrabian [158] proposed PAD model of emotion.

Figure 3: Comparison of 2D and 3D emotion models.

An alternative framework is the wheel of emotions proposed by Plutchik [159] which combines basic and complex emotion categories with dimensional theories, organising emotions into nested circles. Basic emotions reside in the inner circles, while more complex emotions, formed by merging these basic emotions, are found in the outer circles. For example, a primary pair like love results from joy and trust being one segment apart, while secondary and tertiary pairs, such as envy (sadness and anger) and shame (fear and disgust) are determined by their respective distances. The model also notes opposite emotions, like anticipation and surprise, which do not directly blend [159]. This model suggests a total of 56 unique emotional states at one intensity level, with each emotion ranging from mild to intense, exemplifying the depth and variety of human emotional experience.

Considering these models of emotion as a foundation to conceptualise human emotions, they are applied

across various domains to boost emotional intelligence in computer systems. For example, in sentiment analysis, these models facilitate the automatic recognition of feedback in user-generated text, enabling platforms to respond to users' positive or negative emotions effectively [162]. In face recognition, body poses analysis and voice analysis systems, emotion models are crucial for assessing psychological states and improving the communication of non-verbal information between man and machine (*e.g.*, a smile generally indicates happiness or acceptance while frowning typically signals disapproval or sadness; voice tone is considered for understanding sarcasm, irony, and sincerity in the communication) [162–164]. Furthermore, virtual assistants can apply these techniques to adjust their responses to users' emotional state, creating more intuitive and responsive interactions [163, 164].

Important to note that these techniques also present limitations when applying emotion models universally. These models primarily focus on the basic emotions, potentially overlooking complex emotions that don't fit well within the defined dimensions [165]. Also, these frameworks may not sufficiently address cultural and individual differences in emotional experience and expression, as emotions are not universally experienced or expressed similarly across different cultures or individuals [123, 165]. Additionally, these models sometimes struggle to distinguish between emotions with similar valence and arousal levels, such as excitement and anxiety, leading to ambiguity in interpretation [119, 123]. Lastly, these dimensional approaches may not fully reflect emotions' complex nature, which can change rapidly over time and in different contexts, thus limiting the models' ability to capture the fluidity of emotional experiences [123, 165].

2.2 Artificial Intelligence in Stress Detection and Monitoring

The ideal system for measuring stress should be continuous and unobtrusive to capture a person's responses throughout the day without causing additional stress. For example, knowing they have experienced more stress than usual, a person can become aware and include changes to their daily routine, such as taking breaks, adapting work activities or socialising more [166, 167]. Digital devices can also make use of this knowledge to create improved forms of **HCI**. For instance, when a computer user is feeling stressed, the computer could delay system updates or prevent unnecessary notifications [167]. Alternatively, the computer could suggest calming interventions to help avoid stressful situations [166, 167].

Current methodologies for non-intrusive stress detection and monitoring consider various technologies and approaches. Wearable sensors, such as chest straps, wristbands or intelligent rings, have been developed to monitor physiological markers continuously, but their high cost and continuous wear pose

difficulties for overall adoption [168, 169]. Other methods include self-reports and physiological signal measurement, which often require user attention and are not unobtrusive [116, 168]. Alternatives like monitoring stress-influenced behaviours through keyboard typing and mouse usage have been proposed. Additionally, video-based approaches analyse face expressions and body pose [168, 170] while text-based methods examine written communications, such as social media posts or text messages, for linguistic stress cues, despite presenting privacy and ethical concerns [168, 171].

To improve the prediction performance of these approaches, **AI** algorithms are applied to process data from multiple sources, continuously learning and adapting to individual behaviours, offering personalised insights and improving the understanding of user's emotional states [119].

2.2.1 Mental Stress and its Effects in Work Performance

Before exploring the latest advancements in **AI** application for stress detection and monitoring, it is important to provide a brief overview of the definition of mental stress, particularly regarding its cognitive and psychological effects on students and workers.

According to Paul et al. [172], mental stress refers to a state of psychological or emotional excitation triggered by complex challenges in daily life, such as tight deadlines, high workload or academic pressure. When not properly handled, especially in extreme cases, this condition can negatively affect cognitive functions, resulting in decreased productivity, errors in decision-making and an overall decline in performance in academic or professional environments. In Section 4.1, this topic will be further explored into the various forms of stress, its effects on mental and physical health, explore assessment tools for detecting stress levels and discuss coping mechanisms to mitigate the negative impact of high levels of stress.

Building on this information, the next subsection will examine state-of-the-art methods for identifying and monitoring stress, with a focus on the application of digital technologies.

2.2.2 Projects using Artificial Intelligence to address Stress Detection and Monitoring

This subsection explores the latest scientific literature on stress assessment and monitoring technologies to identify practical and non-intrusive digital methodologies, relevant behavioural features and **AI** techniques, including analysis and benchmarking of algorithms' performance across various studies. To ensure a thorough examination of scientific contributions, the selection process is guided by the following key criteria:

- **Search Sources:** Incorporate literature from multiple sources, including *Web of Science*, *SCO-*

PUS, *Science Direct*, *PubMed*, *DBLP*, *IEEE Xplore* and *arXiv*, to ensure the collection of relevant studies across different disciplines and technological approaches;

- **Latest Research:** Focus on scientific research from the past 4 years to ensure the review is current with the latest advancements and trends in the field;
- **Non-Intrusive Methodologies:** Emphasise studies using non-intrusive stress detection methodologies for practical applicability in real-world scenarios;
- **Data Input:** Include research experiments using various sensor or data modalities to evaluate stress detection methods, offering complementary insights into stress indicators;
- **Application Context:** Focus on research experiments in different settings to evaluate the effectiveness of stress detection methods across various scenarios;
- **Stress Measurement Tools:** Include scientific work that uses different stress assessment instruments to assess how these tools impact the effectiveness of stress detection frameworks;
- **Method Efficacy:** Consider scientific research that details biometric or behaviour analysis methodologies for stress detection, including data collection, preparation and preprocessing procedures, main characteristics of the proposed framework, its training and evaluation procedures, and overall prediction performance;

Wearable Sensor-based Approaches

Wearable sensors are increasingly integrated into projects utilising **AI** to address stress detection and monitoring. Found in smartwatches, fitness trackers and medical devices, these sensors continuously and non-intrusively collect data like **HR**, **GSR**, **EDA**, **ECG**, respiratory patterns and skin temperature, which **AI** algorithms analyse to detect stress patterns and provide real-time monitoring and feedback [173–178]. The study of Mishra et al. [173] proposes a system for the continuous detection of stress using the low-cost *Polar H7* **HR** monitor [1], aiming to make stress monitoring more accessible by utilising inexpensive sensors instead of costly clinical-grade ones to capture and analyse **HR** data for determining stress levels. Evaluated with 26 participants in both lab and real-life settings through the analysis of **HR**, accelerometer and **Ecological Momentary Assessment (EMA)** self-reports [179], the system achieved an F1-score of up to 87% in the lab and 66% in the field, matching the accuracy of clinical-grade sensors.

[1] *Polar H7* sensor characteristics available at: `https://support.polar.com/e_manuals/H7_Heart_Rate_Sensor/Polar_H7_Heart_Rate_Sensor_accessory_manual_English.pdf`

Furthermore, Li and Liu [174] describes a scientific study proposing two **Deep Neural Network (DNN)** (*i.e.*, 1-dimensional **Convolutional Neural Network (CNN)** and **Multilayer Perceptron (MLP)**) for classifying emotions and identifying stress using raw physiological signals from chest and wrist sensors, aiming to develop non-intrusive and accurate methods to improve quality of mental healthcare without requiring hand-crafted features. The data collected involved 15 participants who exhibited stressed, amused and baseline psychological states, with stress induced by the **Trier Social Stress Test (TSST)** [180]. The **CNN** model achieved 99.80% accuracy for binary classification (*i.e.*, stressed or non-stressed) and 99.55% for 3-class classification (*i.e.*, baseline, amused and stressed) while the **MLP** achieved 99.65% and 98.38% respectively, significantly outperforming traditional **ML** methods in 3-class emotion classification tasks and binary stress detection.

Campanella et al. [177] presents an alternative approach using the *Empatica E4* wrist bracelet [2], which collects data via skin temperature, accelerometer, **EDA** and **Photoplethysmography (PPG)** sensors for mental stress monitoring through physiological signals, aiming to differentiate stressful from non-stressful situations using **ML** algorithms. The study included tasks such as constructing *Lego* structures, performing mathematical calculations and giving an oral presentation, with rest periods to establish baselines and ensure proper stress measurement. Data from 29 subjects were pre-processed, segmented into 1-minute intervals and filtered for noise, with the **Random Forest (RF)** model showing the highest performance at 76.5% accuracy, validated through ten-fold cross-validation.

Additionally, recent research shows the potential of wearable biosensors in stress and anxiety detection through physiological signals (*e.g.*, **ECG**, **EMG**, **EDA**, **GSR**, **HR**, **BP**) where multi-modal signals are particularly noted for their effectiveness in emotion and stress recognition [181–183]. Considering this hypothesis, the research of Tanwar et al. [178] aims to improve real-time stress detection accuracy and efficiency by integrating multiple biometric signals through a **CNN** and **Long Short-Term Memory (LSTM)** framework with an attention mechanism, recognising three psychological states: "Neutral", "Amusement" and "Stressed". Using data from the **Wearable Stress and Affective State Detection (WESAD)** dataset [184], collected from 15 participants via *Empatica E4* wrist bracelet [2] and *RespiBAN* chest-worn [3] devices under the **TSST** [180], the model achieves 92.7% accuracy and a 90% weighted F1-score by combining **ECG**, **EDA**, respiratory and temperature modalities, outperforming traditional methods.

[2] *Empatica E4* sensor characteristics available at: `https://www.empatica.com/en-eu/research/e4/`

[3] *RespiBAN* sensor characteristics available at: `https://www.pluxbiosignals.com/products/respiban-ble`

Peripheral Sensor-based Approaches

The application of peripheral sensors and **AI** for stress monitoring represents an important advancement in non-invasive mental health assessment. Peripheral sensors such as keyboards, mice, and embedded sensors used in smartphones and tablets offer a continuous and unobtrusive approach to gathering physiological and behavioural data. These sensors capture behavioural biometric features like typing, interaction patterns and mouse movements, which **AI** algorithms analyse in real-time to infer stress levels and detect the individual's mental state [185–188].

The research of Sağbaş et al. [185] proposed a system to unobtrusively detect stress through smartphone typing behaviours by analysing accelerometer and gyroscope sensor data with **ML** techniques. Data from 46 participants performing writing tasks in "Stressed" and "Calm" states was collected, processed and analysed using ten-fold cross-validation, achieving up to 87.56% accuracy with the **K-Nearest Neighbour (KNN)** technique, demonstrating the system's effectiveness in stress detection.

The proposed system by da C. Silva et al. [186] aims to discreetly monitor stress levels using everyday computer devices like keyboards and mice equipped with pressure-sensitive sensors. Integrating into daily routines, the system collects interaction data during induced stress and calm states, extracts relevant behavioural features and classifies them using **ML** techniques (*i.e.*, supervised, unsupervised, semi-supervised, and reinforcement learning), validated with data from 25 participants over four sessions using ten-fold cross-validation. The system achieved a classification accuracy of 74.5% for keyboards and 73.5% for mice with the **KNN** technique.

As per Liu et al. [187], the group presents a real-time driver stress detection algorithm by analysing ultra-short-term **HR** variability in real driving conditions to improve traffic safety. Data was recorded from 17 drivers on a specified route in Boston, with stress levels validated through expert ratings and self-report questionnaires [189]. The proposed system analyses **HR** variability features processed from **ECG** signals within 30-second to 3-minute time windows using **ML** classifiers, with the **Support Vector Machine (SVM)** classifier achieving the highest accuracy at 85.3% with 3-minute features.

In response to autonomous stress detection in desk jobs, Sanchez et al. [188] developed a non-invasive **ML** algorithm to assist employees manage stress proactively. The study monitored 57 employees over five months, using *Fitbit* wrist-worn activity trackers and a developed desktop application to gather data regarding physical activities, **HR**, sleep patterns and user-computer interactions, including keystroke and mouse dynamics. The data, including periodic self-assessed five-point stress levels, were grouped into three stress levels: "Low", "Medium" and "High" [4]. To mitigate the data imbalance issue, the **Synthetic Minority**

[4] Dataset available at: `https://www.dropbox.com/scl/fo/y338853qjb7x9id7sk6pf/ADJa6bSsekowtyCigCltK34?rlkey=`

Oversampling Tech. (SMOTE) technique was applied, resulting in a balanced dataset of 870 samples, split into training and testing sets. Various feature selection techniques, such as Spearman Correlation Analysis, Principal Component Analysis, Greedy Stepwise, Information Gain and Wrapper techniques were utilised to create multiple datasets for training. In the end, the **RF** classifier consistently attained the top F1-score, with the Information Gain-based dataset emerging as the most effective, demonstrating an F1-score of 83% in training and 80% in testing.

Video-based Approaches

Unlike methods that rely on peripheral sensors or wearable devices to measure stress through user interaction or physiological signals, video-based approaches analyse image data. Exploiting advancements in **Computer Vision (CV)** and **ML**, these non-invasive and non-intrusive methods assess stress through body movements, facial expressions and other visual cues, not requiring any physical contact [190–193]. Baran [190] discusses a low-cost mobile thermography system that uses the smartphone infrared camera to detect user's stress by analysing temperature changes and abnormalities. Data was collected by recording participants' facial reactions to a stress-inducing film, processed using OpenCV [194] and validated through thermographic analysis, with results showing temperature and **HR** variability as indicators of stress, highlighting its potential for home-based stress monitoring.

The work by Xin Zhou and Zhang [191] proposes a driver stress detection algorithm employing smartphones and **ML** algorithms to improve driver training, stress intervention and in-vehicle information systems. Data was collected from 30 novice drivers during two driving tasks with eight events each, and the system was validated using psychological (*i.e.*, personality traits, emotional state), physiological (*i.e.*, **HR**, **GSR**), driving behaviour patterns and facial image data. The study shows that incorporating individual profile features improved classification performance, with facial regions including the brow, jaw, eye, mouth and nose being most sensitive to stress, resulting in the system achieving 89.2% accuracy using the **KNN** algorithm.

Singh and Kumar [192] introduces a system using ResNet-101 [195] for real-time stress, depression and anxiety detection through video surveillance, aiming to identify emotional variations from facial expressions without human intervention and reduce the need for expensive medical tests. The system extracts eye, mouth and head activity features from video frames utilising the **Kanade-Lucas-Tomasi (KLT)** algorithm [196], applies a Kalman filter [197] for feature tracking and inputs these processed features into the classification model. Trained and tested on the **Interactive Emotional Dyadic Motion Capture (IEMOCAP)** surveillance video dataset [198], the system achieved 98.4% accuracy using the hold-out

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data split method, outperforming classification models like **KNN** and **SVM**.

The research by Bhosale et al. [193] offers a multi-modal approach for detecting and helping users cope with stress through real-time facial feature capture via live video and textual interaction with an intelligent chatbot, aiming to improve mental health and well-being. The system applies a **CNN** to analyse facial expressions and extract the user's emotion and stress-related characteristics while a **Valence Aware Dictionary and sEntiment Reasoner (VADER)**-built chatbot [199] interacts with the user to perform sentiment analysis on text responses to offer better advice and suggest mood-based music via the Spotify Development API [5]. Considering this system's performance, it achieved 83.79% accuracy for facial stress detection, 79.23% for chatbot textual stress detection and 85.38% in relieving user stress.

Text-based Approaches

The growth of online social media, blogs and forums has resulted in an abundance of user-generated content available in the form of comments, posts, tweets, status updates and emojis. This data offers a valuable opportunity to use **AI** techniques, particularly **Natural Language Processing (NLP)** and sentiment analysis, for detecting and monitoring users' stress levels, helping researchers to better understand users' emotional and psychological states and develop non-invasive and scalable stress detection systems [171, 200–202].

Muñoz and Iglesias [200] proposes an approach for detecting psychological stress through text classification techniques by combining lexicon-based features (*i.e.*, topic-related, syntactic, social and affective aspects) with word embeddings (*i.e.*, language identification, handling out-of-vocabulary words and text classification), aiming to improve non-invasive and non-intrusive stress detection. Data from three public English datasets (*Reddit* Dreaddit [203], **Natural Stress Emotion (NSE)** [204] and *Twitter* TensiStrength [205]) were used to train and validate the approach through multiple experiments, achieving F1-scores above 80%, with the best performance from combining FastText embeddings [206] and lexicon-based features.

The research by Kumar et al. [201] discusses the use of RoBERTa and XLNet transformer-based algorithms for stress recognition in social media posts. Using the *Reddit* Dreaddit dataset [203], the study annotated 3553 posts with "Stress" or "Neutral" labels, enriched them with **Linguistic Inquiry and Word Count (LIWC)** (*e.g.*, positive or negative emotions associated with words), syntactic (*e.g.*, identifying nouns, verbs, adjectives) and social media features (*e.g.*, domain and respective subreddit, hashtags, mentions) and then formatted and tokenised for model input. While both XLNet-Large and RoBERTa-Large

[5] API available at: `https://developer.spotify.com/documentation/web-api`

models demonstrated high accuracy and F1-scores (*i.e.*, above 82%), RoBERTa-Large achieved the highest performance with 83.78% accuracy and an F1-score of 83.73% when using text and additional features. Similarly, Kabir et al. [171] proposes an alternative system for predicting mental stress from social media posts (*i.e.*, *Twitter* and *Facebook*) using traditional **ML** techniques. Among the evaluated models, **Logistic Regression (LogR)** showed the highest accuracy and F1-score at 83.21% and 91%, respectively, followed by **SVM** with 82.89% accuracy and 91% F1-score and **eXtreme Gradient Boosting (XGB)** with 82.55% accuracy and 90% F1-score.

2.2.3 Discussion of Results

In the field of stress sensing, the importance of these techniques is undeniable, given the role of stress management in our overall well-being and productivity. Non-invasive and non-intrusive methods hold a unique advantage, as they enable professionals to assess and address an individual's stress without requiring physiological intrusion, making them broadly applicable and ensuring accessibility for a wide audience. These approaches are promising for individuals seeking stress management support and for healthcare providers, educators and organisations dedicated to creating healthier and more supportive environments. Considering the insights from the previous state-of-the-art analysis, each **AI**-based stress detection approach presents different pros and cons in terms of sensor precision (*i.e.*, data reliability and robustness), invasiveness (*i.e.*, disruption to the user's daily routine), scalability (*i.e.*, ease of expanding the system to a larger population), its financial cost (*i.e.*, expense of required devices and components), system maintenance (*i.e.*, need for specialised human resources) and privacy or ethical concerns (*i.e.*, risks to user data confidentiality or ethical implications). Table 1 provides a benchmark of stress detection and monitoring approaches, considering these factors for the discussed sensor modalities.

Table 1: Comparative Analysis of Stress Detection Approaches.

Approach	Precision	Invasive	Scalable	Cost	Maintenance	Privacy/Ethics Concerns
Wearable Sens.	High	Medium	Low	High	High	Low
Peripheral Sens.	Medium	Low	Medium	Medium	Medium	Medium
Video Analysis	Medium	Low	Medium	Medium	Medium	High
Text Analysis	Medium	Low	High	Low	Low	High

Although wearable sensor-based approaches provide precise real-time monitoring, they can be considered invasive in some cases, as they can disrupt users' routines depending on the sensors used. They are also expensive and require significant maintenance, limiting scalability, but pose low privacy and ethical

considerations when compared to other methods.

Peripheral sensor-based approaches balance precision and invasiveness with moderate scalability and reasonable cost, making them broadly accessible. They require moderate maintenance and have manageable privacy and ethical considerations due to less sensitive data collection when compared to more invasive methods.

Video-based approaches offer moderate precision and are considered non-invasive, providing scalable and cost-effective alternative solutions with moderate maintenance needs. They deliver valuable insights through user behaviour monitoring but raise privacy and ethical considerations due to continuous surveillance and potential user discomfort.

Text-based approaches, using social media and other written communications platforms, are viewed as non-invasive, highly scalable and cost-effective, offering moderate precision with minimal maintenance. However, they face significant privacy issues and potential bias in data interpretation, requiring advanced processing techniques and careful handling of sensitive data to ensure user confidentiality.

In summary, although direct comparisons are challenging in this domain due to different environmental conditions, applicability contexts, tools and methodologies, these results highlight the potential of non-intrusive methods for stress assessment. Most studies treat stress detection as a classification task, distinguishing between "Neutral" and "Stressed" states rather than using regression techniques to quantify stress levels. Each method faces multiple challenges ranging from privacy concerns and potential bias to limitations in real-world applicability and data precision. This emphasises the importance of considering the context and the specific application when designing the appropriate non-invasive stress detection methods.

2.3 Summary

This chapter explored the intersection of **AmI**, education and affective computing, emphasising the role of digital technologies, affective computing and **AI** in improving modern learning environments and describing its relation with psychological dimensions of affect, emotion and mood. Furthermore, one of the chapter's main focuses was on stress detection algorithms, discussing their potential to improve stress management through various non-invasive **AI**-driven projects. The study concluded with a discussion of results, highlighting the promise and challenges of these technologies.

Building on this analysis, the next chapter proposes the research design and methodological choices, describing the strategic plan for this doctoral thesis. This includes the definition of the problem statement, the formulation of the research hypotheses and questions and specific objectives and tasks to accomplish

during the doctoral program.

Chapter 3

Conceptualisation of the Research Problem

"Science is a way of thinking much more than it is a body of knowledge."

—Carl Sagan

This chapter outlines the research's design and methodological choices, detailing the strategic plan for this doctoral thesis. The chapter is structured to clarify the progression from the definition of the problem statement and goals to the formulation of research hypotheses and questions, and the clarification of the work's objectives and tasks. Additionally, the chapter describes the planned work roadmap for this project completion, the research team and host institution involved in this research and the specific tasks performed during the doctoral programme.

3.1 Problem Statement and Goals

As digital education continues to expand, the need to address student's perceived stress within this domain has become imperative. Stress affects students' academic performance and psychological well-being, yet the methods currently employed to assess and manage it are often inadequate (further detailed in Chapter 4). These traditional methods involve processes that students find disruptive or uncomfortable, compromising the educational experience rather than enhancing it. Furthermore, these strategies typically suffer from delays in both detecting stress proactively and applying adequate coping interventions, failing to offer solutions precisely when they are most needed [207–209].

This research addresses these challenges by exploring digital methodologies for real-time stress monitoring. By integrating behavioural biometrics and cognitive analytics, the proposed framework seeks to revolutionise how stress is monitored and managed in e-learning environments, ensuring interventions are

both timely and respectful of students' privacy and comfort.

As such, the goal is to develop a non-invasive and non-intrusive scalable solution capable of analysing shifts in behavioural and cognitive patterns that indicate stress, without making students feel surveilled or uncomfortable. Additionally, anonymisation techniques will be applied to students' sensitive data to safeguard their privacy. This solution aims to operate within the existing digital infrastructure of e-learning platforms, ensuring minimal disruption while providing educators and students with actionable data. By doing so, it seeks to establish a more supportive learning environment that enhances academic performance and positively impacts mental health outcomes.

3.2 Research Hypothesis and Questions

As discussed in Section 1.2, this doctoral research is based on the premise that stress impacts the **HCI** and cognitive performance of individuals during high-demand tasks. To validate this theory, the following research hypothesis and questions have been formulated to guide the research, aiming to explore the extent and nature of stress effects, the variability in the different individual/population responses, and the potential for developing stress predictive models based on the behavioural biometrics and cognitive data analysis. Thus, the main research hypothesis that guided the work throughout this research is as follows:

Research Hypothesis

Mental stress can be monitored by analysing changes in student's cognitive and behavioural patterns through non-invasive and non-intrusive methods, to improve online assessment processes.

A non-invasive e-learning system that assesses and monitors students' stress during high-demanding tasks is important for promoting a supportive academic environment. Such a system can help identify students who are struggling with stress and provide timely interventions to improve their well-being and academic performance before it's too late (further details are discussed in Chapter 4).

The research is structured around specific research questions to ensure the proposed hypothesis is researched and validated properly. These questions are designed to address various aspects of the hypothesis, including the identification of stress effects, the variability of individual or group responses, and the development of stress predictive models. Each research question has been formulated with a clear description, aim and validation procedure. The following key research questions that guided the execution of

this work are as follows:

- **Research Question No. 1:** *How does student's performance correlate with induced stress in real-time during high-demand tasks?*

  Description: This question explores the impact of induced stress on an individual's cognitive and behavioural performance during high-pressure situations, such as online exams. The focus is to understand how stress manifests in real-time and influences the user's cognitive and behavioural biometrics interactions with computer peripheral devices.

  Aim: Identify and quantify the real-time effects of stress on performance metrics, including mouse and keystroke dynamics, and decision-making features.

  Validation: Collect and analyse cognitive and behavioural biometric data during online exams, and correlate these with stress indicators (*e.g.*, physiological biomarkers and self-assessment questionnaire).

- **Research Question No. 2:** *How does stress affect the cognitive and behavioural responses of students within the same course versus those in different courses?*

  Description: This question explores how stress impacts cognitive and behavioural responses, comparing variations among individuals and different courses.

  Aim: Understand the multiple ways stress manifests in user interactions with the computer, focusing on mouse dynamics, keystroke dynamics and decision-making patterns.

  Validation: Perform a comparative analysis of mouse dynamics, keystroke dynamics and decision-making features across different groups of students, and use statistical methods to identify significant patterns and variations.

- **Research Question No. 3:** *How do students' task accuracy and efficiency correlate with different stress levels during online exams?*

  Description: This question focuses on understanding how fluctuations in stress influence the precision and effectiveness of students' task execution in virtual learning settings.

  Aim: Identify the behavioural biometric and cognitive features most affected by different stress levels.

  Validation: Perform a comparative analysis of behavioural performance, including behavioural biometric and cognitive features, under different stress levels as recorded through self-reported

stress.

- **Research Question No. 4:** *How can mouse dynamics, keystroke dynamics, and decision-making behavioural patterns predict students' stress levels during online exams?*

  Description: This question verifies the relationship between behavioural biometrics, cognitive patterns, and users' perceived stress during high-demand tasks.

  Aim: Develop **AI** predictive models that analyse mouse dynamics (*e.g.*, speed, acceleration, click frequency), keystroke dynamics (*e.g.*, typing speed) and decision-making features (*e.g.*, response times, error rates) to estimate real-time stress levels.

  Validation: Collect students' data on mouse and keyboard usage and decision-making during online exams. Use **AI** techniques to build predictive models and validate them against physiological stress indicators and self-reported stress levels.

3.3 Research Objectives and Tasks

Following the definition of the research hypothesis and questions in the previous section, this section summarises the work's objectives and tasks designed to achieve this thesis's goals. The purpose of this thesis research is to propose a technological approach for non-invasive and non-intrusive analysis of performance in groups of academic students. By monitoring behavioural data, this study aims to study stress effects on academic performance in high-demand tasks and to identify how each individual or group is affected by stress.

The research questions that had been previously established enabled the following objectives to be specified:

- **Objective No. 1:** *Monitor students' biometric behaviour, cognitive and activity performance during online assessments*;
- **Objective No. 2:** *Characterise students' mouse and keystroke dynamics, decision-making processes, and stress profiles*;
- **Objective No. 3:** *Test the hypothesis that mouse dynamics, keystroke dynamics and decision-making features can predict a student's perceived stress*;

- **Objective No. 4:** *Develop a predictive model based on collected case studies*;
- **Objective No. 5:** *Implement the prediction model on e-learning platforms for non-invasive and non-intrusive monitoring*;

To achieve these objectives, the following task list has been planned and conducted throughout the doctoral programme:

- **Task No. 1:** *Design a framework for e-learning platforms to monitor and collect students' behavioural biometric and cognitive data during online assessments*;
- **Task No. 2:** *Collect data on online exam performance (via mouse and keyboard usage) and students' mental stress (via self-reported questionnaires and physiological measurements)*;
- **Task No. 3:** *Characterise students' mouse dynamics, keystroke dynamics, decision-making and stress profile*;
- **Task No. 4:** *Test the hypothesis that mouse and keystroke dynamics and decision-making features can predict perceived stress levels using statistical methods*;
- **Task No. 5:** *Develop and benchmark multiple prediction models for assessing and monitoring students' perceived stress based on previously collected data during online exams. Conduct tests to validate and correct potential bugs*;
- **Task No. 6:** *Select an efficient stress prediction model to be implemented on e-learning platforms for non-invasive stress monitoring*;
- **Task No. 7:** *Disseminate results by detailing all research steps, developed frameworks and algorithms, and derived conclusions in reports and scientific publications*;

The definition of the project's objectives and tasks establishes the foundation for addressing the challenges tackled in this doctoral research, providing a structured approach for the continuous development, evaluation and refinement of the proposed solution.

3.4 Research and Development Methodologies

A research methodology is a structured approach for collecting, analysing and interpreting data, designed to ensure the scientific research's reliability and validity [210]. This involves choosing appropriate research

methods, such as experiments, surveys, or case studies, and employing techniques that facilitate proper data collection and analysis, ensuring that the findings are credible and can be used to make informed conclusions and recommendations.

In alignment with this approach, the adopted research plan in this project follows the action-research methodology [19]. This methodology was chosen for its ability to continuously refine and adapt to new findings, ensuring the research remains dynamic and responsive, and addressing evolving problems while providing a structured framework for robust and applicable outcomes. This strategy considers the following cyclical processes, as presented in Figure 4:

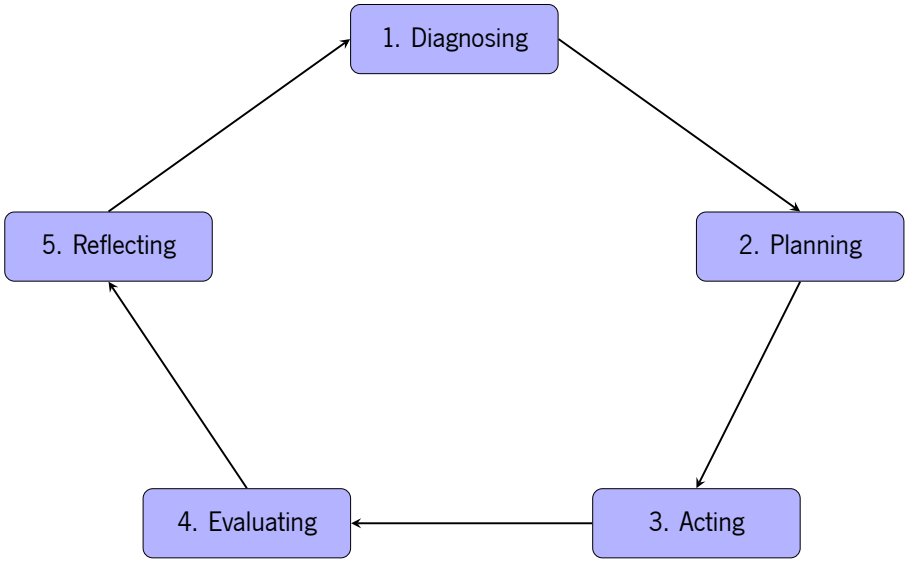


Figure 4: Cyclical process of the action-research methodology.

1. **Diagnosing:** The problem is identified and defined, including its characteristics and main causes. Researchers gather initial data to understand the scope and context of the issue, ensuring that the problem is articulated and understood;

2. **Planning:** Consider developing a strategic plan to address the identified problem. This involves setting objectives, updating the state-of-the-art knowledge, and designing an approach to tackle the problem. The plan must be flexible to incorporate new insights as the research progresses;

3. **Acting:** Regards implementing the planned actions by designing and developing a prototype to achieve the proposed objectives. This phase focuses on practical application and initial testing of the proposed solutions;

4. **Evaluating:** Results analysis obtained from the actions taken. Researchers assess the prototype's

performance, identify any discrepancies or issues, and determine its impact. This evaluation helps understand the initial implementation's success and areas that require adjustments;

5. **Reflecting & Iterating:** Researchers reflect on the outcomes of the evaluation, considering what has been learned from the process. They refine the approach based on these reflections, updating the plan and strategies for the following iterations. This cyclical process ensures continuous improvement and adaptation, making the research dynamic and responsive to new findings;

Considering the software solutions development, the methodology used is adapted from Scrum [211, 212] (as illustrated in Figure 5). Scrum is a development methodology designed to overcome the difficulties of long product development cycles by enabling developers to focus on clearly defined goals. This approach mitigates the common mismatch between a solution's requirements and its actual implementation, which often arises in complex framework development [213].

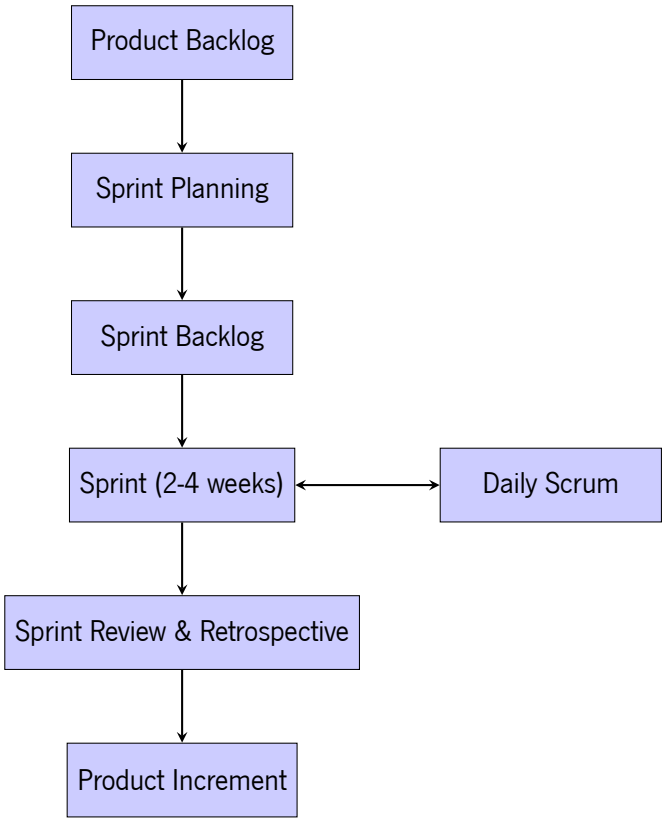


Figure 5: Scrum methodology overview.

Similar to the action-research methodology, this process begins with diagnosing the problem and updating the state-of-the-art knowledge and objectives of the work. This information is compiled into the Product Backlog, a prioritised list of tasks and requirements. During the Sprint Planning meeting, items are selected from the Product Backlog and moved to the Sprint Backlog for focused development. The development

team then works on these tasks during a fixed timeframe called a Sprint. Upon the Sprint's completion, the completed work is reviewed, evaluated and documented and new issues are identified, leading to the next cycle of development and further refinement of the work.
Together, the integration of both methodologies promotes a flexible and functional approach to tackling complex research and development challenges, leading to more reliable and applicable outcomes.

3.5 Research Plan

This research is structured into seven main phases to accomplish the proposed objectives. Each phase is designed to build upon the previous one, ensuring a consistent progression toward the primary goal of developing a real-time stress monitoring system:

- **The first phase (Problem Statement & Requirements Definition)** focuses on introducing and contextualising the problem. This involves conducting a literature review to understand existing knowledge, define the problem and its specific characteristics, and identify the requirements to address it. This phase establishes a foundation for the following phases, ensuring the project's objectives align with real-world needs and constraints;

- **The second phase (State-of-the-Art Review)** studies the latest technologies and methodologies in stress monitoring solutions aimed at identifying users experiencing high stress levels. More specifically, it involves a study of recent advancements and existing applications to determine the main technologies and architectures currently deployed, highlighting their strengths and limitations, and laying the groundwork for future enhancements to better meet user needs. This in-depth review provides a basis for developing innovative solutions that are adaptable to evolving technological contexts;

- **The third phase (Solution Design Proposal)** involves the design and proposal of a solution platform, considering the framework's development for stress monitoring and assessment in e-learning environments. This phase is essential as it sets the foundational architecture and functional specifications for the solution. The focus is on ensuring that the system is non-invasive and non-intrusive, yet scalable and easy to implement, capable of meeting the needs of different educational settings while adhering to data privacy and ethical standards;

- **In the fourth phase (Proof of Concept Development)**, the project builds on the outcomes of the third phase by selecting technologies best suited for the software implementation. This phase

involves the planning of procedures to monitor **HCI** during e-assessments, specifically focusing on mouse/keystroke dynamics and decision-making patterns. Also, developing and evaluating **AI** algorithms is necessary for quantifying individual stress levels. Additionally, this phase includes a thorough verification process to ensure the selected technologies align with project requirements and are capable of achieving the defined goals;

- **The prototype will be implemented and tested in the fifth phase** based on the algorithms developed in the previous phase. This prototype will undergo validation and testing across different case studies to ensure its robustness and efficacy. Through this process, the research aims to highlight the prototype's strengths and potential areas for improvement and to confirm its performance in enhancing student well-being and academic performance. This iterative process is essential for refining the prototype and achieving the project's goals;

- **During the last phase (Results Dissemination)** the research's findings will be made public to maximise their impact and contribution to the field. This dissemination will be accomplished by publishing scientific articles in conference proceedings and international journals relevant to the field, alongside compiling these findings in the current thesis report. This approach ensures that the insights achieved reach the academic and scientific community, promoting further research of the developed methodologies in similar contexts;

3.6 Research Team and Host Institution

The research team consists of two main investigators, each bringing unique expertise and perspectives to the research project: Filipe Gonçalves holds a Master's degree in Informatics Engineering from the University of Minho in Braga, Portugal. He is a data scientist at the ALGORITMI Centre, a research division of the School of Engineering - University of Minho; Paulo Novais, the supervisor, is a scientific researcher in the **AI** field. He is also a Full Professor of Computer Science at the Department of Informatics - University of Minho. He is a founder of the **Synthetic Intelligence Laboratory (ISLab)** and the coordinator of the research line in " **AmI** for Well-being and Health Applications".

The research team conducts scientific research at the ALGORITMI Centre [1], a research division of the School of Engineering - University of Minho, centring its activities around projects that strengthen ties with the community. Filipe Gonçalves and Paulo Novais are members of the **ISLab** [2], renowned for

[1] ALGORITMI Centre website: `https://algoritmi.uminho.pt/`

[2] **ISLab** website: `https://algoritmi.uminho.pt/research_teams_labs/synthetic-intelligence-group-islab/`

their contributions to the domains of **AI** and Intelligent Systems over the years. The group maintains collaborative ties with various faculties, including the School of Medicine, the School of Law and the Institute of Social Sciences - University of Minho, alongside a network of national and international institutions, having extensive experience in joint projects.

3.7 Tasks Performed during the Doctoral Programme

The work conducted and described in this thesis has resulted in a collection of studies and tasks performed during the doctoral programme, highlighting the application of various techniques to analyse behavioural biometric and cognitive patterns for non-invasive and non-intrusive assessment of the user's mental stress. Below is a list detailing its contributions, including the corresponding Chapter/Section:

1. **Identification of stress detection methods and current solutions:** The first contribution offers a review and summary of relevant information regarding current stress detection and monitoring digital solutions, including its various methods and their respective benefits and drawbacks (Chapter 2);

2. **Analysing computer interaction patterns based on human performance and stress mental states:** The investigation analyses behavioural biometric and cognitive data from the University of Minho students across different academic years and courses. This analysis also included their respective **PSS** survey scores, salivary cortisol values and perceived stress values, aimed to assess variations in human performance during high-demand computer tasks (*i.e.*, online exams) and understand how physiological and psychological stress levels differ across various stages of their academic journey. This approach demonstrated the potential of behavioural biometric features as an important enabler for assessing mental stress and its effects on human performance, in a non-intrusive and non-invasive way (Chapters 4 and 5);

3. **Proposal of a distributed intelligent architecture:** One of the difficulties faced in this research work involved collecting, anonymising and preprocessing raw behavioural biometric information from multiple computers when the online exam was completed. Addressing this, the proposed architecture was designed with scalability in mind, facilitating the easy integration of modular services. This design allows for the addition of different data sources and computational models to process this information efficiently (Chapter 4);

4. **Development and validation of ML models designed to analyse behavioural biometric**

and cognitive patterns for monitoring students' perceived stress during online exams: Given the feasibility of using behavioural biometric and cognitive data to assess student's mental stress during computer usage on high-demanding tasks, this contribution focuses on the digital pipeline regarding data preprocessing, training and testing procedures of **AI** stress assessment models, to estimate students' perceived stress intensity. Due to its complexity, the study considered the usage of questionnaires and statistical methods to validate the models developed and take advantage of the data available. The following list presents a summary of the proposed **ML** models (Chapter 5):

(a) **A regression model** designed to estimate the perceived stress of first, second and third-year medical students during an online single-best-answer exam. It analyses the collected behavioural biometric and cognitive data (*i.e.*, mouse dynamics and decision-making features) combined with previous **PSS** scores to calibrate the model to a specific student. This approach enables the estimation of stress levels, customised to each student's unique perceived stress and response patterns over time (Subsection 5.1.3);

(b) **A three-level classification model** designed to determine the perceived stress levels (*i.e.*, "Low", "Medium" or "High") of third-year medical students during an online single-best-answer exam by exclusively analysing their behavioural biometric and cognitive data (*i.e.*, mouse dynamics and decision-making features). This model relies on real-time interaction data to categorise stress intensity, offering an alternative approach to stress assessment and potentially enabling more immediate interventions (Subsection 5.1.4);

(c) **A five-level classification model** designed to assess perceived stress levels (*i.e.*, "Very Low", "Low", "Medium", "High" or "Very High") among fourth-year informatics engineering students during online written exams, based solely on behavioural biometric data (*i.e.*, mouse dynamics and keystroke features). Similar to the previous experiments, it provides a non-invasive method for stress assessment in e-learning environments, potentially facilitating prompt interventions (Subsection 5.2.4);

5. **Additional Experiments:** Building on the previous work and know-how acquired, an additional experiment has been conducted to broaden the scope and applicability of these technologies, more specifically:

(a) **Analysing computer interaction patterns based on students' academic performance and preference:** Building on previous work, this task involved analysing computer

interaction patterns based on students' academic performance and preferences. It explored the correlations between behavioural biometrics, attentiveness and learning outcomes of high school students during digital media production exams. This approach aims to better understand how high-school students' engagement and performance in multimedia tasks can be predicted and improved (Section 5.3);

(b) **Development and validation of prediction models designed to analyse behavioural biometric and user attentiveness patterns for estimating students' activity during online exams:** Considering the outcomes of the previous study, an intelligent mentoring system is proposed that assesses students' behavioural biometric and attention levels to enable the application of a **ML** model that recognises student's digital activities during online multimedia assessments. These contributions further enrich our understanding of the interplay between student behaviour, attention, and learning outcomes. Additionally, the application of non-invasive monitoring techniques ensures a less intrusive learning environment, promoting better engagement and performance (Subsection 5.3.4);

3.8 Summary

This chapter presented the research design employed in this doctoral programme to address the scientific problem identified. The objective was to formulate a detailed research plan, summarising the main tasks, their interdependencies, and their approximate duration. This approach ensured the project was well-organised to answer the proposed research questions and achieve the planned contributions. While some aspects of the plan were concrete and could be scheduled with precision, others were more complex and required flexibility, potentially needing further validation or adjustments. This methodology provided a basis for the overall research plan, supporting its successful execution and achieving its scientific objectives.
The next chapter introduces the proposed e-learning framework for non-invasive and non-intrusive stress assessment during online exams. This framework uses soft sensors to analyse user behaviours and performance, including behavioural biometric features and cognitive/academic performance, to monitor students' stress levels in real-time.

Chapter 4

A Stress Monitoring Tool for E-learning Environments

"One never notices what has been done, one can only see what remains to be done."

—Marie Curie

This chapter describes a structured approach to designing a framework for monitoring and assessing the stress levels of academic students during e-learning high-demanding tasks, such as online exams. The framework is designed to be non-invasive and non-intrusive, utilising data collected from students' interactions with a computer interface without requiring changes to the student's routines. To better understand this approach, the chapter focuses on the key aspects and theoretical perspectives of mental stress (*i.e.*, by providing a definition of stress and identifying its effects on human well-being, identifying the main tools for stress assessment, and outlining coping strategies for managing high levels of stress). It proposes a technological framework for assessing and monitoring students' stress (*i.e.*, considering its system architecture and methodology, its data workflow and feature engineering procedures, and by describing the key behavioural biometric features and the dataset preparation procedures regarded to enable the training and validation of stress prediction models). Unlike many types of physical biometrics, behavioural biometrics can often be gathered with existing standard hardware, requiring the deployment of analytical software, which can be easily integrated and replicated across multiple devices. This capability makes it easier and less costly to collect behavioural biometrics and provides an opportunity to develop new technologies that can be employed to enhance users' well-being.

The collaboration with the Life and Health Sciences Research Institute [1] (ICVS, University of Minho), Cen-

[1] ICVS website accessible at: `https://icvs.uminho.pt/`

tro ALGORITMI [2] (University of Minho) and LITEC [3] (Optimizer) have played crucial roles in advancing the "Eustress" project [4], an initiative closely aligned with the objectives of this thesis research. These partnerships have been essential to promote data collection, anonymisation and annotation procedures, enabling the research and development of the proposed **AI** models focused on behavioural biometric-based stress assessment.

4.1 Key Aspects and Perspectives on Mental Stress

Stress is a complex concept with no universally accepted definition, presenting a challenge for research that needs to pinpoint its effects on student well-being and performance. Stress can manifest in various dimensions (*e.g.*, acute, episodic acute or chronic, positive or negative, perceived or physiological) each with different characteristics and implications [214, 215]. This research considers these diverse forms to ensure a proper analysis of stress within an academic setting. The effects of stress can significantly influence an individual's well-being and daily life [216, 217]. Specifically in the academic environment, high stress levels can impact cognitive function, concentration, and overall mental health, leading to negative effects on learning, performance, and personal growth [32, 218, 219].

Current methods for assessing and monitoring stress range from self-reported questionnaires to physiological sensors and laboratory exams. However, these approaches exhibit several concerns that require attention [220–222]. Furthermore, addressing and managing high levels of stress requires a suite of coping mechanisms. These vary from psychological interventions to lifestyle alterations encompassing exercise, mindfulness, and time management strategies [223–225].

This study is conducted to address the need for adequate stress management in educational settings, particularly within e-learning platforms where traditional support mechanisms may be lacking. By understanding stress in its many forms, we can develop accurate tools to measure its impact on student performance and well-being. This insight allows the research to implement timely interventions, enhancing the educational experience and fostering a healthier learning environment. The goal is to improve academic outcomes and support students' mental health in a rapidly evolving educational environment.

[2] Centro ALGORITMI website accessible at: `https://algoritmi.uminho.pt/`

[3] Optimizer website accessible at: `https://www.eustress.pt/pt/consorcio/optimizer/`

[4] Eustress website accessible at: `https://www.eustress.pt/`

4.1.1 What is Stress?

Currently, the world still faces high stress levels, a direct result of COVID-19's impact, further aggravated by economic inflation, climate concerns, racial injustices, and global social and warfare-related conflicts [226, 227]. Despite better recognition of mental health and advocacy for well-being, obstacles in accessing care persist. The shift to remote work, while flexible, often mixes work and personal life, adding to the ongoing stress. Also, the need for mental health services outpaces the current infrastructure's capacity, highlighting gaps in health care [226, 228]. This situation calls for an urgent emphasis on mental health from both the public and private sectors, endorsing comprehensive support, accessible care, and policy changes to tackle the fundamental causes of stress in our society.

Exploring the nature of stress presents a challenge in the scientific community, as it regards a universal reaction experienced by everyone at various moments throughout their lives [229]. The stress concept was introduced by Selye [230], describing it as the physiological and psychological reaction to external or internal pressures, known as stressors, that disrupt the body's homeostasis. Stress triggers physiological responses through the **Autonomic Nervous System (ANS)**, composed by the **Sympathetic Nervous System (SNS)** and the **Parasympathetic Nervous System (PNS)**, affecting **HR**, **BP**, **GSR**, breathing, sweating, digestive system, and more [231]. In response to stress, the **SNS** activates, releasing hormones like adrenaline and cortisol, initiating the "fight, freeze or flee" response. Contrarily, the **PNS** is more active during relaxation, balancing the body's response to stress [231]. Stress can arise from various sources, including work and family responsibilities, relationships, financial difficulties, health problems, personal safety or traumatic events [232, 233].

In educational environments, the nature of stress in academic students is particularly significant, facing unique stressors such as academic deadlines, exam pressures, and balancing their educational responsibilities with personal commitments, all of which can impact their learning capabilities and overall mental health [234, 235]. In the wake of the pandemic, as educational institutions evolve, it becomes imperative to comprehend and address students' stress. This endeavour transcends academic interest and becomes crucial for cultivating resilient individuals who can thrive in our dynamic global society.

4.1.2 Stress and its Effects

While stress is often associated with negative connotations, not all stress is harmful. The association between stress and its effects may be represented as an inverted "U" shape (as presented in Figure 6), where under-stimulating stress fails to activate the body's coping mechanisms while moderate and

short-term stress can be constructive, encouraging adaptation and positive outcomes known as eustress. Contrarily, prolonged exposure to high-intensity distress causes adverse consequences. The classification of a stressor being identified as eustress or distress depends on the individual's ability to cope and adjust to life's various stresses [236].

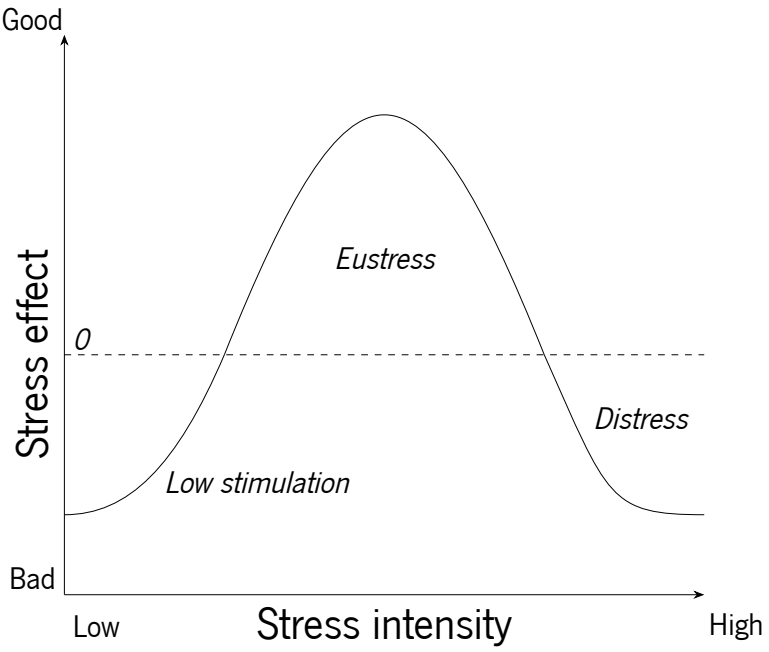


Figure 6: Stress intensity pattern concerning its effects. Based on: [236]

Eustress is often labelled as positive or beneficial stress. It represents a healthy, positive, constructive response to stress triggers, contributing to optimal health and well-being by stimulating productivity and supporting performance for both individuals and organisations. Since stress is a response mechanism, eustress occurs when the stress trigger is perceived as a positive challenge [237–239]. Eustress examples include the birth of a newborn, winning a competition, getting married, buying a new home, receiving a job promotion, forming new friendships, celebrating key cultural milestones like ceremonies that mark the passage into adulthood, and the motivation that drives us to tackle challenges and tasks effectively [238, 239].

In the academic context, eustress arises when students view academic challenges as opportunities for growth rather than threats. It stimulates motivation, enhances focus, and improves overall academic performance [234, 235]. For instance, the stress associated with preparing for a significant exam can lead to better study habits and ultimately a higher performance if the student perceives it as a challenge to be met with enthusiasm and dedication. Other examples include engaging in competitive academic events, receiving scholarships, achieving personal goals in coursework or participating in group projects.

Contrarily, distress is the stress response to triggers perceived as negative or to overwhelming stress that

exceeds an individual's capacity to cope, characterised as an unhealthy, negative, and destructive reaction to stress, leading to harmful effects for both the individual and the organisation [238–240]. When people typically consider stress, they often refer to moments of unpleasant pressure to perform, the occurrence of catastrophic events, or the daily stressors that lead to overall frustration. Examples of distress include facing continuous work pressure with unrealistic deadlines, coping with the profound loss of a close family member, friend or loved one, enduring financial difficulties, having relationship conflicts, suffering from long-term health issues or injuries, dealing with job loss or unemployment, facing legal challenges, and experiencing instances of bullying or harassment [238, 239].

Distress in educational settings often occurs when academic demands exceed a student's coping ability. It manifests as a negative stress response that can deteriorate mental health and hinder academic performance [234, 235]. Common triggers include when students perceive academic tasks as overwhelming or unfair, such as facing overwhelming workloads, dealing with poor interpersonal relationships with peers or faculty, experiencing constant fear of failure, or managing the pressure of maintaining high grades. Distress can also stem from external factors impacting academic life, such as personal or family health issues, financial difficulties or inadequate social support. Recognising and addressing these factors is crucial for mitigating their detrimental effects on students' well-being and educational success.

4.1.3 Forms of Stress

Mental stress can manifest in various forms, each with distinct characteristics and impacts on an individual's well-being. Considering the negative effects of stress (*i.e.*, distress), it is important to differentiate between these forms to understand and address how they affect mental and physical health. As indicated by the **American Psychological Association (APA)**, stress can be categorised into three main forms [216, 217, 241], specifically:

- **Acute stress** is the most prevalent form, occurring in the short term and not inherently negative. This type of stress can serve a constructive role by enhancing the brain's ability to adapt and prepare for future stressful situations. It typically arises from immediate reactions to recent events or anticipated challenges, fostering a state of alertness and readiness to tackle new obstacles. For instance, when an individual heading to an important meeting gets caught in traffic and fears being late, the stress response activates. However, upon learning they can join the meeting via conference call while still in traffic, their stress decreases as the problem is mitigated;
- **Acute episodic stress** originates from frequently facing acute stress, typically caused by exces-

sive responsibilities or unrealistic expectations, like overcommitting at work or constant worrying. Individuals often experiencing acute episodic distress usually show symptoms such as fatigue, anxiety, sleep issues, headaches, and concentration difficulties, impacting their physical and mental well-being. However, adopting behaviour changes and coping methods can diminish these negative effects;

- **Chronic stress** is considered the most harmful form of distress. Unlike acute stress, chronic stress persists over time, disrupting life and negatively impacting physical and mental health. The prolonged activation of the body's stress response system can lead to overexposure to cortisol and other stress hormones, affecting nearly all body processes and elevating the risk of various health issues, including anxiety, depression, burnout, digestive disorders, headaches, muscle pain, heart disease, hypertension, sleep disturbances, and memory problems or forgetfulness. Furthermore, chronic stress can also weaken the immune system, making it more difficult to recover from illnesses and potentially leading to disease through unhealthy coping behaviours such as overeating and smoking;

Individual differences play an important role in how stress is experienced and managed. Factors such as age, gender, personal history, and cultural background can significantly influence the perception of stress and the significance of coping mechanisms. For example, younger students might experience and react to stress differently compared to older students due to variations in maturity and life experiences [242]. Similarly, gender can affect how individuals respond to stress, with research suggesting different coping strategies may be employed by men and women [243]. Additionally, personal resilience, which can be shaped by past experiences and cultural context, also determines how an individual can manage stress [244]. Recognising these individual differences is necessary for personalised stress management interventions to be more inclusive and practical for diverse student populations.

In summary, distinguishing between acute, episodic acute, and chronic stress is essential for developing targeted health strategies and improved coping interventions adjusted to academic students. Each form of stress presents unique triggers and distinct effects that can impact students' learning and overall well-being. Understanding these differences enables educators, health professionals, and students to identify stress patterns and implement proactive measures. Implementing such strategies can promote better psychological and physical health outcomes, enhancing academic performance and the overall educational experience.

4.1.4 Stress Assessment Tools

Stress responses, covering emotions, cognitions, behaviours, and physiological reactions to stressors, can be assessed through several tools, including psychological self-report questionnaires, physiological sensors, laboratory exams and intelligent applications.

Self-report instruments such as **PSS** [245], **Stress Response Inventory (SRI)** [246] and **Perceived Stress Questionnaire (PSQ)** [247] offer insights into participants' thoughts, feelings, and behaviours, reflecting their perceived stress. However, the items on stress scales often represent general categories rather than specific events, leading to varied interpretations among individuals. Consequently, those experiencing higher stress levels might interpret items more severely, introducing bias and diminishing the scales' validity [207].

On the physiological front, technologies like belts or smartbands, chest strap sensors, and **EEG** headsets monitor bodily responses indicative of stress. These devices measure variables such as **HR**, **BP** variability, **GSR**, **EDA** and brain activity via **EEG**, providing insights into the body's stress response. Intelligent applications that integrate data from these varied sources provide an overview of the individual's state, improving the stress assessment accuracy and supporting targeted intervention strategies [209, 248–250]. Additionally, laboratory exams further ascertain these findings by analysing biomarkers like cortisol in saliva, blood, or urine samples [208, 251, 252]. These objective indicators offer a more precise assessment of the body's reaction to stress, unaffected by personal bias or subjective interpretation [207].

However, the available solutions present several concerns to be addressed [207–209]:

- Firstly, the accuracy rate of some tools may be relatively low, potentially leading to misinterpretation of stress levels;
- Secondly, tools such as **EEG** headsets and body strap sensors, while useful, can be intrusive and inconvenient for continuous use, affecting user compliance;
- Thirdly, the implementation of these technologies can be expensive and often requires specialised human resources to manage and interpret the data accurately;
- Fourthly, the capability for real-time monitoring is limited, which restricts the timely application of personalised coping mechanisms to mitigate stress as it occurs;
- Finally, in certain cases, the information provided by these methods may be unreliable, further complicating the assessment of stress and the usefulness of intervention strategies;

Despite these limitations, the integration of psychological and physiological data provides a holistic view of an individual's stress response. This all-around approach enhances the accuracy of stress assessments and facilitates the development of more target intervention strategies customised to the individual's needs.

4.1.5 Stress-Coping Mechanisms

Adequate coping strategies and evidence-based approaches are essential to manage stress and foster resilience. Beyond fundamental self-care practices like maintaining a healthy lifestyle through exercise, proper sleep and nutrition, and engaging in fulfilling hobbies, integrating meditation and relaxation activities has proven to be instrumental in alleviating stress and promoting overall well-being [253, 254].

Seeking aid from social networks, whether it be friends, family, or support groups, offers invaluable emotional expression and guidance during challenging and stressful times [255]. Workplace initiatives that promote stress management programs and work-life balance are vital in supporting employee well-being and creating a healthier work environment [256]. Cultivating a culture that prioritises mental health and encourages open dialogue about stressors can significantly contribute to a supportive atmosphere. Furthermore, exploring specialised interventions like cognitive-behavioural therapy [257], stress inoculation training [258], and resilience-building exercises enhance individuals' stress management capabilities [255], enabling them to navigate life's challenges with increased resilience and improved well-being.

In academic settings, students face unique stressors that require personalised coping mechanisms [259–261]. Key strategies include implementing structured study schedules, facilitating peer support groups, and ensuring access to mental health resources. Educational institutions should offer time management workshops and therapy sessions designed to address academic pressures. Integrating relaxation spaces within campus environments and promoting regular mental health days are also useful in mitigating academic stress. Moreover, encouraging faculty and staff to monitor students' stress levels and engage in supportive interactions further enriches the educational experience.

Collectively, these strategies equip individuals with the means to better handle stress and foster a supportive environment that recognises the significance of mental health. By understanding the causes and effects of stress and applying suitable coping strategies, individuals can enhance their capacity to manage stress and contribute to their overall well-being.

4.2 Framework Proposal to Assess and Monitor Students' Stress

This research introduces a framework specifically developed for e-learning environments, employing non-invasive and non-intrusive methods to monitor academic students' stress and performance throughout the academic period. It utilises **AI** techniques to unobtrusively predict and track stress levels during high-stakes tasks, facilitating real-time identification of students experiencing stress, and allowing the immediate application of targeted coping strategies. The system integrates data analysis from computers' soft sensors and e-learning platform activities, including user decision-making and mouse activity, enabling it to scale and support multiple users simultaneously. Complementary to this, the **PSS** questionnaire is conducted monthly, and salivary cortisol levels are measured before and after exams to provide a comprehensive assessment of student well-being.

This work seeks to create a distributed system for stress assessment in e-learning settings that combines data from various computer devices. The framework is designed with a focus on minimising the invasiveness and intrusiveness of the monitoring process, addressing privacy concerns, ethical considerations, and legal implications to ensure a respectful and compliant approach to stress assessment.

4.2.1 System Architecture

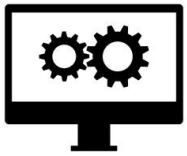
The proposed framework's architecture is organised into three main components (as illustrated in Table 2): the Data Source Infrastructure, consisting of multiple **Information Technology (IT)** sources that generate behavioural biometric raw data, the system's cloud, central to data storage, processing and user's stress prediction, and the MedQuizz App, represented by the client interface.

At the Data Acquisition Layer, data-generating devices capture students' interactions with the mouse and keyboard and log decision-making activities during e-exams. Each action is recorded, detailing timestamps, coordinates, types of clicks, keystrokes, and the nature of decisions made inside the e-learning platform. This raw data is locally preserved before being periodically synchronised with the web server in the cloud, ensuring logging for subsequent analysis.

Within the system's cloud, the Storage Layer serves as the foundational layer, employing a MongoDB database to store and manage logged data upon synchronisation. MongoDB goes beyond simple data warehousing by offering data processing features, including data anonymisation, and ensuring temporal data synchronisation between various data sources. These tools allow for proper data manipulation within a distributed network, facilitating scalability and enhancing the system's capacity to handle large datasets.

At the Analytical Layer, data cleansing techniques are initially applied to ensure dataset integrity and utility,

Table 2: Proposed framework's architecture.

MedQuizz App	**Client Layer** 
System's Cloud	**Stress Prediction Layer** 
	User Profile Layer 
	Analytics Layer 
	Storage Layer 
Data Source Infrastructure	**Data Acquisition Layer** 

including identifying and treating missing or corrupt data and using statistical methods to handle outliers. Subsequently, data processing techniques transform and refine this raw input into relevant features. This refined data is then analysed in real-time, yielding insights into behavioural biometric patterns for user stress prediction.

The User Profile Layer functions as an interpretative centre, utilising the users' profiles and historical metadata to enhance the model stress prediction procedure. This integration helps calibrate the system and adapt it to the specific user, reducing the errors generated by the stress prediction model.

The Stress Prediction Layer focuses on data interpretation, training prediction models, and evaluating their performance. As the data repository expands, this layer increasingly refines its ability to interpret patterns in biometric behaviours during e-exams. This analysis helps accurately assess and predict users' stress levels, continuously improving through iterative model training and adjustments based on new insights.

At the framework architecture's top level lies the Client Layer, featuring the web application MedQuizz. In this platform, students engage with academic tasks while teachers manage course content and tasks customised to their respective courses. This setup features tools for generating charts and constructing virtual environments, facilitating management and behavioural oversight while enabling educators to guide and respond to students' needs. It also includes features to trigger alarms based on specified criteria and offer recommendations, enhancing both learning and teaching experiences.

4.2.2 Data Workflow

Key to this system's functionality is the analysis of two types of information: mouse dynamics and decision-making patterns. Consequently, the framework is structured by two key components (presented in Figure 7), each addressing a specific aspect of this approach:

- **MedQuizz** [5]**:** An e-assessment management system designed for trainers, educators, and testing professionals that enables the creation, scheduling, delivery, and reporting of various assessments such as surveys, quizzes, tests, and exams. It allows the management of information regarding the quality of the items/questions, supporting the user in the decision to design custom assessments. It also presents fail-safe mechanisms to ensure functionality during network failures and includes features for logging the user's decision-making actions. This component is used to study the student's cognitive performance and behavioural decision-making patterns;
- **MouseDynamics:** A MedQuizz's module, adapted from Carneiro et al. [132], Carneiro and Novais

[5] MedQuizz website accessible at: `http://www.medquizz.com/`

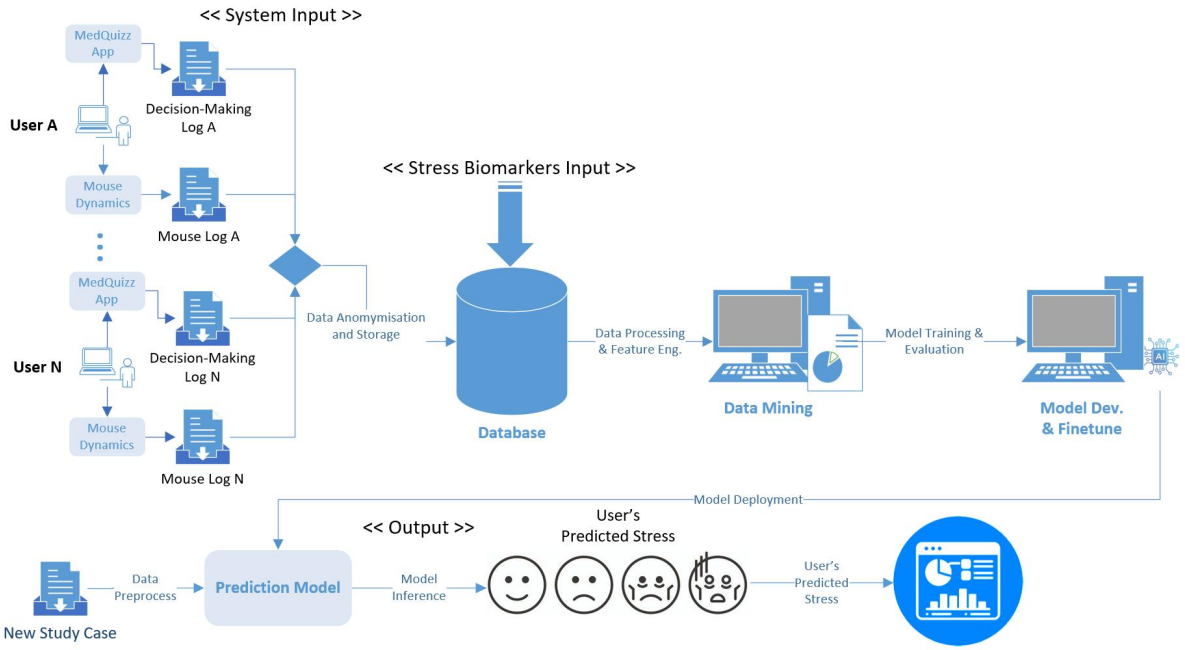


Figure 7: Proposed framework data-flow pipeline. Adapted from: [262]

[219], responsible for extracting and logging data from the mouse input device while the user interacts with the computer. This component is applied to analyse the student's interaction patterns and behavioural tendencies reflected via mouse dynamics during e-exams;

MedQuizz serves as the central management platform operating in a software-as-a-service environment, providing scalability and the capability to integrate various modules into the framework, customised to the user's configurations. MedQuizz is distributed with native Windows and Mac OS clients and is compatible with all major web browsers. Furthermore, all data collected through these components is stored and anonymised within a MongoDB database (described in Subsection 4.2.3).

A necessary prerequisite is the use of physiological and psychological stress assessment tools to predict and track the variations of an individual's stress levels during high-demanding tasks, as a way to train and validate the usefulness of the proposed prediction model. Among these, the **PSS** questionnaire proposed by Cohen et al. [245] is a widely used psychological instrument that allows healthcare professionals to assess a patient's psychological appraisal of stress. Specifically this questionnaire was designed to assess the individual's perceptions of unpredictability, lack of control, and life overload over the past month, while directly addressing current stress levels. These questions are universally applicable, not specific to any sub-group, and focus on thoughts and feelings experienced recently. Their simplicity ensures ease of understanding and response [263].

Given the wide variety of **PSS** survey scales (*e.g.*, **PSS**-14, **PSS**-10, **PSS**-4, *etc.*), the academic student's

stress was measured in a monthly basis using the **PSS**-13 Portuguese version, translated and validated by Ribeiro and Marques [264] (for clarity and ease of understanding, the English version is illustrated in Table 3). This survey consists of thirteen questions that focus on work-related stress encountered in the previous month. Each response is evaluated on a Likert scale from 0 ("Never") to 4 ("Very Often"), with items 4, 5, 6, 7, 9, and 10 scored inversely. The **PSS**-13 score varies between 0-52 points and provides a measurable evaluation of an individual's perceived stress levels, where a high **PSS** score value has been correlated with increased biomarkers of stress [235, 264]. Additionally, each student's **PSS**-13 questionnaire score was synchronised with the respective data collected from the nearest upcoming exam, ensuring a comprehensive and accurate assessment of stress levels in relation to academic demands.

Considering the physiological stress biomarker, the study by Chojnowska et al. [265] verified that cortisol in saliva offers a practical and cost-effective way to measure stress responses in real-world situations, such as during exams or in the workplace. This method is easy to apply and accessible, allowing for timely and frequent monitoring of cortisol levels, which fluctuate under stress. By analysing salivary cortisol, it is possible to gain additional insights into an individual's stress reactions, potentially aiding in creating personalised stress management strategies.

For this study case, students provided saliva samples before and after each exam, referred to as PreCortisol and PosCortisol, respectively. These data points were synchronised with the information gathered from the corresponding e-exams, enabling the analysis of cortisol level variations within their biological systems in conjunction with academic assessments. To quantify these variations, Equation 4.1 is applied (named as DeltaCortisol):

$$DeltaCortisol_{\alpha,\beta} = PreCortisol_{\alpha,\beta} - PosCortisol_{\alpha,\beta}, \tag{4.1}$$

where:

α represents the identification of the student;

β represents the identification of the exam;

With data collected from all sources mentioned, all information is properly synchronised, preprocessed, and analysed to extract relevant behavioural biometric features. Using these features in conjunction with the user's previous stress assessment data serves as the basis for studying behavioural patterns and developing calibrated predictive models aimed at estimating the user's stress levels. Once a robust prediction model is produced, fine-tuned and thoroughly tested, it is deployed within the proposed framework to make

Table 3: PSS-13 survey applied for student's stress assessment, translated from the Portuguese version. Adapted from: [264]

Question	**Answer (0-4)**
1. In the last month, how often have you been annoyed with something that occurred unexpectedly?	
2. In the last month, how often have you felt unable to control the things that are important in your life?	
3. In the last month, how often have you felt nervous or "stressed"?	
4. In the last month, how often have you successfully dealt with boring and annoying things? (*)	
5. In the last month, how often have you felt you were effectively facing important changes that were occurring in your life? (*)	
6. In the last month, how often have you felt confident in your capacity to handle your personal problems? (*)	
7. In the last month, how often have you felt that things were going the way you wanted? (*)	
8. In the last month, how often have you noticed you couldn't do all the things you had to do?	
9. In the last month, how often have you felt capable of controlling your irritations? (*)	
10. In the last month, how often have you felt that things were going well for you? (*)	
11. In the last month, how often have you felt irritated with things that happened that were beyond your control?	
12. In the last month, how often have you been able to manage your time?	
13. In the last month, how often have you felt that difficulties were piling up to the point where you were unable to overcome them?	

Notes: Questions marked with (*) indicate an inverted question score.

real-time inferences concerning new study cases. These predictions are later recorded in the MongoDB database, providing a student's historical perspective on stress variations throughout the educational period. This data accumulation enables the continuous model refinement to better adapt to specific user profiles.

As a last point, while the feature wasn't integrated into the proposed solution, theoretically, the framework could be configurable by students to notify themselves, educators or healthcare professionals when the prediction model consistently detects high stress levels. Notably, this feature would be implemented in adherence to ethical and data privacy regulations. Such notifications would prompt the consideration of targeted stress-coping interventions. This proactive approach would ensure that the educational environment can address the psychological needs of its students, potentially leading to improvements in both academic performance and overall well-being.

4.2.3 Database Structure

As mentioned in Subsection 4.2.1, the proposed framework's Storage Layer employs a MongoDB database for its proficiency in storing, managing, and analysing the vast collection of students' behavioural biometric data gathered during online exams. MongoDB was selected for its flexible data model, suited to handle large volumes of various data types inherent in biometric information. Its document-oriented approach facilitates the continuous integration and evolution of the data structure as the research progresses, ensuring that the database structure can adapt to the ever-changing landscape of data requirements (*e.g.*, include information from additional data sources such as keyboards, smartbands, microphones, **EEG** headsets, among others). Furthermore, its indexing capabilities, aggregation framework, and real-time processing features enhance the efficiency of operations performed on the dataset preparation.

Upon the student's completion of an e-exam, collected data is stored by the e-learning framework in the MongoDB database and subsequently anonymised to adhere to privacy concerns and ethical research standards. Specifically, the anonymisation process involves replacing the 'RealStudentID' with a unique identifier (named 'AnonStudentID') that cannot be traced back to the individual, and characteristics such as first and last name, gender, nationality and birth date information are omitted from the following research steps (*i.e.*, dataset preparation and analysis). This procedure is imperative to maintain the confidentiality of student identities and ensure that the research findings are generalised and do not inadvertently disclose sensitive information. Moreover, the database structure is designed as represented in Figure 8.

Central to this structure is the Student and Exam tables, which store details about students and the exams they undertake, including academic and personal information for students (like Anonimised StudentID,

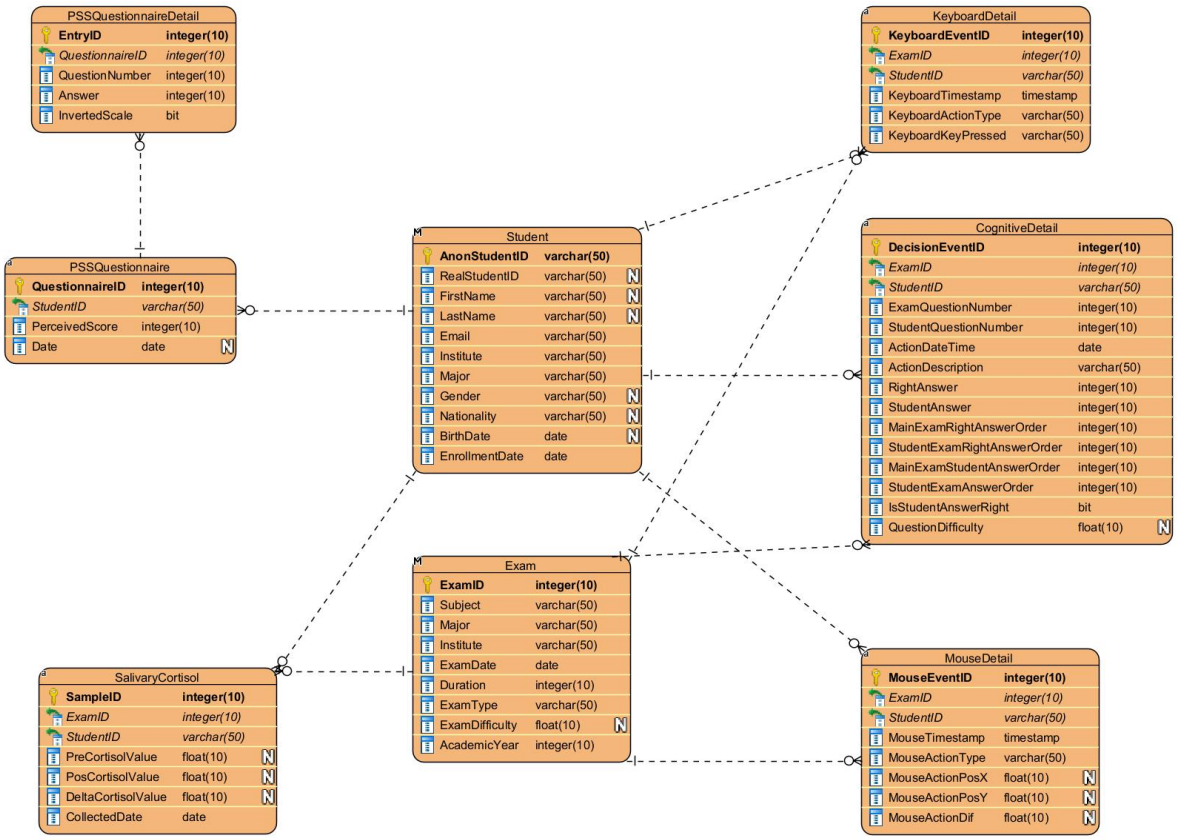


Figure 8: Database structure considered for data log collection procedure.

academic institute and major, enrolment date, *etc.*) and specific details of each online exam (like subject/topic, major, institute, exam date and duration, academic year, *etc.*).

The structure extends to specialised tables like PSSQuestionnaire and PSSQuestionnaireDetail, which capture data from the Perceived Stress Scale questionnaires completed by students, storing overall perceived stress scores and detailed answers to individual questions. Additionally, physiological stress biomarkers are tracked through the SalivaryCortisol table that logs cortisol measurements linked to specific exams and students, providing insights into the physical stress responses during exams.

User's interactions during exams are recorded and organised in the KeyboardDetail and MouseDetail tables, capturing keyboard and mouse activities. Complementing these, the CognitiveDetail table records decisions made during the exams, including responses to exam questions and the sequence and correctness of these responses.

Regarding the storage and management of the processed behavioural biometric features, these are organised in the MongoDB table structure illustrated in Figure 9. The CognitiveFeatures table considers cognitive behavioural features observed during exams, including decision-making patterns and correctness ratios, providing an understanding of the student's cognitive load and performance under high-demanding tasks.

Likewise, the KeyboardFeatures and MouseFeatures tables regard students' interactions with keyboards and mice, respectively, during exams, offering behavioural biometric data on typing and clicking behaviours indicative of stress and anxiety levels. Additionally, the StressAssessmentHistory table serves as a repository for monitoring stress variations over time, capable of storing the predicted and annotated stress scores linked to individual students and specific exams.

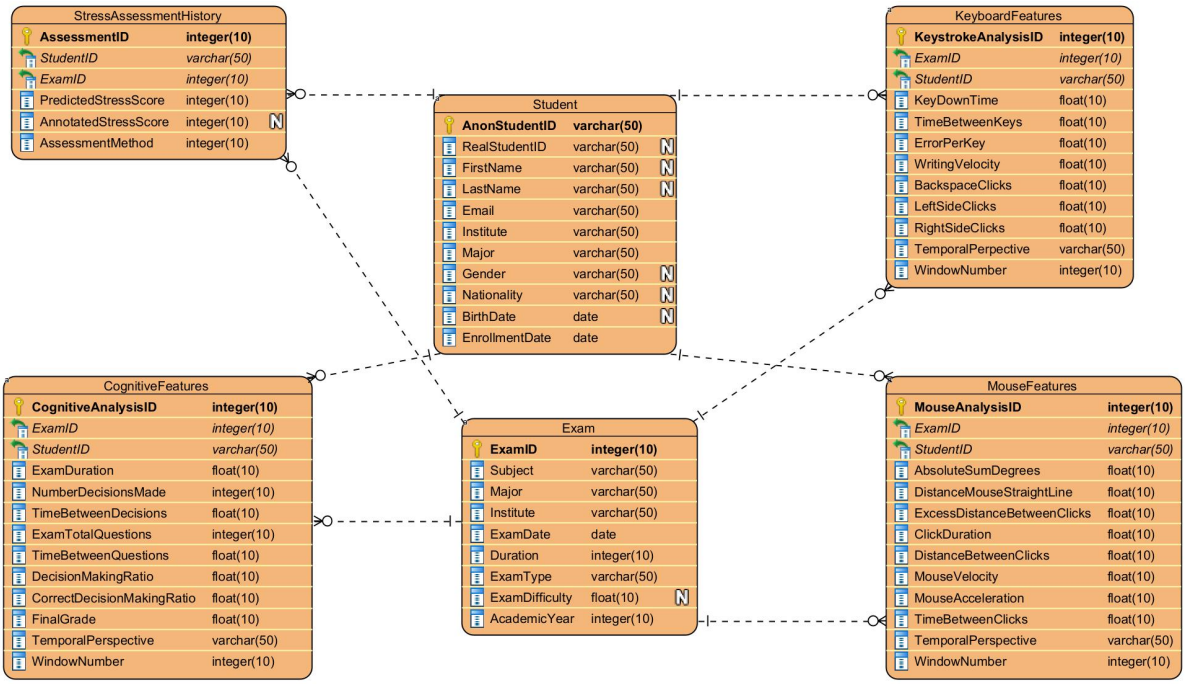


Figure 9: Database structure considered for feature engineering procedure.

In conclusion, the proposed database structure facilitates data storage and management, encompassing details about students, exams, stress assessments, and various behavioural features necessary for the research's analysis procedure. The considered anonymisation process ensures the privacy of student identities, mitigating ethical concerns and safeguarding sensitive information. In addition, Tables such as CognitiveFeatures, KeyboardFeatures, MouseFeatures, and StressAssessmentHistory play important roles in capturing cognitive and behavioural biometric insights, enabling the monitoring of student's stress levels and cognitive performance over time. Overall, this structured approach lays the foundation for conducting research in the fields of affective computing and biometric pattern recognition.

4.2.4 Data Preparation and Temporal Analysis

To examine the cognitive and mouse performance of a student, it is vital to sort, process and synchronise the collected events by their time of occurrence. Furthermore, analysing these events through various temporal perspectives provides valuable insights to consider for future data mining and the development

of prediction models. However, it was necessary to first address issues related to missing or ambiguous information in the dataset, including handling anomalies like situations where students needed to access an exam multiple times, handling missing data situations (*e.g.*, the absence of **PSS** scores or cortisol values), or dealing with study cases where sensor measurements contribute ambiguous information, resulting in inaccurate and misleading data that adds complexity to data analysis procedures.

To cover these challenges, several data cleaning and preparation measures were taken. First, instances affected by anomalies, such as multiple exam attempts, were excluded from the dataset to ensure data integrity, preserving only the most recent session. Second, ambiguous cases were identified using the Z-Score method, a statistical approach which supports detecting outliers based on their deviation from the mean [266, 267]. Cases identified as significantly noisy were removed from the prepared dataset, ensuring that only relevant and reliable data were retained. For less severe instances, the specific field was marked as missing rather than removing the entire case. This approach balanced the need to cleanse the dataset while preserving as much valuable information as possible. Finally, to deal with the missing data issue, conditional mean imputation was implemented across the dataset [253]. This method estimates missing values by using the known relationships between data points, based on the observed portions of the dataset, enhancing the dataset's completeness and reliability. In the end, five distinct datasets have been prepared, each offering a unique temporal viewpoint (detailed in Table 4).

Table 4: Temporal perspectives considered for the dataset analysis. Adapted from: [262]

Temporal Perspectives	**Description**
Chronological Time	Events are compiled into 5-minute intervals during the exam (*e.g.*, minutes 0-5, 5-10, 10-15, *etc.*)
Sliding Time	Events are compiled into 5-minute intervals with a sliding window (*e.g.*, minutes 0-5, 1-6, 2-7, *etc.*), differing from Chronological Time in the transition of intervals
Percentage Time	Events are compiled into intervals, each representing 5% of the total exam duration (*e.g.*, 0-5%, 5-10%, 10-15%, *etc.*)
Quarter Time	Events are compiled into four intervals, each covering 25% of the total exam duration (*e.g.*, 0-25%, 25-50%, 50-75%, 75-100%)
Complete Time	Data is analysed without dividing into intervals, presenting a complete feature set for the entire exam duration

The choice of temporal perspective impacts the analysis's usefulness and complexity. For example, chronological time provides a structured, easy-to-understand approach but may overlook subtle changes between intervals. Sliding time offers more detailed insights through overlapping intervals, at the cost of increased complexity and computational demands. Regarding the percentage and quarter time perspectives, while they offer scalability and simplicity by adjusting to exam lengths and dividing the exam into segments, they sacrifice precision and overlook slight variations due to their broader approach. Complete Time provides an overview of the entire exam duration, facilitating an understanding of overall patterns without segmenting data. However, this can lead to overlooked insights. The selection of a temporal perspective should thus be considered by the specific goals of the analysis, considering the data's characteristics and available computational resources.

4.2.5 Behavioural Biometric Features

Based on the goals and research characteristics defined, a detailed description of the compiled mouse dynamics and decision-making features is provided, regarding the data collection and processing stages computed by the MedQuizz and MouseDynamics components (detailed in Subsection 4.2.2).

MedQuizz Data

MedQuizz framework collects and outputs a data log file containing the student's cognitive activity during the online assessment. This log includes a chronological list of activity events, organised by the student ID and timestamp, aiding researchers to analyse the user's decision-making behaviour. Each MedQuizz data log is structured by the data fields presented in Table 5. Furthermore, a sample of the activity log is presented in Figure 10.

Exam Code	Student Code	Exam Duration	Exam Restarts	Exam Question No.	Student Question No.	Action Time	Action Description	Question Enter Counter	Action Result
2555	2016.01.159	02:07:02	1	1	4	20-02-2018 14:52:34	ENTER_QUESTION	1	
2555	2016.01.159	02:07:02	1	1	4	20-02-2018 14:55:10	ANSWER_INSERT	1	O-V
2555	2016.01.159	02:07:02	1	1	4	20-02-2018 14:55:10	ANSWER_REMOVE	1	V-O
2555	2016.01.159	02:07:02	1	1	4	20-02-2018 14:55:11	ANSWER_INSERT	1	O-V
2555	2016.01.159	02:07:02	1	1	4	20-02-2018 14:55:13	LEFT_QUESTION	1	
2555	2016.01.159	02:07:02	1	1	4	20-02-2018 16:23:25	ENTER_QUESTION	2	
2555	2016.01.159	02:07:02	1	1	4	20-02-2018 16:23:35	LEFT_QUESTION	2	
2555	2016.01.159	02:07:02	1	2	12	20-02-2018 15:05:22	ENTER_QUESTION	1	
2555	2016.01.159	02:07:02	1	2	12	20-02-2018 15:05:39	LEFT_QUESTION	1	
2555	2016.01.159	02:07:02	1	2	12	20-02-2018 15:05:41	ENTER_QUESTION	2	
2555	2016.01.159	02:07:02	1	2	12	20-02-2018 15:05:43	LEFT_QUESTION	2	
2555	2016.01.159	02:07:02	1	2	12	20-02-2018 16:25:36	ENTER_QUESTION	3	
2555	2016.01.159	02:07:02	1	2	12	20-02-2018 16:26:18	ANSWER_INSERT	3	O-X
2555	2016.01.159	02:07:02	1	2	12	20-02-2018 16:26:19	LEFT_QUESTION	3	

Figure 10: Log sample from the decision-making activity recorded during an exam.

Every act made by an individual, consciously or unconsciously, is the outcome of a decision. To make a choice, an individual must first understand the problem, the necessity and purpose of the decision, the

Table 5: Log data structure for exam decision-making behavioural analysis. Adapted from: [262]

Data Field	Description
Start Exam	Specifies the date and time when the exam started
End Exam	Specifies the date and time when the exam was concluded
Exam Duration	Specifies the time duration between "End Exam" and "Start Exam" data fields
Exam Code	Unique identification number of the exam
Student Code	Unique identification number of the student
Exam Question Number	Unique identification number of the question where the decision was made
Question Enter Counter	Number of times the user accessed a particular question during the exam
Action Time	Describes the timestamp of the decision-making event, in date and hour format
Action Description	Describes the type of decision made by the individual, *e.g.*, entering or leaving a question, inserting or removing an answer, *etc.*
Action Result	Indicates the correctness of the decision made (*e.g.*, an inserted or changed answer) by comparing it against the correct answer to the question

decision's criteria and the multiple decisions to consider, and identify the best choice [268]. Assuming this approach, the MedQuizz framework seeks to assess a student's performance based on a group of features, such as the time intervals between decisions, the accuracy of the choices made, whether the choices advance the user's goals, and the frequency with which a question is visualised. Table 6 shows a detailed overview of the features computed based on the decision-making logs.

Table 6: Cognitive features processed based on decision-making events logged. Adapted from: [262]

Feature	Description
Exam Duration	Represents the total amount of time used by the individual to complete the exam (in milliseconds)
Number of Decisions Made	Quantifies the total number of decisions an individual takes upon the completion of the exam (*e.g.*, entering or leaving a question, modifying answers, or marking questions for review)
Time Between Decision (TBD)	Measures the average time taken by an individual to make decisions (in milliseconds)
Exam Total Questions	Quantifies the total number of questions included in the exam
Time Between Questions (TBQ)	Determines the average time spent by an individual between all viewed questions (in milliseconds)
Decision-Making Ratio (DMR)	Assesses the ratio of the number of answers inserted, changed, and removed to the total number of recorded actions (in percentage)
Correct Decision-Making Ratio (CDMR)	Evaluate the ratio of decisions deemed correct (inserting/changing to a correct answer or removing an incorrect one) to the total number of answer modifications (in percentage)
Final Grade	Represents the total percentage of correct answers given by an individual upon completion of the task

MouseDynamics Data

The data collected and logged from the user's computer mouse is the main focus of the MouseDynamics module. Specific operating system events that are triggered by this device are used to track how the user interacts with the solution's interface during online exams. The event types considered for this study are detailed in Table 7. Furthermore, a sample of the mouse log is presented in Figure 11.

Table 7: Mouse events collected and logged by MouseDynamics. Adapted from: [262]

Event Type	Description
MOV, timestamp, posX, posY	An event describing the mouse's movement, in a given time, to coordinates (**posX**, **posY**) in the screen
MD[L|R], timestamp, posX, posY	An event describing the click's first half (when the mouse button is pressed down) in a given time. It also describes which of the buttons was pressed (left [L] or right [R]) and the position of the mouse in that instant
MU[L|R], timestamp, posX, posY	An event similar to the previous one but describing the second part of the click, when the mouse button is released. It also describes which of the buttons was pressed (left [L] or right [R]) and the position of the mouse in that instant
MW, timestamp, dif	This event describes a mouse wheel scroll of amount dif in a given time

```
MOV,635296942232274986,1303,354
MDL,635296942232284986,1303,354
MOV,635296942232514986,1302,354
MOV,635296942232594986,1301,355
MOV,635296942232754986,1301,356
MOV,635296942232994986,1301,357
MOV,635296942233074986,1300,357
MOV,635296942233154986,1299,358
MOV,635296942233474986,1298,358
MOV,635296942233554986,1298,359
MOV,635296942233794986,1297,359
MUL,635296942233804986,1297,359
MOV,635296942233974986,1296,359
```

Figure 11: Log sample from the mouse activity recorded during an exam.

To assess an individual's mouse performance, the MouseDynamics component analyses the user's mouse dynamics. Table 8 presents the list of the most relevant features processed by this module, based on the logged mouse activities.

Table 8: Mouse dynamics features processed based on mouse events logged. Adapted from: [262]

Feature	Description
Absolute Sum of Degrees (ASD)	This feature seeks to find how much the mouse turned, independently of the direction to which it turned (in degree units)
Distance of the Mouse to the Straight Line (DMSL)	This feature measures the average sum of the mouse's consecutive distances to the straight line depicted by two successive clicks (in pixels)
Excess of Distance Between Clicks (EDBC)	This feature assesses the average extra distance travelled by the mouse between every two successive clicks (in pixels)
Click Duration (CD)	This feature calculates the time between the press and release of a mouse click (in milliseconds). Longer clicks indicate less efficient interaction
Distance Between Clicks (DBC)	The mouse's total distance covered between two successive mouse clicks (in pixels)
Mouse Velocity (MV)	The mouse's distance covered (in pixels) over time (in pixels/milliseconds)
Mouse Acceleration (MA)	The mouse's velocity (in pixels/milliseconds) over time (in pixels / milliseconds^2)
Time Between Clicks (TBC)	The period between two consecutive mouse clicks (in milliseconds)

4.3 Summary

This chapter explored multiple key aspects and perspectives on mental stress, including its definition, effects, current assessment tools, constraints, and coping mechanisms to mitigate high stress situations. Additionally, a technological framework was introduced to offer an alternative approach to assess and monitor stress in e-learning environments, focusing on non-invasive and non-intrusive methods. Furthermore, it outlines the extraction of behavioural biometric features required for stress assessment based on soft sensors. Through these elements' integration, the framework aims to provide a holistic understanding of

students' stress levels.

A positive aspect of this framework is its potential to provide real-time, continuous stress monitoring without disrupting the learning process. Moreover, its non-invasive nature ensures user comfort and privacy, aligning with ethical considerations. However, several challenges are to be addressed, including ethical and legal considerations associated with assessing the user's mental state through behavioural biometric data. Furthermore, robust cybersecurity measures are necessary to safeguard sensitive information. Lastly, ensuring the scalability and adaptability of the framework across various e-learning platforms and student demographics requires further investigation.

In Chapter 5, the focus will shift towards conducting research experiments aimed at developing and testing the performance of several prediction models for stress detection. More specifically, these experiments will encompass the analysis of collected and prepared datasets, the application of data augmentation and feature engineering techniques, and the training and evaluation of the performance of stress prediction models.

Chapter 5

Experiments Performed and Analysis of Results

"Failure is simply the opportunity to begin again, this time more intelligently."

—Henry Ford

This chapter showcases the experiments conducted as part of this doctoral research, aimed at assessing students' stress in e-learning environments through the analysis of behavioural biometric and decision-making data, through a non-invasive and unobtrusive approach. It begins with a study of the collected and prepared dataset, outlining its characteristics, composition, and relevance to the study. Following this, the focus shifts to the development of stress assessment prediction models, first for medical students (detailed in Section 5.1) and later for informatics engineering students (described in Section 5.2), highlighting the challenges and results insights gained from each experiment.

Through this comparison, the research aims to identify and understand the variations in stress prediction performance between different methodologies and user groups. These approaches apply the mentioned behavioural biometric and decision-making features (previously described in Subsection 4.2.5) as predictive indicators, aiming to enable an understanding of stress patterns over time in the academic lifecycle.

Additionally, the chapter expands the research's scope by exploring user attentiveness in e-learning activities, examining how it can be monitored and applied for personalised teaching (discussed in Section 5.3).

The chapter concludes with a discussion regarding the key findings and their implications for future research and practical applications.

5.1 Stress Assessment via E-learning Platforms for Medical Students

Author Contribution Statement

The research described in this experiment was conducted as part of the "Eustress" project [a], in collaboration with Radu Albastroiu, Anisia Iova, Professor Davide Carneiro and Professor José Pêgo, under the supervision of Professor Paulo Novais. The author of this thesis contributed to the conceptualisation of the proposed framework and was responsible for the research practices related to data collection, data preparation, data analysis, feature engineering, prediction model development and evaluation, and the dissemination of results through scientific publications.

The research insights and outcomes were published in the following scientific works:

- Filipe Gonçalves, Davide Carneiro, José Pêgo, and Paulo Novais. Monitoring mental stress through mouse behaviour and decision-making patterns. In Paulo Novais, Jason J. Jung, Gabriel Villarrubia González, Antonio Fernández-Caballero, Elena Navarro, Pascual González, Davide Carneiro, António Pinto, Andrew T. Campbell, and Dalila Durães, editors, *Ambient Intelligence – Software and Applications –, 9th International Symposium on Ambient Intelligence*, pages 40–47, Cham, 2019. Springer International Publishing. ISBN 978-3-030-01746-0. doi: 10.1007/978-3-030-01746-0_5. URL `https://doi.org/10.1007/978-3-030-01746-0_5`
- Radu Albastroiu, Anisia Iova, Filipe Gonçalves, Marian Cristian Mihaescu, and Paulo Novais. An e-exam platform approach to enhance university academic student's learning performance. In Javier Del Ser, Eneko Osaba, Miren Nekane Bilbao, Javier J. Sanchez-Medina, Massimo Vecchio, and Xin-She Yang, editors, *Intelligent Distributed Computing XII*, pages 404–413, Cham, 2018. Springer International Publishing. ISBN 978-3-319-99626-4. doi: 10.1007/978-3-319-99626-4_35. URL `https://doi.org/10.1007/978-3-319-99626-4_35`
- Filipe Gonçalves, Davide Carneiro, José Pêgo, and Paulo Novais. X3S: A multi-modal approach to monitor and assess stress through human-computer interaction. *Computer Science and Information Systems*, 15(3):683–703, 2018. doi: 10.2298/CSIS180115033G. URL `https://doi.org/10.2298/CSIS180115033G`
- Filipe Gonçalves, Davide Carneiro, Paulo Novais, and José Pêgo. *EUStress: A Human Behaviour Analysis System for Monitoring and Assessing Stress During Exams*, pages 137–147. Springer International Publishing, Cham, 2018. ISBN 978-3-319-66379-1. doi: 10.1007/978-3-319-66379-1_13. URL `https://doi.org/10.1007/978-3-319-66379-1_13`
- Paulo Novais, Davide Carneiro, Filipe Gonçalves, and José Pêgo. Ambient intelligent systems: The role of non-intrusive and sensitive approaches. In *Proceedings of the 9th International Joint Conference on Computational Intelligence (IJCCI 2017) - IJCCI*, pages 11–17. INSTICC, SciTePress, 2017. ISBN 978-989-758-274-5. doi: 10.5220/0006810900010001. URL `https://doi.org/10.5220/0006810900010001`

[a] Eustress website accessible at: `https://www.eustress.pt/`

Based on the architecture previously described in Section 4.2, this research aims to design a non-invasive and non-intrusive e-learning framework capable of monitoring and assessing a student's stress levels.
In an initial approach, a comparative analysis was considered based on the data collected during medical school exams across the first three years. Furthermore, two key experiments are described to tackle this challenge. The first experiment adopts a holistic strategy, developing and evaluating a **ML** model designed to predict students' stress levels throughout their first, second, and third academic years. This method incorporates both current and previous behavioural biometric data and stress measurements to enhance the accuracy of predicting students' stress levels. The second experiment considers the design of a **ML** model aiming to predict stress levels in third-year students, focusing only on analysing behavioural biometric data obtained during online exams. This experiment seeks to assess the model's accuracy performance specifically for this academic group, without analysing past data.
Through this comparison, the research aims to identify and understand the variations in stress prediction performance between these two methodologies. Both approaches apply the mentioned behavioural biometric features (previously described in Subsection 4.2.5) as predictive indicators, aiming to enable an understanding of stress patterns over time in the academic lifecycle.

5.1.1 Data Collection

Research data was collected from two hundred and seventy medical students (from the first, second and third academic years) who took computer-based high-stakes exams every month to test their educational knowledge. In these tests, students are assigned seats, and at the designated time, they log in to the testing platform using their personal credentials, and the exam begins. Participation in the data-collection process does not alter the student's routine, and all monitored metrics are calculated using background processes (executed by the MedQuizz and MouseDynamics components, detailed in Subsection 4.2.2), making the data-collection process completely transparent from the student's perspective, just like a regular exam. Notably, this research considers data exclusively from participants who provided informed consent via legal documentation, authorising the Eustress project team to capture, process and utilise their data strictly for the project research purposes, in compliance with Portuguese **General Data Protection Regulation (GDPR)** regulations.
These exams comprise single-best-answer multiple-choice questions, with students simply using the mouse as an engagement tool. Students may exit the room once the exam is over. The data acquisition strategies were considered since any external aspect can impact variances in an individual's cognitive and mouse performance behaviour. As a result, it was essential to incorporate non-intrusive and non-invasive methods

as mandatory requirements throughout the exam administration.

Each case study was categorised into one of three groups, corresponding to the respective school year, presenting **HCI** data collected during the medical e-assessments, incorporating the set of features described previously in Subsection 4.2.5. The dataset includes information from 102 first-year students, 87 second-year students and 81 third-year students from the School of Medicine - University of Minho.

As mentioned in Section 4.2.1, to train and evaluate the proposed prediction models, data from stress assessment tools (*i.e.*, **PSS**) is required, enabling to estimate the student's stress levels once a month and compare it with the predicted stress levels output by the stress assessment framework. Another potential source of data consists of the use of physiological measurements, such as salivary cortisol stress biomarkers, to provide further information in the identification of user variation stress levels. This is accomplished by taking a sample of the subject's saliva both before and after each exam.

Through the application of **ML** techniques, it is critical to identify the main characteristics that can impact a person's psychological state and pick the best prediction models with the highest performance in properly estimating the user's stress levels during online exams.

5.1.2 Data Analysis

There is an inherent relationship between features shown in Table 9 and student performance. For example, while moving a mouse device between two spots, it is never moved in a straight line, instead, there is always some degree of curvature (*i.e.*, as the curvature grows, the movement becomes less efficient). Except for mouse acceleration and velocity, a rising value indicates a decrease in performance. Also, longer clicks and an increased **Distance of the Mouse to the Straight Line (DMSL)** are related to lower performance, indicating that the user is relaxed [132]. It is interesting to note how the average values of each feature vary from year to year, especially when comparing the first and the third academic years: overall there is a tendency to increase, except for **PSS** score, which tends to decrease (*i.e.*, likely result from increased familiarity with academic tools, better adaptation to the environment and improved cognitive and motor skills over time).

Table 9: Behavioural feature comparison among first, second and third-year medical students considering the complete time perspective. Adapted from: [262]

Feature	School Year	Std. Dev.	Median	Avg.
Mouse Velocity (MV)	1st	0.14 px/s	0.73 px/s	0.73 px/s
	2nd	0.17 px/s	0.76 px/s	0.75 px/s
	3rd	0.17 px/s	0.77 px/s	0.80 px/s
Absolute Sum of Degrees (ASD)	1st	7409.35 °	11028 °	12151 °
	2nd	4498.43 °	9418 °	10424 °
	3rd	7030.60 °	11376 °	13334 °
Excess of Distance Between Clicks (EDBC)	1st	1.37 px	7.56 px	7.41 px
	2nd	1.17 px	7.56 px	7.31 px
	3rd	3.13 px	7.56 px	8,00 px
Distance of the Mouse to the Straight Line (DMSL)	1st	12.78 px	92.96 px	90.84 px
	2nd	12.61 px	92.96 px	90.88 px
	3rd	11.93 px	92.96 px	94.37 px
Decision-Making Ratio (DMR)	1st	0.74 %	31.72 %	31.69 %
	2nd	0.65 %	32.97 %	34.03 %
	3rd	0.88 %	32.99 %	32.83 %
Correct Decision-Making Ratio (CDMR)	1st	1.01 %	51.63 %	51.54 %
	2nd	1.10 %	50.78 %	51.68 %
	3rd	0,70 %	61.29 %	61.11 %
Time Between Decision (TBD)	1st	5907.57 ms	19212 ms	19460 ms
	2nd	6120.79 ms	20456 ms	20926 ms
	3rd	6130.61 ms	20940 ms	21113 ms
PreCortisol	1st	0.30 nmol/L	0.29 nmol/L	0.37 nmol/L
	2nd	0.18 nmol/L	0.42 nmol/L	0.40 nmol/L
	3rd	0.25 nmol/L	0.38 nmol/L	0.44 nmol/L

Continue on next page

Table 9 – *Continued from previous page*

Feature	School Year	Std. Dev.	Median	Avg.
PosCortisol	1st	0.06 nmol/L	0.15 nmol/L	0.16 nmol/L
	2nd	0.08 nmol/L	0.17 nmol/L	0.17 nmol/L
	3rd	0.11 nmol/L	0.17 nmol/L	0.18 nmol/L
DeltaCortisol	1st	0.28 nmol/L	0.19 nmol/L	0.23 nmol/L
	2nd	0.15 nmol/L	0.25 nmol/L	0.26 nmol/L
	3rd	0.24 nmol/L	0.25 nmol/L	0.24 nmol/L
Perceived Stress Scale (PSS)	1st	6.65 pts	27 pts	27.46 pts
	2nd	6.87 pts	23 pts	23.41 pts
	3rd	7.63 pts	24 pts	23.66 pts

Concerning the analysis of the students' cortisol levels over the academic years (specifically the PreCortisol and PosCortisol), the average values rise from 0.37 and 0.16 to 0.44 and 0.18 nmol/L, respectively. This indicates that students' PreCortisol and PosCortisol concentration levels tend to increase across the three academic years, with third-year students exhibiting higher overall stress biomarker levels. Despite this increase, the student's perception of stress seems to decrease, where the average values vary from 27.76 to 23.66 score points. However, PosCortisol and **PSS** score standard deviation tends to increase each year, while PreCortisol varies widely.

A similar trend is observed for all the interaction features (*i.e.*, mouse dynamic and decision-making behavioural characteristics), which indicates a decrease in performance over the years [262]. The joint analysis of these two groups of features puts forward an interesting hypothesis: the student's stress level rises as they advance in their course, which is accompanied by a drop in performance. Furthermore, this pattern indicates a potential relationship between these two groups of variables, suggesting the possibility of predicting users' stress levels through behavioural analysis during online exams.

Despite these observations, these are general conclusions and not every student is expected to behave the same. While this may reveal the overall behaviour, it should be emphasised the significance of developing individual models, trained with data from each user, that may be used to identify students who have poorer stress-coping strategies more accurately. The main conclusion of this data is, nonetheless, that when the students exhibit higher stress levels and are closer to a state of burnout, their performance declines. This

is evidenced by less efficient interaction patterns (*e.g.*, longer mouse clicks, larger distances travelled by the mouse, longer key downtimes, faster and less efficient decisions made, *etc.*). This conclusion, which comes as no surprise, is nonetheless important in the sense that it allows, for the first time, to quantify and study this relationship between an objective stress measure (*i.e.*, cortisol levels and **PSS** score) and the monitored features.

5.1.3 Prediction Across Medical Students

In this study, it was important to implement a calibration process to improve the predictive accuracy of the learning model for stress detection within the proposed framework. Every student exhibits a unique stress-coping profile, significantly varying their **PSS** scores. Therefore, a personalised analysis is applied for each student to assess their mental stress by examining their previous stress mental states, designated as the user stress profile. This calibration involves analysing three specific features derived from previous **PSS** submissions, specifically the maximum, minimum and average **PSS** score. Students with less than three **PSS** surveys are excluded from this analysis due to insufficient data to assemble a reliable user stress profile.

The holdout method is also used to split the available data samples into two subsets for a train-test experiment. This approach involves randomly separating the study participants between a train set, which comprises 70% (100 cases) of the data for model training, and a test set, which contains the remaining 30% (43 cases) for model evaluation [273].

Given the extensive number of behavioural biometric features (thirty-three in total, considering mouse behaviour features and decision-making patterns), it was necessary to identify the most relevant subset of behavioural features for accurately predicting a student's stress levels. To achieve this, the feature selection process considered the application of the recursive feature elimination method [274]. This method, which applies a **RF** algorithm in each iteration, uses a recursive elimination strategy to discard the least important features identified based on their impact on the learning model's performance. This process is executed iteratively until an optimal feature subset is identified. Unlike filter or embedded methods, the recursive feature elimination method, when combined with cross-validation, ensures the identification of important features for the prediction task.

Several tests and performance comparisons were made considering different feature combinations to determine the optimal number to be selected by this method. This ensures the learning model presents the necessary features to capture patterns without excessive complexity. Figure 12 shows the **Root Mean Squared Error (RMSE)** value of the **RF** model when exploring different subset combinations, which are

validated using the ten-fold cross-validation strategy [275]. This value is the lowest when the selected number of features is 9 (with a **RMSE** value of 4.5). Considering this option, the following list considers the features list selected under this study case: exam duration, exam total questions, number of decisions made, the time between clicks (named also as time double click), **DMSL** and **Excess of Distance Between Clicks (EDBC)**.

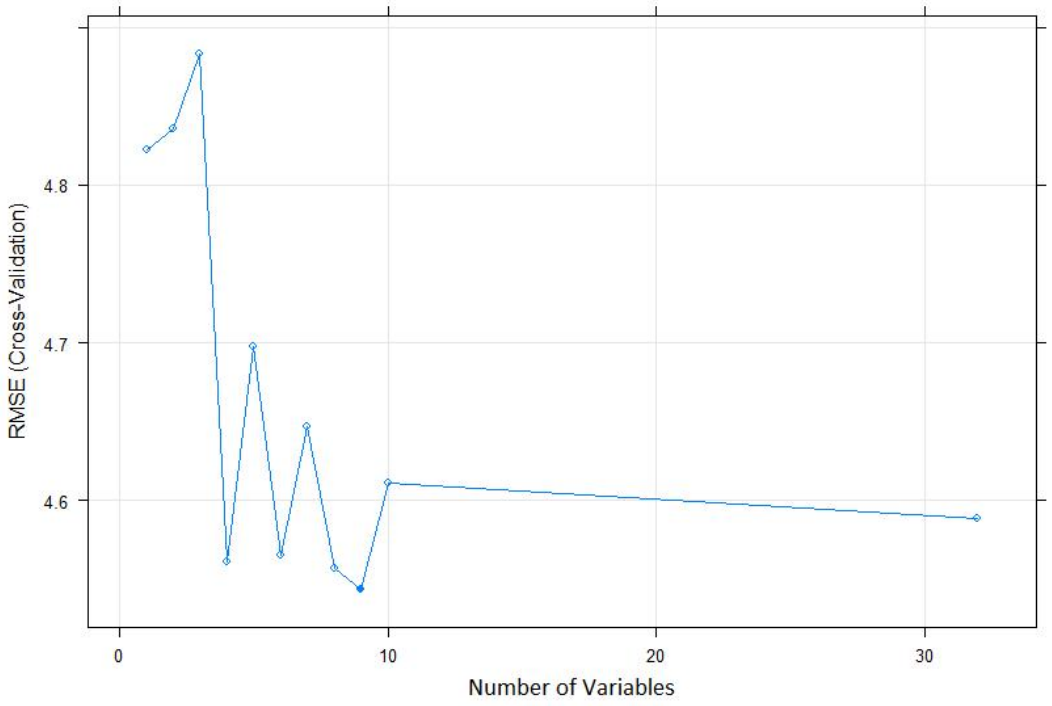


Figure 12: Analysis of RMSE results from the recursive feature elimination method across multiple number of features.

Next, a regression model was trained to predict the **PSS** score of students. Given the limited number of samples, multiple regression algorithms were trained and tested using a ten-fold cross-validation technique to ensure the results' robustness [275]. Techniques such as **Linear Regression (LR)**, **SVM**, **DT**, multi-layer perceptron, and gradient boosting were among the methods explored. Yet, the technique that demonstrated superior performance was the **RF**. This algorithm uses an ensemble of decision trees to predict the intended value, where each decision tree is trained on a random subset of the training set and only uses a random subset of the features, enhancing the model's robustness against overfitting.
Additionally, to achieve optimal performance, a hyperparameter tuning process was done via a grid search exploration [276], as a way to consider a balance between complexity and **Mean Squared Error (MSE)** minimisation while avoiding overfitting the model. The outcomes of this exploration are shown in Figures 13 and 14. This led to the configuration of the model with 400 trees (*i.e.*, **DT** number within the **RF**) and

leaf size of 4 (*i.e.*, each leaf node in the trees must contain at least 4 samples before considering a further split at a deeper level).

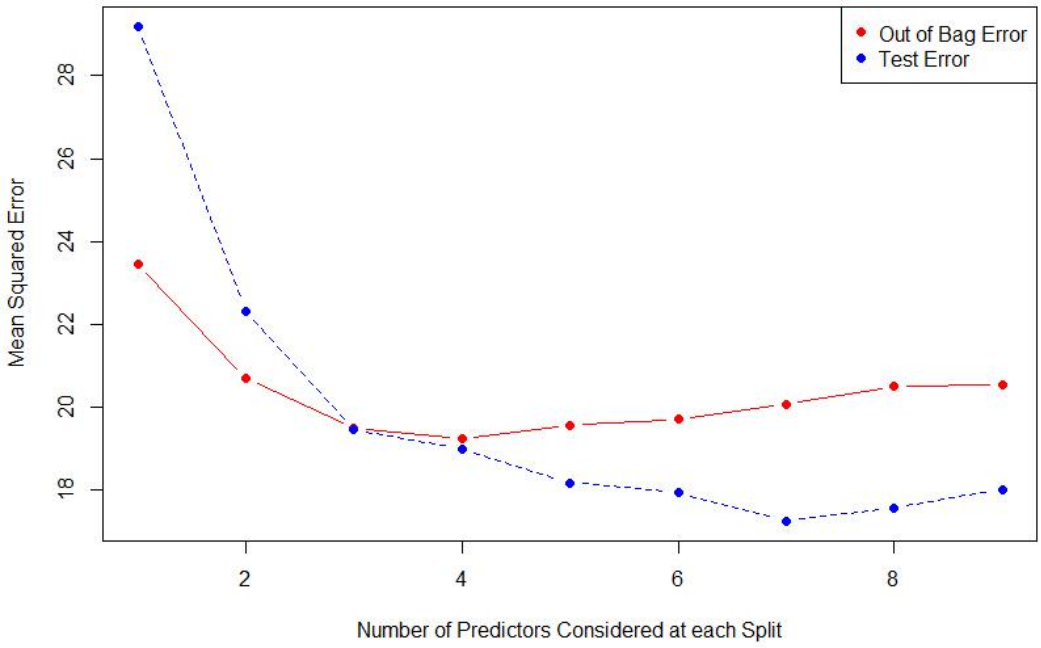


Figure 13: Impact evaluation of leaf size on RF model.

Upon completing the algorithm's training, its performance is evaluated using the test set. Figure 15 shows a plot of the real values versus the predicted ones, where its coefficient correlation value presented a positive result of 85.1%. Specifically, this analysis indicates that **PSS** scores above 38 points present an increased **RMSE** in the model, resulting from insufficient samples with high **PSS** scores in the training dataset. Furthermore, Figure 16 indicates each feature's relevance in the regression performance of the developed algorithm, highlighting the relevance of the features related to the user's stress profile, especially the average **PSS** and maximum **PSS**.

5.1.4 Prediction in Third-Year Medical Students

Regarding the medical education journey, first and second-year medical students mainly engage in classroom-based learning, concentrating on acquiring theoretical knowledge without the immediate pressures associated with clinical environments. In contrast, third-year medical students face a transition from pre-clinical to clinical environments, engaging with real patients, complex healthcare environments and increased responsibilities. This shift often results in increased stress, as students must apply theoretical knowledge in

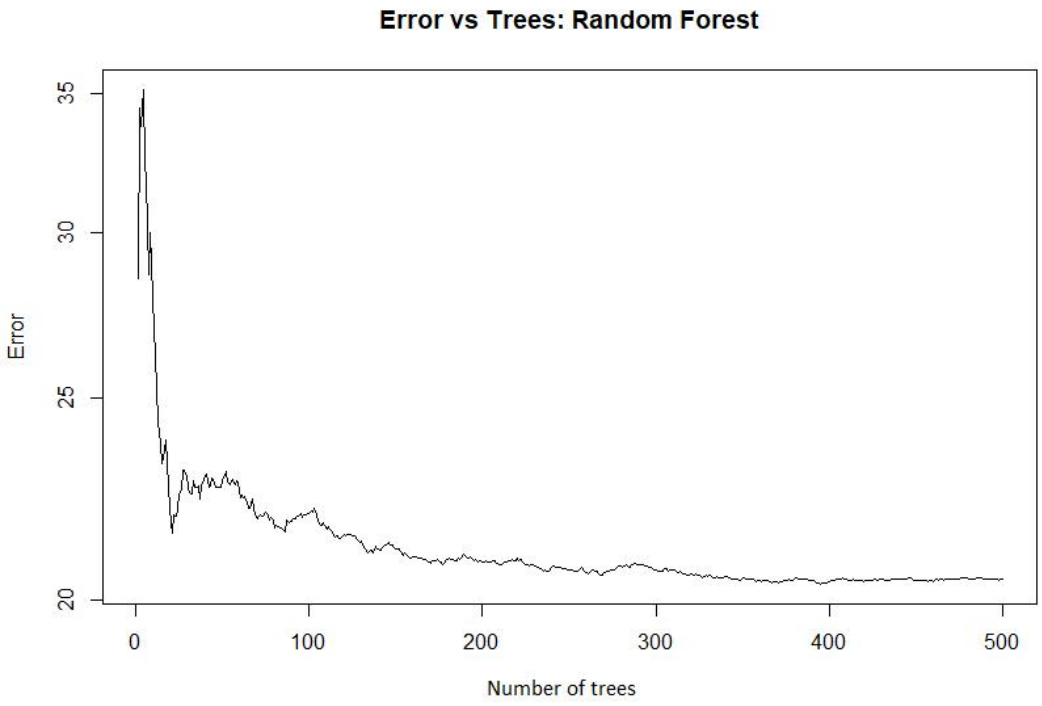


Figure 14: Impact evaluation of decision tree quantity on RF model.

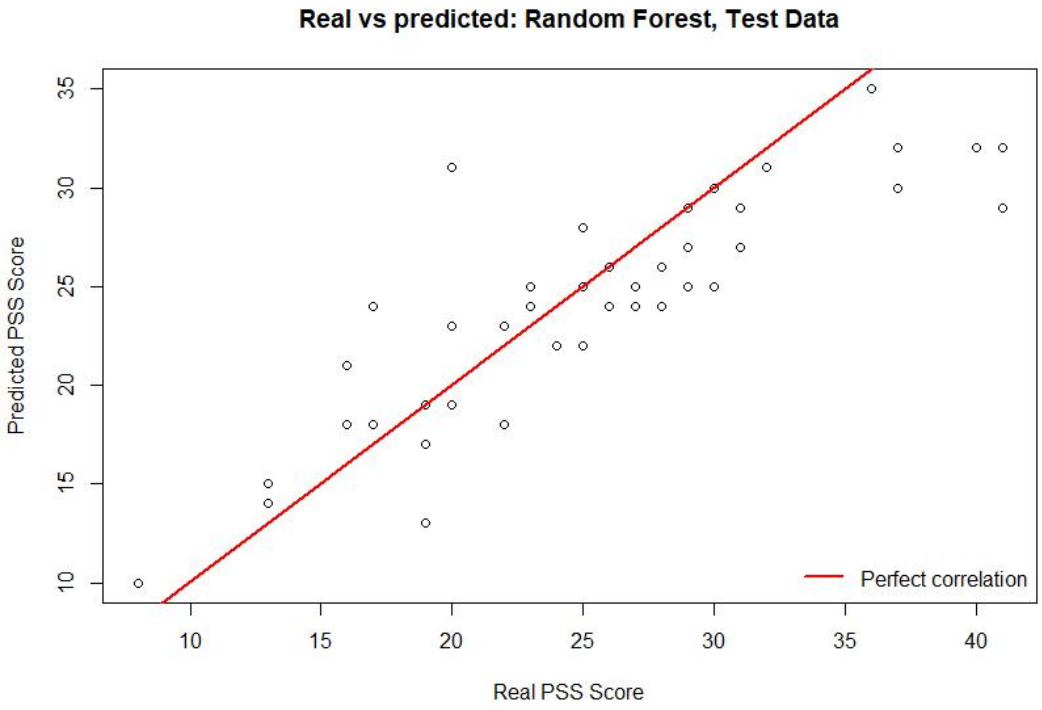


Figure 15: Real PSS score vs Predicted PSS score values.

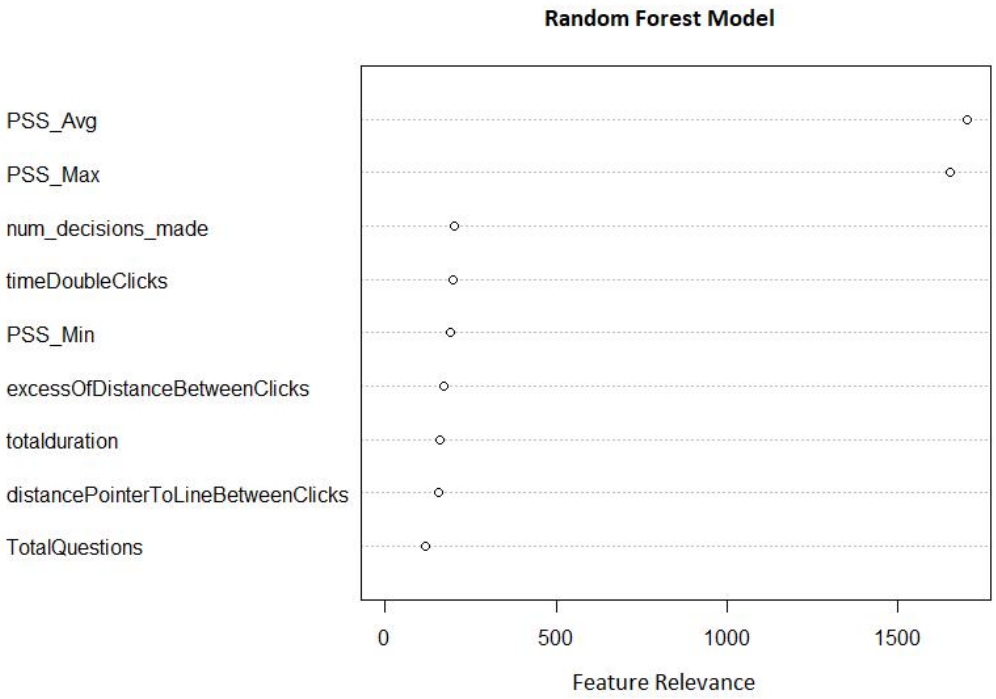


Figure 16: Relevance of selected features sorted by descending order.

practical scenarios and meet high-performance expectations. This theory is corroborated by the increasing values of cortisol and **PSS** score across the first, second and third-year medical students.

With this in mind, in this experimental study, the decision-making and mouse behaviour patterns of 54 third-year medical students are studied during 3 sequential exams. This study seeks to analyse the increased stress experienced by third-year medical students, to understand how the academic and clinical pressures impact their well-being.

Based on the **PSS**-13 questionnaire score, each instance was classified into one of the following categories: 'Low' stress (0-17), 'Moderate' stress (18-35), and 'High' stress (36-52). Given this context, the problem was formulated as a multi-class classification task, aiming to develop a **ML** model to classify students' stress levels during online learning exams.

To ensure the development of robust classification models and provide a reliable evaluation of their performance, the holdout method was applied to split the participants into two sets: the train set, making up 70% of the total samples (113 instances), and a test set, comprised of the remaining 30% (49 instances) [273].

Similar to the previous experiment, there is a higher number of 'Moderate' stress cases compared to the 'Low' and 'High' stress (*i.e.*, 76% of all cases present the 'Moderate' stress classification). To improve the representation of minority classes (*i.e.*, 'High' and 'Low' stress), two data pre-processing techniques

are explored, specifically the **Random Oversampling Examples (ROSE)** and **SMOTE**, to provide a balanced dataset for training the classification models. Oversampling and undersampling techniques were excluded from this process to avoid generating a large number of duplicated observations, resulting in model overfitting. The dataset distribution provided by each method is presented in Figure 17.

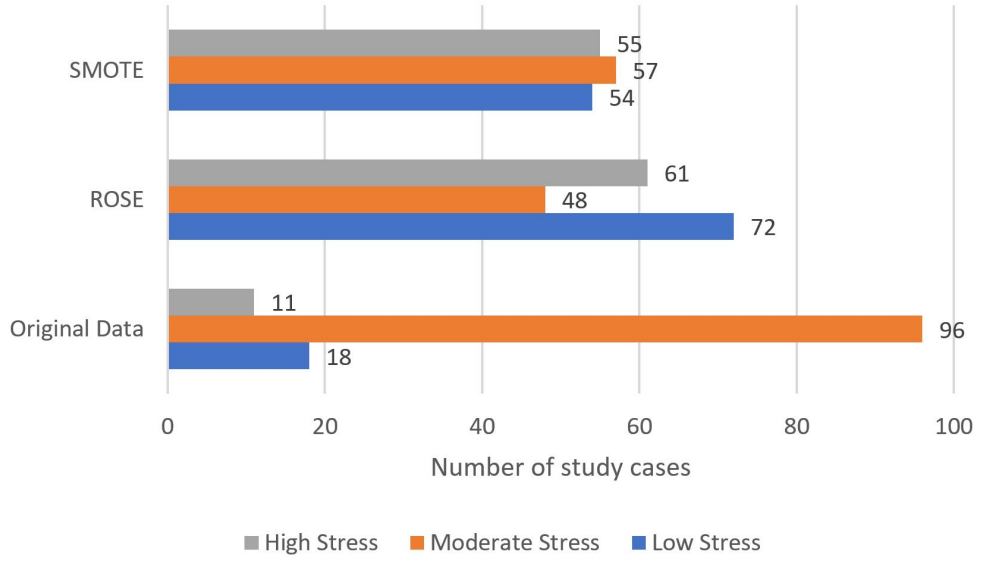


Figure 17: Train set distribution considering the application of the pre-processing techniques. Adapted from: [270]

Regarding these synthetic-based data pre-processing methods, **ROSE** generates artificially balanced samples through a smoothed bootstrap approach, which involves taking existing data samples from the dataset and adding small perturbations (noise) to create new synthetic data samples [277] while **SMOTE** creates synthetic samples by interpolating between existing instances. For each data point belonging to the minority class, this method finds its 'K' nearest neighbours (also within the minority class), and synthetic instances are generated by choosing one of the 'k' nearest neighbours at random and then drawing a line between the two points in feature space (as presented in Figure 18). New instances are created along this line, effectively generating data points that are similar to existing ones [278].

Furthermore, the Min-Max normalisation and Z-score standardisation methods are applied to address the scale variance of the dataset features. The Min-Max method normalises a dataset's feature values to a specific range (normally [0,1] or [-1,1]). Although this method is effective and straightforward, it is also sensitive to outliers, which can affect the normalisation results [280]. This method is formulated by Equation (5.1):

$$x'_{i,n} = \frac{x_{i,n} - \min(x_i)}{\max(x_i) - \min(x_i)}(nMax - nMin) + nMin, \tag{5.1}$$

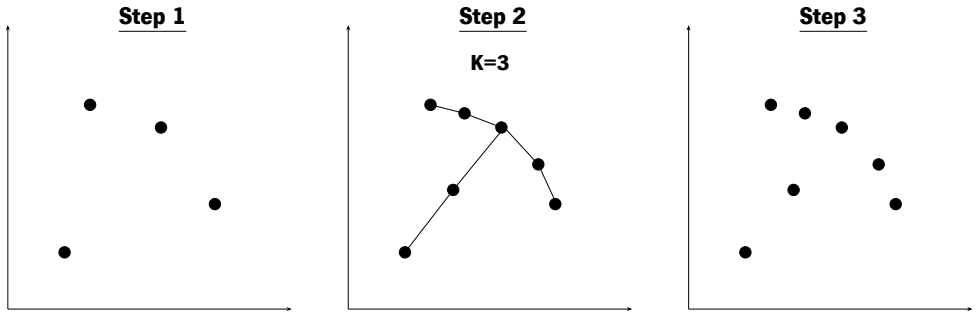


Figure 18: Graphical illustration of SMOTE synthetic data generation. Adapted from: [279]

where:

$x'_{i,n}$ represents the normalised value;

$x_{i,n}$ represents the original value;

min(x_i) and max(x_i) represents the minimum and maximum value of the i^{th} feature;

$nMin$ and $nMax$ represent the lower and upper bounds of the new scale, typically set to [0,1] or [-1,1];

As for the Z-score method, it's a process that adjusts the dataset's feature values to achieve a mean of 0 and a standard deviation of 1 for all values. This statistical method standardises the distribution of data points, facilitating comparisons across different scales [280]. This method is formulated by Equation (5.2):

$$x'_{i,n} = \frac{x_{i,n} - \mu_i}{\sigma_i}, \tag{5.2}$$

where:

$x'_{i,n}$ represents the normalised value;

$x_{i,n}$ represents the original value;

μ_i represents the mean value of the i^{th} feature;

σ_i represent the standard deviation value of the i^{th} feature;

Applying these two scaling methods resulted in three different dataset categories (named original data, Min-Max normalisation and Z-score standardisation), forming a total of 9 prepared datasets for analysis. The purpose of this procedure is to evaluate how different preprocessing techniques affect the performance of the classification models within the same study case.

To improve the precision of the classification process and remove redundant or irrelevant features for this use case, Pearson's correlation coefficient and recursive feature elimination methods (employing ten-fold cross-validation) are used [274, 281], resulting in the identification of the following relevant features for user's stress classification: **Correct Decision-Making Ratio (CDMR)**, **DMSL**, **Time Between Decision (TBD)** and **Distance Between Clicks (DBC)**.

After completing the data preparation and feature selection procedures, the next step involved training classifier models designed to predict students' stress levels during online exams. To achieve this, several **ML** models are trained and validated using the training sets prepared in the earlier stages, by applying the ten-fold cross-validation method [275]. The list of **ML** techniques considered are the **Naive Bayes (NB)**, **DT**, **Neural Networks (NN)**, **RF** and **SVM**.

Considering these results, the study verified that on the **ROSE** datasets (*i.e.*, considering the original data, Min-Max normalisation and Z-score standardisation) the average accuracy presented a result of 55.55%, while on the **SMOTE** datasets, it increased to 70.16%. Scaling the feature values through Min-Max normalisation or Z-score standardisation improved the model's classification performance by an average of 5%. Among these **ML** techniques, **SVM** and **RF** are identified as the most effective, achieving average accuracies of 75.05% and 68.74% respectively across all datasets, as demonstrated in Figure 19.

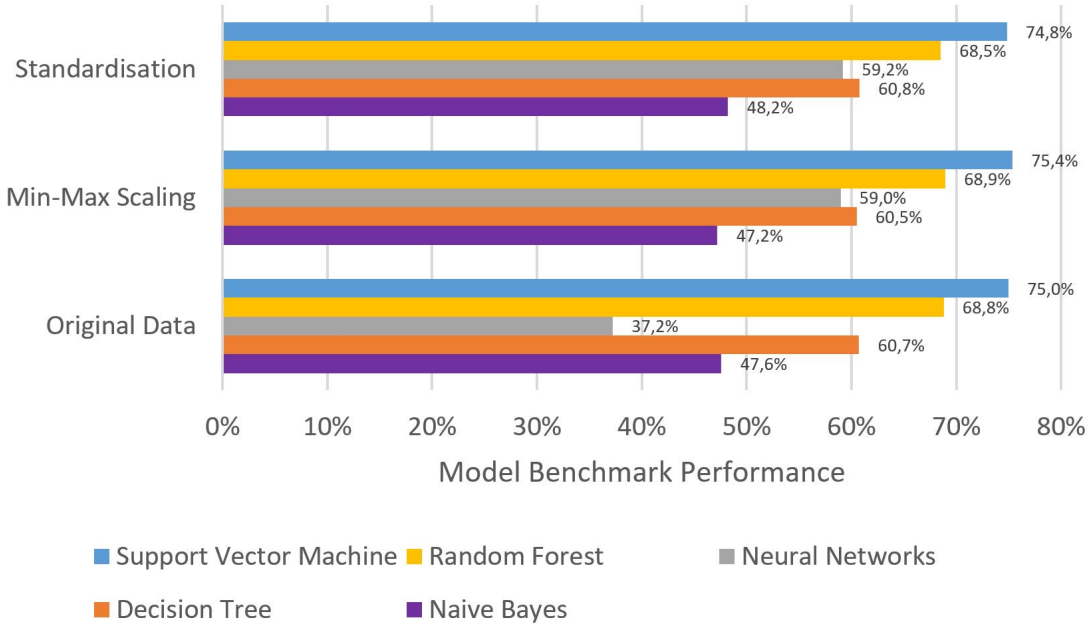


Figure 19: Comparative performance analysis of ML techniques on train set preprocessed with SMOTE. Adapted from: [270]

Based on these findings, the hyperparameters for the **SVM** and **RF** models were optimised using an exhaustive grid search approach with ten-fold cross-validation [275, 276], as a way to fine-tune their clas-

sification performance. Additionally, these models were tested by comparing their predicted results with the real stress labels from the test set. The optimal settings identified for each model are as follows:

- **SVM:** the model applies a radial basis function kernel to map data into an increased dimensional feature space for linear separation, considers the use of C regularisation parameter of 1.5 to balance the trade-off between low training error and minimising weight norms, and a gamma value of 0.3 which adjusts the influence range of training samples on the decision boundary. The model's performance evaluation on the test set is detailed in Table 10;

Table 10: Confusion matrix evaluation of SVM model. Adapted from: [270]

		Predicted			
		Low	**Moderate**	**High**	**Correct Pred. (%)**
Actual	**Low**	14	2	0	87.5%
	Moderate	0	17	0	100%
	High	1	2	13	81.25%
	Accuracy (%):	89.8%		**Recall (%):**	89.58%
	F1-score (%):	89.82%		**Precision (%):**	91.43%

- **RF** the model is configured with 500 trees (*i.e.*, **DT** number within the **RF**) and a leaf size of 6 (*i.e.*, each leaf node in the trees must contain at least 6 samples before considering a further split at a deeper level). This model's performance evaluation on the test set is presented in Table 11;

Table 11: Confusion matrix evaluation of RF model. Adapted from: [270]

		Predicted			
		Low	**Moderate**	**High**	**Correct Pred. (%)**
Actual	**Low**	15	1	0	93.75%
	Moderate	6	10	1	58.82%
	High	1	0	15	93.75%
	Accuracy (%):	81.63%		**Recall (%):**	82.11%
	F1-score (%):	81.38%		**Precision (%):**	84.28%

Considering the evaluation of both models in the test set, the **SVM** model demonstrates superior performance with an overall accuracy of 89.8%, compared to the **RF** model's accuracy of 81.63%. Specifically, the **SVM** model exhibits consistent effectiveness across the stress categories with a recall rate of 89.58% and a precision rate of 91.43%. The F1-score of 89.82% further emphasises the model's balanced precision and sensitivity. As for the **RF** model, it exhibits an overall accuracy of 81.63%, accompanied by recall and precision rates of 82.11% and 84.28%, respectively, and an F1-score of 81.38%. This performance indicates a generally effective approach but shows a less consistent output across various metrics when compared to the **SVM**.

Given the emphasis on identifying mental stress during online exams, the **SVM** should be preferred for this task. This decision is supported by the model's superior overall accuracy and a positive performance in accurately classifying 'High' stress levels with an 81.25% correctness in prediction. Although the **RF** model shows a slightly higher individual category accuracy for 'High' stress at 93.75%, its overall performance across all stress categories is less consistent and notably lower in accuracy. Furthermore, the **SVM**'s higher precision rate ensures that the classification of 'High' stress is accurate and reliable, minimising the risk of false positives, which is important for stress management in an educational setting. Therefore, the **SVM** model offers a more balanced and effective solution for accurately identifying high stress levels among students during online exams.

5.1.5 Discussion of Results

This experiment demonstrates the promising application of **ML** algorithms to assess medical students' stress levels through behavioural biometric and cognitive analysis, considering their mouse dynamics and decision-making variation patterns during online exams. In the first experiment, the proposed regression model performance revealed a positive coefficient of correlation value at 85.1% between real and predicted **PSS** score values for first, second and third-year medical students. This correlation indicates a strong predictive relationship between the algorithm's predictions and actual stress levels, although values above 38 points showed an increased **RMSE** justified by the reduced number of samples with high **PSS** scores in the training data. As for the second experiment, the proposed classification model performance achieved an accuracy prediction of 89.8% for third-year medical students, showing its robustness in accurately identifying moderate **PSS** levels and in distinguishing between 'Low' and 'High' **PSS** levels with minimal misclassification. These findings, while important, are not definitive and require further research and more data samples, particularly to improve the reliability and accuracy of the detection of high stress levels in a minimally invasive and discreet manner.

This experiment also explored additional approaches to improve stress prediction among individuals. One approach considered the incorporation of physiological biometric features tracked by smartwatches, such as **HR**, **BP**, **GSR**, daily steps, sleeping hours, oxygen saturation and skin temperature, to offer a comprehensive view of an individual's biological state, potentially providing additional insights into estimating the user's stress levels. However, the experiment faced considerable challenges due to the limited quantity of samples available, which restricted the study from providing meaningful conclusions. Another approach attempted to estimate the salivary cortisol concentration (stress biomarker) of medical students before and after each online exam (*i.e.*, PreCortisol and PosCortisol respectively) through the use of mouse dynamics and decision-making behaviour patterns as predictive indicators, with the hypothesis to explore whether the variations in an individual's interaction with their computer could serve as predictors of their physiological stress levels. Yet, its main challenge was the substantial variance in stress responses among individuals, requiring a larger number of samples per individual to accurately correlate **HCI** behavioural patterns with cortisol variations.

The next steps should address the study's limitations and enhance the model's accuracy in predicting stress levels among medical students. This involves collecting a larger and more balanced dataset with varied stress levels across different academic years and diverse exercise types beyond e-learning multiple-choice questions. Integrating additional physiological biometric features from smartwatches and further academic data (*e.g.*, exercise difficulty, exam impact on final grades, current student grade) is also essential. Additionally, exploring the correlation between **HCI** behavioural patterns and physiological stress markers will offer a better understanding of stress level variations.

5.2 Stress Assessment via E-learning Platform for Informatics Students

Author Contribution Statement

The research described in this experiment was conducted in collaboration with João Noivo, under the supervision of Professor Paulo Novais. The author of this thesis contributed to the formulation and implementation of the proposed framework and was responsible for improving the research practices related to data collection, data preparation, data analysis, feature engineering and prediction model development and evaluation.

Additionally, the author co-supervised the following Master's thesis research, providing guidance and support throughout the study process:

- João Miguel Amorim Noivo. Análise de padrões biométricos para otimização do desempenho académico.

Informatics engineering master's thesis, School of Engineering of the University of Minho (EEUM), 2019. URL https://hdl.handle.net/1822/79959

Given the results presented earlier, exploring whether these stress assessment methodologies can be effectively applied to other academic student populations is important. This experiment extends the research on stress assessment methodologies, originally developed for university medical students who face intense academic pressures, to a different group: fourth-year informatics engineering students from the University of Minho [279]. By extending the validation of the proposed stress assessment technology to this group, this study aims to validate the proposed framework's effectiveness and address stress-related challenges faced by informatics engineering students in high-stakes tasks such as online exams.

5.2.1 Data Collection

Identical to previous experiments, behavioural biometric data, including mouse dynamics and keystroke features, are collected and processed. Manually acquiring users' stress perception required significant resources and effort to manage and digitise this data for research purposes. To address this, the framework was adapted to automatically request this information during online exams, with students indicating their perceived stress level on a scale from 1 ('Very Low' stress) to 5 ('Very High' stress) at intervals configurable by the framework. This approach aims to correlate behavioural biometric patterns with self-reported stress levels to optimise academic performance analysis.

The data collected and logged from the user's stress self-assessment scores, mouse dynamics and keystrokes are required for the experiment at hand. The self-assessment stress log data is characterised by entries that reflect the user's perceived stress level at regular intervals. Each entry consists of a timestamp marking the exact time when the user recorded their stress level and the stress level rating itself. For this study, data is collected automatically at 1-minute intervals, ensuring consistent and frequent updates on the user's stress levels throughout the session. For the mouse dynamics, the mouse logging events and processed features applied in this experiment are described in Sub-subsection 4.2.5. Likewise, the interaction events triggered by the keyboard device support tracking how the user interacts with the solution's interface during online exams. For logging the keyboard events, the pressing and releasing timestamps along with the key pressed are considered. Also, the hierarchical classification of keystrokes based on hand and finger usage (illustrated in Figure 20) is applied to analyse and log the keystroke patterns of users while maintaining the anonymity of the text being typed. At the top level, the keystrokes are divided into two main categories: those performed with the left hand and with the right hand. Each hand category

is further subdivided into specific fingers: little finger, ring finger, middle finger, and index finger. The diagram illustrates which keys are typically associated with each finger, offering a breakdown of keystroke assignments. Furthermore, a keyboard diagram at the top right visually demonstrates the areas corresponding to left-hand and right-hand usage, with a colour-coded overlay indicating which keys are pressed by which fingers.

Based on all collected logs during online exams, the keystroke features considered include the average, median, standard deviation, and variance according to the number of times a specific key is pressed per timeframe. These features are presented in Table 12.

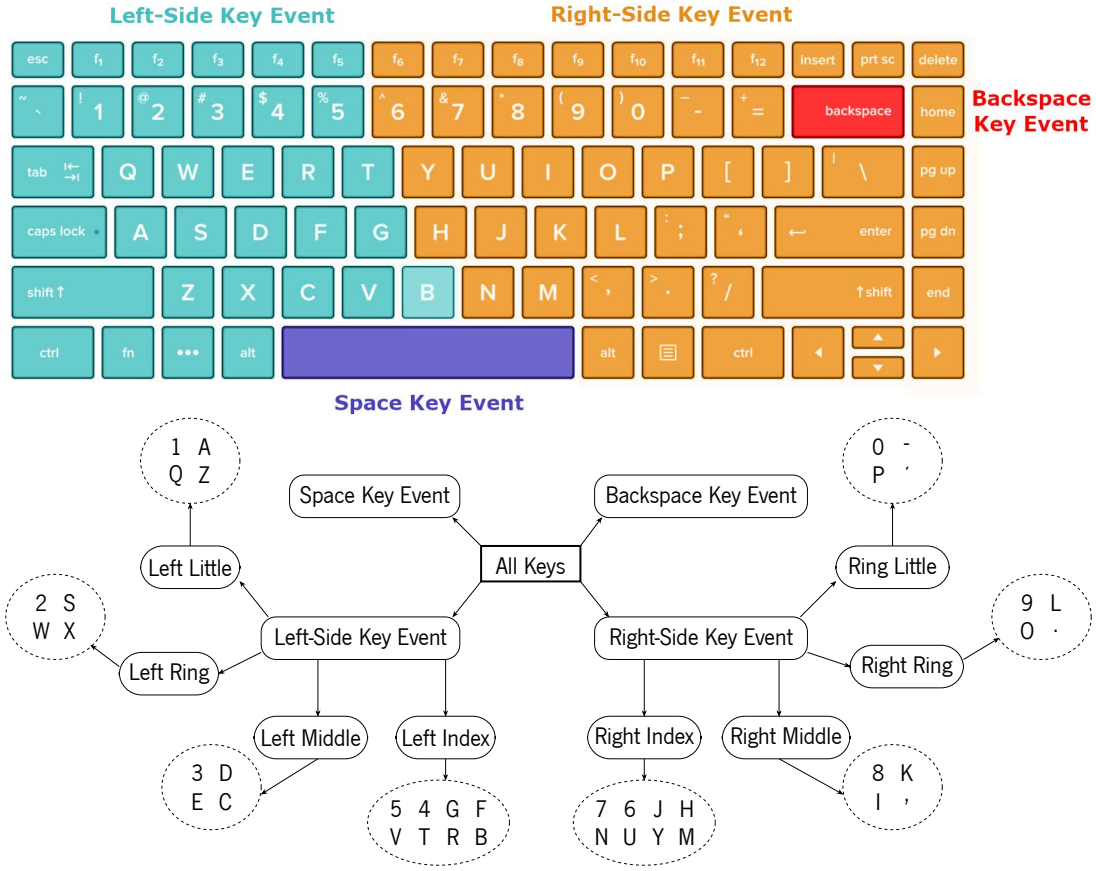


Figure 20: Hierarchical classification of keystrokes by hand and finger usage. Based on: [282]

In the data processing phase, all defined mouse dynamics and keystroke activity features are processed and synchronised with the time frames established in the stress self-assessment data collection process. These features, along with the collected logs, are then stored in the MongoDB database. The aim is to utilise the stored information to generate insights and analyse correlations between behavioural biometric data and the reported stress levels.

Table 12: Keystroke features processed based on keyboard events logged. Adapted from: [279]

Feature	Description
Backspace Key Event	This feature calculates the average, median, standard deviation and variance of the number of times the Backspace key is pressed per timeframe
Space Key Event	This feature calculates the average, median, standard deviation and variance of the frequency with which the Space key is pressed within each timeframe
Left-Side Key Event	This feature calculates the average, median, standard deviation and variance of the frequency with which keys on the left side of the keyboard are pressed within each timeframe
Right-Side Key Event	This feature calculates the average, median, standard deviation and variance of the frequency with which keys on the right side of the keyboard are pressed within each timeframe

5.2.2 Data Analysis

Based on the prepared dataset, an imbalanced distribution of study cases corresponding to the different stress levels was observed between the lower and higher stress levels. Table 13 presents the percentages of samples attributed to each stress level out of a total of 180 samples collected from 6 individuals over a thirty-minute online exam, which comprised multiple academic questions designed to assess the student's knowledge of software architecture and programming topics requiring typed answers.

Table 13: Dataset samples distribution considering the documented stress levels. Adapted from: [279]

Stress Level	# Total Samples	# Train Split Samples	# Test Split Samples
Very Low	41 (22.78%)	23 (21.90%)	18 (24.00%)
Low	50 (27.78%)	33 (31.43%)	17 (22.67%)
Moderate	32 (17.78%)	20 (19.05%)	12 (16.00%)
High	28 (15.56%)	15 (14.29%)	13 (17.33%)
Very High	29 (16.11%)	14 (13.33%)	15 (20.00%)
Total	**180**	**105**	**75**

As a result, several preprocessing techniques were necessary to address the dataset's imbalance issue. Initially, a stratified split approach was used to split the study cases between the train and test sets to preserve the class distribution in both subsets [283]. This process ensures that each split maintains a similar sample quantity per target class (*i.e.*, stress level), considering the dataset's characteristics. By ensuring balanced classes, this approach ensures proper validation of the model's performance, mitigates bias, and enhances the model's generalisation capabilities. The study cases distributed between train and test split are also displayed in Table 13.

5.2.3 Data Processing

Following this procedure, synthetic data generation techniques such as **ROSE** and **SMOTE** are applied to mitigate the data imbalance issue in the train split. As described previously, **ROSE** helps mitigate the effects of an unbalanced class distribution by generating balanced artificial samples using a bootstrap approach [277] while **SMOTE** creates artificial data samples based on the similarities between minority samples [278]. These techniques are not applied in the test split study cases to avoid compromising the test of the model's performance, ensuring that validation focuses solely on real study cases and not artificial data.

Since the prepared dataset consisted of features that were not standardised to the same scale, the next step was to normalise it. This was achieved using the Min-Max normalisation method [280] which converges all variable values to a fixed range, typically between 0 and 1. This resulted in two different datasets: one normalised and the other consisting of the original data. Furthermore, performance was assessed using various **ML** techniques (*i.e.*, **DT**, **RF**, **KNN**, **LogR**, and **SVM**) and by applying ten-fold cross-validation on the train set to ensure robust evaluation. For the **DT**, the original dataset achieved 71.47% accuracy while Min-Max normalisation resulted in 70.29%. **RF** showed an improvement from 72.68% to 73.82% with scaling. **KNN**'s accuracy increased significantly from 46.37% to 55.03%. **SVM** also demonstrated an improvement from 72.65% to 74.08% with Min-Max normalisation. **LogR** showed an improvement from 32.81% to 43.63% with scaling. By averaging the results obtained from different data preprocessing and **ML** methods, the application of Min-Max normalisation showed a slight overall performance increase of 4.17% compared to the original dataset (benchmark results available in Figure 21).

Furthermore, to ensure the proper selection of the most relevant behavioural biometric features to predict the user's stress levels, Pearson's correlation coefficient was applied. This method measures the linear correlation between two variables, providing a value between -1 and 1, where 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no correlation [281]. By calculating

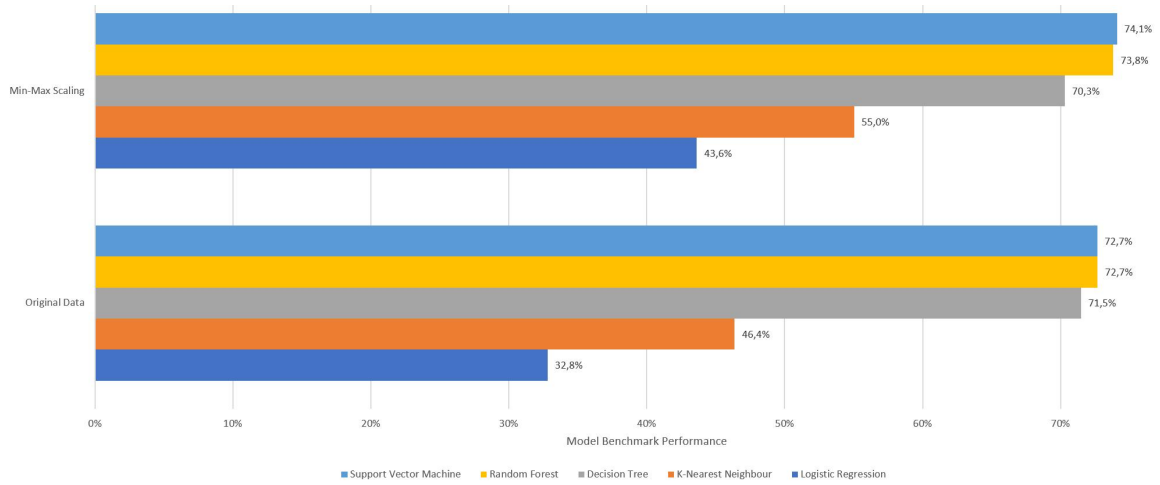


Figure 21: Performance benchmark between original and Min-Max scaled datasets across different ML algorithms. Adapted from: [279]

the correlation coefficient for each pair of variables, we identified and selected the features most strongly correlated with user stress for inclusion in the preparation of the prediction model. This analysis also revealed features with redundant correlations, which did not provide additional useful information, allowing us to exclude them from the model. Based on this procedure, the features selected included:

- **Mouse Dynamics:** mouse speed and angles, the difference between the actual and straight-line distance of consecutive clicks, the total number of clicks and their respective duration;
- **Keytroke:** the average of backspace key utilised and the use of left and right-side key events;

5.2.4 Prediction in Fourth-Year Informatics Engineering Students

Finally, the next phase involved developing and selecting the most appropriate **ML** techniques to predict stress levels during online exams. The analysis began with selecting a set of **ML** techniques suitable for the study, including **DT**, **RF**, **KNN**, **LogR**, and **SVM**. These models were trained considering the train data split (augmented with the generated synthetic data) and the ten-fold cross-validation technique, and tested with the respective test data split. When the **ROSE** method was used for data balancing, it achieved an average accuracy of 50.67% between all models. In contrast, the **SMOTE** method achieved an average accuracy of 51.69% between all models. Notably, these results did not consider the application of Min-Max normalisation, which had been previously demonstrated to increase accuracy. In terms of stress prediction accuracy, the best-performing algorithms were the **SVM** and **RF**. The **RF** model achieved an average accuracy of 73.49%, followed closely by the **SVM** with 72.41%.

Based on these results, hyperparameter tuning strategies were employed to adjust the models' parameters to further reduce misclassification. The search for optimal parameters to fine-tune the models' performance was conducted using the grid search exploration [276]. The analysis of the fine-tuned **RF** and **SVM** models' performance on the test set reveals different strengths and weaknesses, particularly in misclassifying stress levels.

Table 14 presents a detailed view of the **RF** model's performance across various stress categories. This model achieved an overall accuracy of 81.33% (reflecting an improvement of 7.84% over its previous iteration), indicating a positive performance in classifying stress levels based on behavioural biometric features, especially for higher categories. High accuracy levels in the categories of "High" and "Very High" stress, at 100% and 93.33% respectively, suggest the model's strong capability in identifying more extreme stress levels. However, it exhibits some challenges with the 'Very Low', 'Low', and 'Moderate' categories, where the correct predictions are relatively lower, at 66.67%, 76.47% and 75% respectively. This variation is due to overlapping characteristics between these categories and insufficient distinctive features in the training data. Precision and recall stand at 81.53% and 82.29% respectively. The F1-score, which balances precision and recall, is 81.22%, indicating a good harmonic mean between these metrics. Overall, the model demonstrates positive predictive performance, though there may be room for improvement in distinguishing between lower levels of stress.

Table 14: RF fine-tuned model confusion matrix evaluated on the test set. Adapted from: [279]

		Predicted					
		Very Low	**Low**	**Moderate**	**High**	**Very High**	**Correct Pred. (%)**
Actual	**Very Low**	12	1	3	1	1	66.67%
	Low	1	13	2	1	0	76.47%
	Moderate	0	2	9	1	0	75%
	High	0	0	0	13	0	100%
	Very High	0	1	0	0	14	93.33%
Accuracy (%):		81.33%				**Recall (%):**	82.29%
F1-score (%):		81.22%				**Precision (%):**	81.53%

Furthermore, Table 14 presents a detailed view of the **SVM** model's performance across various stress categories. This model, with a slightly lower average accuracy of 78.67% (reflecting an improvement of 6.26% over its previous iteration), exhibits diverse prediction performance across different stress categories according to the provided confusion matrix. The model performs optimally when classifying 'Low' and

'High' stress levels, as evidenced by the 100% accuracy in predictions for these categories. However, its performance on 'Very Low' and 'Moderate' stress levels is less robust, with accuracies of 55.56% and 58.33% respectively. This suggests the model struggles to identify small differences in "Low" stress levels. The 'Very High' stress level is better recognised with a relatively high accuracy of 80%. Overall, the model's precision is high at 90.30%, suggesting that when it predicts a stress level, those predictions are usually correct. However, the recall rate of 78.78% indicates that the model sometimes fails to identify all instances of particular stress levels. The F1-score stands at a respectable 80.40%, suggesting that the model, while generally reliable, could benefit from improvements in recognising subtler stress variations to enhance its application in environments such as e-learning, where stress detection must be both sensitive and precise.

Table 15: SVM fine-tuned model confusion matrix evaluated on the test set. Adapted from: [279]

		Predicted					
		Very Low	**Low**	**Moderate**	**High**	**Very High**	**Correct Pred. (%)**
Actual	**Very Low**	10	8	0	0	0	55.56%
	Low	0	17	0	0	0	100%
	Moderate	0	5	7	0	0	58.33%
	High	0	0	0	13	0	100%
	Very High	0	3	0	0	12	80%
Accuracy (%):		78.67%				**Recall (%):**	78.78%
F1-score (%):		80.40%				**Precision (%):**	90.30%

5.2.5 Discussion of Results

The evaluation of both models in the test set reveals that the **RF** model surpasses the **SVM** in the overall accuracy and F1-score. While the **SVM** demonstrates higher precision, the **RF** offers superior performance across various stress levels, particularly in the 'Very High' and 'Moderate' categories, achieving higher correct prediction percentages. This more balanced performance makes the **RF** model particularly effective in minimising misclassifications in critical stress categories (*i.e.*, "Moderate", "High" and "Very High"). Consequently, the **RF** model is recommended for more reliable and generalised stress detection in e-learning environments, as it also aligns better with reducing misclassification rates in higher stress categories. Despite its positive accuracy, these misclassifications suggest areas for further model refinement to improve precision, especially for lower and moderate stress levels. This can be achieved

by collecting additional use cases for less represented classes (to mitigate class imbalance), including further academic features to be analysed by the prediction model (*e.g.*, type and difficulty of exercises, current student grades, exam impact on final grades) and conducting temporal analysis of the evolution of previous insights (*e.g.*, perceived stress and academic performance).

5.3 Student Attentiveness in E-learning Activities

Author Contribution Statement

The research described in this experiment was conducted in collaboration with Ramón Toala and Professor Dalila Durães, under the supervision of Professor Paulo Novais. The author of this thesis contributed to the conceptualisation of the proposed framework and was responsible for the research practices related to data preparation, data analysis, feature engineering, prediction models development and evaluation, and the dissemination of results through scientific publications.

The research insights and outcomes were published in the following scientific works:

- Dalila Durães, Ramón Toala, Filipe Gonçalves, and Paulo Novais. Intelligent tutoring system to improve learning outcomes. *AI Communications*, 32(3):161–174, 2019. ISSN 1875-8452. doi: 10.3233/AIC-190624. URL `https://doi.org/10.3233/AIC-190624`
- Paulo Novais, Filipe Gonçalves, and Dalila Durães. Forecasting student's preference in e-learning systems. In Max Bramer and Miltos Petridis, editors, *Artificial Intelligence XXXV*, pages 198–203, Cham, 2018. Springer International Publishing. ISBN 978-3-030-04191-5. doi: 10.1007/978-3-030-04191-5_18. URL `https://doi.org/10.1007/978-3-030-04191-5_18`
- Ramón Toala, Filipe Gonçalves, Dalila Durães, and Paulo Novais. Adaptive and intelligent mentoring to increase user attentiveness in learning activities. In Guillermo R. Simari, Eduardo Fermé, Flabio Gutiérrez Segura, and José Antonio Rodríguez Melquiades, editors, *Advances in Artificial Intelligence - IBERAMIA 2018*, pages 145–155, Cham, 2018. Springer International Publishing. ISBN 978-3-030-03928-8. doi: 10.1007/978-3-030-03928-8_12. URL `https://doi.org/10.1007/978-3-030-03928-8_12`

One of the challenges in today's education is the extent to which students get distracted by external digital stimuli, particularly with the increased prevalence of the internet (*e.g.*, email notifications, messaging applications) and social media usage. These platforms grab the users' attention with endless and engaging content, leading to an adverse effect on students' capacity to focus on their educational tasks [287–289]. Recognising and addressing these distractions is important for improving the overall learning process and mitigating problems that may occur in technologically enriched environments.

Despite the different definitions across fields such as psychology and neuroscience, attention is described as the brain's complex process of selectively concentrating on specific information while disregarding other

stimuli [290, 291]. This selective concentration allows for efficient management of the brain's limited cognitive resources, thereby optimising information processing. Typically, individuals can focus only on a small number of stimuli simultaneously, which limits their ability to process multiple sources of information [290, 292].

To address the challenge of student distraction in digital learning environments, educational technologies have evolved significantly. One of the key developments has been the transformation of e-learning technologies from basic instructional aids (*e.g.*, facilitating the management and sharing of educational content between teachers and learners) to refined frameworks that enhance cognitive skills and facilitate high level academic reasoning [293, 294]. Central to this evolution are **ITS** which customise learning experiences to individual student profiles by monitoring behaviours and interactions between the user and machine, generally not requiring the teacher's intervention. These systems take into account each user's learning style, characterised as the most effective means by which an individual acquires knowledge, processes information and demonstrates an understanding of the subject topic in question [284, 295]. By adapting teaching strategies to meet the unique needs and preferences of each learner, these systems apply **AI** methodologies to simulate the guidance provided by a human tutor, aiming to optimise learning outcomes by offering personalised content and targeted feedback, helping to maintain student focus and engagement [296].

Building on the knowledge and results obtained from the previous experiments, this doctoral program's scope was extended to include this interdisciplinary research that merges behavioural biometrics [297], **AmI** [298] and human behaviourism [299]. The motivation behind this experiment is rooted in the potential of adaptive and intelligent systems to significantly improve the learner's engagement and educational outcomes by leveraging real-time data analytics and behavioural biometric monitoring. The research hypothesis assumes that different types of assessment activities impact each student differently, and this approach is useful for measuring these variations [285].

In this study, the data collection process must not disrupt students' computer-based assessments, as any disturbance could negatively affect the results. By non-intrusively exploring the relationship between students' behaviour patterns during e-assessments (*i.e.*, based on mouse and keystrokes dynamics, student attention and academic performance), the proposed algorithm aims to monitor and analyse relevant data to determine the student's performance. This information supports the system's ability to personalise learning experiences according to users' needs. This approach can enhance engagement, optimise resource utilisation, align educational strategies with individual learning preferences, improve academic performance, and make e-learning more effective and inclusive [284–286].

5.3.1 Data Collection

The research was conducted at Caldas das Taipas High School (north of Portugal) involving the participation of 14 female volunteer students from the final year of the high school vocational course (with an average age of 15.9 years old and standard deviation of 1.5 years). These students participated in four different computer-based assessment tasks, each lasting up to two hours, designed to test their knowledge and skills in various multimedia editing domains using the Adobe Photoshop application. Conducted on separate days, the assessments encompassed video-based editing, image-based editing, text-based editing, and audio-based editing tasks.

All participants, who demonstrated computing proficiency, were randomly assigned to similar computers in the equipped rooms, each using a computer or laptop connected to a keyboard, mouse, and monitor. The assessment activity began simultaneously for all students, who logged into the pre-defined software using their personal credentials. All data collection software ran unobtrusively in the background, gathering relevant behavioural biometric information without disrupting the students' routine. Furthermore, each case study was annotated with the respective assessment activity (*i.e.*, 'Video', 'Image', 'Text' or 'Audio' activity).

To understand the time requirements and complexity of the different assessments, the data logs of each activity were analysed, revealing the minimum, maximum, average, median and standard deviation duration in minutes, as illustrated in Table 16. The study includes a total of 48 study cases, composed of 14 video-based assessments, 11 image-based assessments, 13 text-based assessments and 10 audio-based assessments.

Table 16: Summary of the characteristics of each exam activity. Adapted from: [284, 285]

		Duration (mins)				
Assessment	**Study Cases**	**Min.**	**Max.**	**Avg.**	**Median**	**Std. Dev.**
Video	14	79.69	90.69	85.33	86.45	3.63
Image	11	115.29	124.80	121.37	121.8	2.78
Text	13	70.56	75.74	72.92	72.93	1.4
Audio	10	76.27	94.83	88.89	91.06	5.38

Image-based tasks are the most time-consuming, with the highest average duration of 121.37 minutes and relatively low variability (standard deviation of 2.78 minutes), suggesting significant complexity. Video

and audio tasks exhibit similar average duration (85.33 and 88.89 minutes, respectively), but audio tasks show higher variability, indicating different levels of student proficiency. Text tasks are completed the quickest, with an average duration of 72.92 minutes and the least variability (standard deviation of 1.4 minutes), indicating their relative simplicity when compared to other task types. These findings suggest that different task types can significantly impact time requirements, likely due to differences in activity complexity or student familiarity with the topic, with image editing activities being the most complex and time-consuming, and text editing activities being the simplest and quickest to complete.

5.3.2 Data Analysis

Building on this understanding, a more in-depth analysis of user interactions was conducted during these assessments. For each data log created per assessment, behavioural biometric features are extracted from the user's interactions with the mouse and keyboard. These features, including Keystroke Dynamics, Mouse Dynamics and Attention Performance Metrics, are monitored and preprocessed by the system, enabling the reconstruction of each student's actions and providing high level information on the user's interaction patterns. This information can be used to extract the necessary knowledge to quantify each student's interaction performance. Additionally, it facilitates the development of prediction models capable of determining the task being executed by the user, influenced by their behaviours. The behavioural biometric features under consideration are detailed in Table 17.

Table 17: Behavioural biometric features processed based on logged data. Adapted from: [286]

Modality	**Feature**	**Description**
Mouse	**Click Duration (CD)**	Average duration (in milliseconds) between consecutive mouse button releases, measured when this interval is less than 200 milliseconds
	Distance Between Clicks (DBC)	Average total distance the mouse pointer travels between two consecutive clicks (in pixels)
	Duration Distance Clicks (DDC)	Average time interval between the release of one mouse button and the press of the next (in milliseconds)

Continue on next page

Table 17 – *Continued from previous page*

Modality	Feature	Description
	Distance Point to Line Between Clicks (DPLBC)	Average shortest distance between the paths taken by the mouse pointer between two consecutive clicks (in pixels)
	Mouse Velocity (MV)	Average speed at which the mouse pointer moves across the screen (in pixels/seconds)
	Mouse Acceleration (MA)	Average rate of change of the mouse pointer's speed over time (in pixels/seconds^2)
Keyboard	**Key Down Time (KDT)**	Average time duration from pressing a key to releasing it (in milliseconds)
	Time Between Keys (TBK)	Average time interval between the release of one key and the press of the next (in milliseconds)
Task Perf.	**Assessment Duration**	Total time taken to complete a given task from start to finish (in milliseconds)
	Assessment Grade	The score achieved by the student in a given assessment. The grade is calculated based on the correctness and completeness of the tasks performed (in percentage)
	Main App. Total Time Usage	Total duration spent using the primary application required for the task (in milliseconds)
	Main App. Percentage Usage (APU)	Percentage of total task time spent in the primary application

Following a survey administered to the students, it was concluded that 70% preferred image-based tasks while 30% favoured video-based tasks. Based on these survey results and the outcomes from the assessment exercises, as presented in Table 18, it reveals the following insights: (1) despite only 30% of students favouring video-based activities, this assessment recorded the highest **Application Percentage Usage (APU)** (94.14%) and **Mouse Velocity (MV)** (0.5931 px/ms) and the total time spent, indicating high engagement; (2) in contrast, image activities, preferred by the majority of students, showed lower **APU**

(91.36%) and **MV** (0.5413 px/ms) but had the highest **Key Down Time (KDT)** (2669.1 ms); (3) text activities had the lowest **APU** (89.23%) and shortest **Time Between Keys (TBK)** (1073.1 ms), while audio activities had the highest **Click Duration (CD)** (281.0 ms) and a high **APU** (93.7%). These findings suggest that while students prefer image-based tasks, video tasks require more time and attention, reflecting the variation of cognitive and physical demands for each activity type.

Table 18: Summary of the behavioural biometric features variation for each activity. Adapted from: [285]

Activity	CD	DBC	DDC	DPLBC	KDT	MV	APU	TBK
Video	188.31 ms	206.1 px	214.24 ms	2819.12 px	1002.8 ms	0.59 px/ms	94.14 %	1865 ms
Image	150.73 ms	150.73 px	161.88 ms	3725.35 px	2669.1 ms	0.54 px/ms	91.36 %	1738 ms
Text	146.43 ms	227.4 px	152.52 ms	2838.14 px	1223 ms	0.53 px/ms	89.23 %	1073.1 ms
Audio	281 ms	189.2 px	119.1 ms	2408.52 px	714.1 ms	0.5 px/ms	93.7 %	1758 ms
Avg.	187.66 ms	227 px	165.7 ms	2946.41 px	1384.2 ms	0.55 px/ms	92.08 %	1599.3 ms

5.3.3 Data Processing

Based on the biometric features recorded from different soft sensors, the distribution of each feature is represented in different scales. To address these discrepancies, feature scaling techniques, such as Mix-Max normalisation and Z-score standardisation techniques, were applied to ensure consistency and comparability across all features [300].

Moreover, the focus is shifted to the relevance of the analysed features for predicting students' learning method preferences. This step aims to identify and remove unnecessary, irrelevant, and redundant features from the dataset that don't contribute to predicting learning preferences. Additionally, it seeks to rank and identify the relevant features by their degree of importance, ensuring that relevant features are prioritised in the development of less complex prediction models.

In this study, filter methods were excluded as an absence of direct correlation between a feature and the prediction class (*i.e.*, student's learning preference) does not conclusively indicate the feature's irrelevance when combined with other features. As such, the Boruta technique [301], a wrapper method designed around the **RF** algorithm, was applied alongside a ten-fold cross-validation process. This technique aims to identify important features in a dataset that are relevant to the outcome variable under certain circumstances. It starts by first creating a randomised copy of the dataset (shadow features) and then combining it with the original dataset. A classifier is then used to assess each feature's relevance, determining a feature as important if its score surpasses the highest score of the shadow features. This process repeats

until all features are categorised as important or unimportant, or until a specified number of iterations is reached [302, 303].

Based on its results, the assessment duration feature is identified as the most relevant for predicting students' learning preferences, followed by the assessment grade, **KDT**, **Mouse Acceleration (MA)** and **Duration Distance Clicks (DDC)**. In other words, by analysing both performance and behavioural biometric features during complex tasks, educators and **ITS** can more accurately predict and address students' learning needs, thereby facilitating the creation of personalised and effective learning experiences.

5.3.4 Predicting Student Activity During Online Assessments

With this, various **ML** classification models were trained and tested to predict the student's activity, considering the most commonly used methods in the scientific literature. The classification methods included the **SVM**, **KNN**, **NB**, **NN** and **RF**.

The hold-out technique was used to train and validate the models' classification performance due to its simplicity in providing an unbiased evaluation of model performance on unseen data. Two-thirds of the study cases were used for training the classifiers while the remaining one-third was used for testing (presented in Table 19). This balance is vital to ensure that the models are not overfitting to the training data and can generalise well to new, unseen data. Furthermore, Figure 22 presents a benchmark analysis of the different **ML** classifiers' performance.

Table 19: Distribution of dataset samples by activity assessment.

Activity	# Total Samples	# Train Split Samples	# Test Split Samples
Video	14 (29.17%)	9 (28.13%)	5 (31.25%)
Image	11 (22.92%)	5 (15.63%)	6 (37.5%)
Text	13 (27.08%)	10 (31.25%)	3 (18.75%)
Audio	10 (20.83%)	8 (25%)	2 (12.5%)
Total	**48**	**32**	**16**

Among these **ML** methods, **RF** demonstrated the highest overall prediction performance, achieving an 87.5% accuracy rate when applying feature calling techniques, while the **SVM** exhibited the lowest overall performance. The application of feature scaling techniques generally results in classification performance improvements across the different techniques, ranging from 6.25% to 25%, with the most significant enhancement observed in the **NN** classifier. Additionally, the classifiers' performance is influenced by the

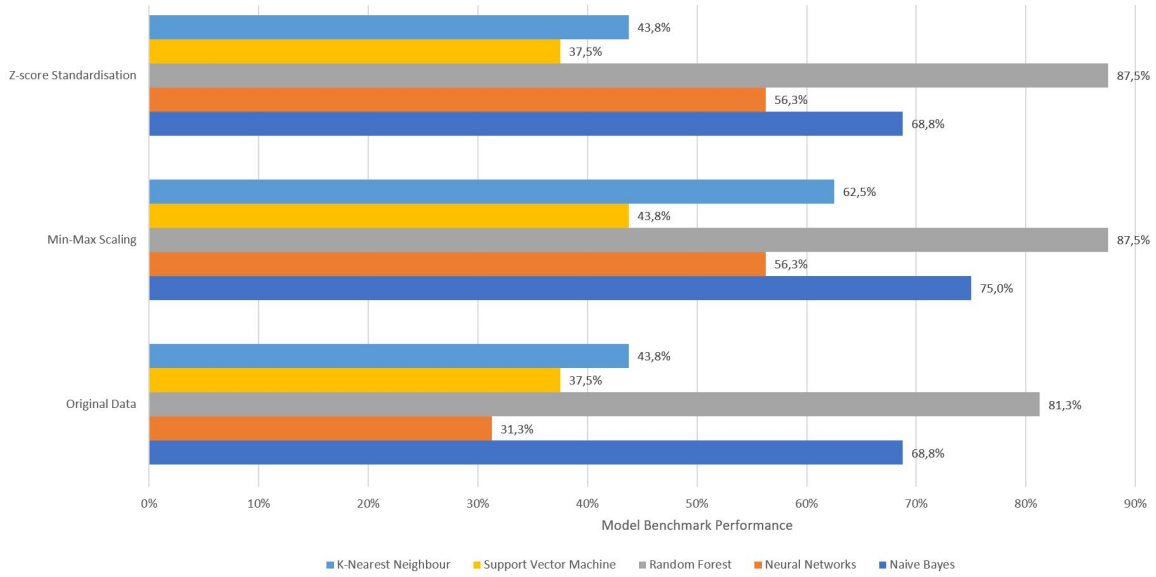


Figure 22: Comparative analysis of ML categorisation performance in the test set. Adapted from [284, 286]

quality of each feature (*i.e.*, feature distribution) and the number of case studies analysed (*i.e.*, comprised of a total of 48 study cases).

These findings indicate that the **RF** is the most effective classifier to categorise students' activity. To optimise this model, a hyperparameter optimisation was conducted through an exhaustive grid search, ensuring the lowest classification error rate. This approach aimed to identify the optimal number of leaves/features (modelled between 1 to 11) and the **DT** number (modelled between 1 to 500) that best suited the model. The hyperparameters search process results demonstrated that the model achieved an average minimised error with 80 trees and 9 leaves/features per tree.

To analyse the classification performance of this fine-tuned model and confirm the absence of overfit/underfit issues, it was necessary to examine its confusion matrix, which provides detailed insights into the model's performance on the test set for each class. The respective confusion matrix is presented in Table 20, indicating that only the 'Video' activity exhibits a significant misclassification rate, with 40% of total cases (*i.e.*, 2 out of 5 cases) being incorrectly classified as 'Audio' editing activity. This misclassification could result from the intricate nature of the 'Video' activity, which may contain complex features that are harder to distinguish from activities such as 'Audio' activity. Additionally, the insufficient representation of 'Video' activity in the train (*i.e.*, 9 instances) and test sets (*i.e.*, 5 instances) aggravates this issue, which may not be sufficient for the model to learn the patterns needed for accurate classification. Addressing these issues by increasing instances of underrepresented activities or handling class imbalance can improve the model's performance. Despite this, the model shows an overall accuracy of 87.5%, a recall of 90%, an F1-score of 85.42% and a precision of 87.5%, indicating balanced performance except for 'Video'

activity.

Table 20: Confusion matrix evaluation of fine-tuned RF classifier. Adapted from: [284, 285]

		Predicted				
		Audio	**Image**	**Text**	**Video**	**Correct Pred. (%)**
Actual	**Audio**	2	0	0	0	100%
	Image	0	6	0	0	100%
	Text	0	0	3	0	100%
	Video	2	0	0	3	60%
Accuracy (%):		87.5%			**Recall (%):**	90%
F1-score (%):		85.42%			**Precision (%):**	87.5%

5.3.5 Discussion of Results

This experiment presents a non-invasive and non-intrusive approach to an **ITS** based on the behavioural biometric analysis of online assessments during different multimedia editing classes. The system monitors and analyses mouse and keyboard dynamics and users' assessment activity to determine user performance.

Through this study, it was verified that the main behavioural biometric features to be analysed for this prediction focus on the variation of assessment duration, followed by the assessment grade, **KDT**, **MA** and the **DDC**. Furthermore, different **ML** categorisation models were developed and benchmarked, with the **RF** model demonstrating the best overall classification performance, achieving an overall accuracy rate of 87.5%, with misclassifications primarily occurring in the video activity.

Based on the activity duration, the findings are as follows: for activity times less than 75 minutes, the most frequently categorised style is text; for activities over 90 minutes, the best-categorised styles are image (60%) and audio (40%); for activities between 75 and 90 minutes, the best-categorised styles are video (80%) and audio (20%). Additionally, mouse and keyboard interaction support the classification model in determining users' activities.

With these findings, future work will focus on increasing the number of case studies available for analysis, enhancing the number and quality of biometric features to improve monitoring of the user's attention performance, conducting an in-depth analysis of characteristics that influence user performance, such as

correlating users' final grades with their biometric behaviours, and define multiple user profiles to improve the adaptive learning mechanisms of the framework.

5.4 Key Findings and Conclusions

This chapter presents the doctoral program's evolution through several study cases, aggregated into three separate experiments.

The first experiment (Section 5.1) focused on developing a stress assessment framework within an e-learning environment to predict the perceived stress states of medical students during high-stakes online exams, without being invasive or intrusive. To achieve this, a set of behavioural biometric features, including mouse dynamics and decision-making patterns, were analysed and employed in the development of various regression and classification algorithms.

The second experiment (Section 5.2) extended the application of the stress assessment framework to a new population, specifically fourth-year informatics engineering students. In this study, stress labels were automatically acquired by the framework, in contrast to the manual labelling used in the previous experiment. The electronic assessments included multiple typing questions, providing a relevant context for this student population. The analysis was expanded to include both keyboard and mouse dynamics as behavioural biometric features. Furthermore, multiple classification **ML** algorithms were developed and benchmarked to evaluate the framework's effectiveness in predicting stress states accurately.

The third and final experiment (Section 5.3) proposed a framework to predict high-school students' activity during online assessments. This framework employed non-invasive and non-intrusive methods to analyse mouse and keyboard dynamics, along with users' attention and academic performance. Similar to the previous experiments, multiple classification algorithms were developed to automatically predict students' activities based on their behavioural data. This approach aimed to improve the understanding of student engagement and performance in e-learning environments, providing valuable knowledge for improving educational outcomes and **ITS** technologies.

Additionally, the study brings to light the need for legal and ethical considerations, particularly regarding **GDPR** compliance, in the collection and processing of **HCI** data. Clear guidelines and protocols must be established to safeguard the users' privacy and confidentiality, ensuring that data acquisition and analysis are conducted responsibly. This is essential for ethical compliance and for building participant trust and willingness to share data for research. Additionally, it serves to promote students' mental healthcare and performance by ensuring their well-being is prioritised, encouraging proactive mental health monitoring,

and facilitating the development of targeted interventions to address stress or performance issues.

While this research provides a significant step toward applying **AI** algorithms for stress and activity assessment in educational environments, it also proposes the path for future studies. These should focus on collecting further data samples, refining prediction models and addressing legal and ethical concerns to harness the full potential of non-invasive and non-intrusive stress detection methods. Such advancements could provide the means to enhance the mental well-being and academic performance of students by facilitating timely and appropriate interventions.

Chapter 6

Conclusions

"Remember to look up at the stars and not down at your feet. Try to make sense of what you see, and wonder about what makes the universe exist. Be curious."

—Stephen Hawking

The value proposition of this doctoral research lies in the design of a technological approach for non-intrusive and non-invasive analysis of academic performance and mental stress assessment among students. This approach is implemented as a distributed system that collects, processes, stores and monitors data describing the behavioural biometric (via soft sensors such as mouse and keyboard) and cognitive patterns (*e.g.*, decision-making) of multiple individuals simultaneously during online high-demanding exams. Additionally, anonymisation methodologies are integrated to prevent the invasiveness of user-sensitive data and to comply with privacy, ethical, and legal issues under **GDPR**.

The present research draws interesting conclusions regarding students and their behaviour during e-assessments. First, it demonstrated that stress affects how students interact with computers during high-stakes exams, as detailed in Chapters 4 and 5. This finding enables the development of digital methodologies to assess and monitor users' mental stress, particularly in academic settings. The research also demonstrated the feasibility of implementing prediction models in e-learning platforms to perform this task in real-time. Moreover, this framework shows potential for extension to other domains, such as workplace environments, although this requires further research due to the different characteristics of both settings.

One of the limitations of this research was the challenge of collecting and annotating sufficient data to support the study. Ensuring a large and diverse dataset is essential for validating the prediction models and achieving reliable results. Future work should aim to enhance data collection procedures and expand

the dataset to include further behaviours and stress responses. This will improve the models' robustness and ensure their applicability across different populations and contexts.

In this chapter, the contributions of the doctoral thesis will be analysed against its initial objectives, detailing the validation of the research hypothesis through the obtained results. It also provides final reflections and highlights future directions for this research. The discussion concludes with a dissemination activities summary.

6.1 Summary of Contributions

The research described in this doctoral thesis led to the following theoretical and practical contributions (as previously detailed in Section 1.4), considering both the research hypothesis and questions presented in Section 3.2 and the research objectives and tasks detailed in Section 3.3. The contributions are clarified for each one as follows:

- **Objective No. 1:** *Monitor students' biometric behaviour, cognitive and activity performance during online assessments.*

  In Chapter 2, Section 2.1 explore the theoretical concepts and characteristics of **AmI**, **HCI** and affective computing, including different types of behavioural biometrics use cases while Section 2.2 showcases the latest state-of-the-art systems to demonstrate the advancements and applications of **AI** in stress detection and monitoring.

  Chapter 4, Section 4.2 details the non-invasive and non-intrusive methodologies and tools used in the proposed framework to collect, process and monitor behavioural biometric, cognitive and activity performance.

  Chapter 5, Subsections 5.1.1, 5.2.1 and 5.3.1 showcase the data collection procedures for biometric behaviour (*i.e.*, mouse and keystroke dynamics), cognitive and activity performance (*i.e.*, decision-making, attentiveness, academic performance) across different research experiments while Subsections 5.1.2, 5.2.2 and 5.3.2 focus on analysing these features' characteristics and variations.

  The main conclusion is that students' behavioural biometrics, cognitive and activity performance can be collected and monitored during online exams using non-intrusive and non-invasive methods with peripheral devices such as computer mice and keyboards.

- **Objective No. 2:** *Characterise students' mouse and keystroke dynamics, decision-making processes and stress profiles.*

In Chapter 2, Sections 2.1 and 2.2 provide an overview of the concept and characterisation of behavioural biometrics and examine the relationship between these features and the user's affect and stress state.

Chapter 4, Subsections 4.2.4 and 4.2.5 details the various types of behavioural biometrics and cognitive features considered in this research, accounting for different temporal perspectives.

Chapter 5, Subsection 5.1.2 analyse the relationship between the medical student's mouse dynamics and decision-making patterns with their performance and perceived stress profiles (based on **PSS** survey) during online single-best-answer exams. Subsections 5.2.2 and 5.2.3 examine the relation between informatics engineering students' mouse and keystroke dynamics patterns and perceived stress profiles (considering the 5-point Likert scale) during online written exams. Subsections 5.3.2 and 5.3.3 study the relation between high-school students' mouse and keystroke dynamics patterns, attentiveness, learning outcomes and academic preferences during online multimedia assessments.

The main conclusion is that higher stress levels and proximity to burnout in students correlate with a decline in performance. This is shown by less efficient interaction patterns, including longer mouse clicks, greater mouse travel distances, longer key downtimes, reduced attentiveness, and faster but less effective decision-making. These findings highlight the potential of behavioural biometric, cognitive performance, and attentiveness features as key enablers for non-intrusive and non-invasive assessment of students' mental stress and its effects on performance.

- **Objective No. 3:** *Test the hypothesis that mouse dynamics, keystroke dynamics and decision-making features can predict a student's perceived stress.*

  In Chapter 5, Subsection 5.1.2 explores the connection between variations in mouse dynamics and decision-making features with student's mental stress, as determined by physiological measurements and psychological surveys. Subsections 5.1.3 and 5.1.4 employ feature selection methods, including filter and wrapper methods, to identify relevant mouse dynamics and decision-making features for assessing the perceived stress of medical students. Subsection 5.2.4 focuses on identifying the key mouse and keystroke dynamics features to assess perceived stress in informatics engineering students' using a filter-based feature selection method. Subsection 5.3.4 applies a wrapper-based feature selection method to determine the relevant mouse and keystroke dynamics and attention features for predicting students' learning preferences.

  The main conclusion is that predicting a student's perceived stress level is feasible by analysing

variations in mouse dynamics, keystroke dynamics, and decision-making performance features. This conclusion is supported by applying filter and wrapper-based feature selection methods, which identified relevant features from data collected from medical and informatics engineering students.

- **Objective No. 4:** *Develop a predictive model based on collected case studies.*

  In Chapter 5, Subsection 5.1.3 presents a case study involving first, second, and third-year medical students. Their mouse dynamics and decision-making patterns during online single-best-answer exams, combined with past **PSS** scores, were used to develop a regression model for predicting the student's perceived stress (considering the **PSS** survey scores). The proposed regression model achieved an overall correlation coefficient value of 85.1% between real and predicted **PSS** scores.

  Chapter 5, Subsection 5.1.4 presents a case study exclusively involving third-year medical students. Their mouse dynamics and decision-making patterns collected during online single-best-answer exams were used to develop a classification model for predicting the user's stress levels (*i.e.*, 'Low', 'Moderate' or 'High', established by the **PSS** survey scores). The proposed classification model attained an overall accuracy prediction of 89.8%, demonstrating its robustness in accurately identifying moderate **PSS** levels and distinguishing between 'Low' and 'High' **PSS** levels with minimal misclassification.

  Chapter 5, Subsection 5.2.4 presents a case study involving fourth-year informatics engineering students. Their mouse and keystroke dynamics patterns collected during online written exams were used to develop a classification model for predicting the user's stress levels (*i.e.*, 'Very Low', 'Low', 'Moderate', 'High' or 'Very High', considering the 5-point Likert scale). The proposed classification model achieved an overall accuracy prediction of 81.33%, demonstrating positive performance, particularly in the 'Moderate', 'High' and 'Very High' stress categories, where it achieves higher correct prediction percentages. As an additional experiment, Subsection 5.3.4 presents a case study involving high-school students, where their mouse and keystroke dynamics, attentiveness and academic performance are collected during different multimedia editing assessments and used to develop a classification model for predicting student activity (*i.e.*, 'Video', 'Audio', 'Image' and 'Text'). The proposed classification model achieved an overall accuracy prediction of 87.5%.

  The main conclusion is that prediction models can be developed and deployed to assess and monitor users' perceived stress based on their behavioural biometrics, cognitive and activity performance.

- **Objective No. 5:** *Implement the prediction model on e-learning platforms for non-invasive and*

non-intrusive monitoring.

Chapter 4, Section 4.2 introduces the proposed non-invasive and non-intrusive framework for e-learning platforms, which monitors **HCI** behaviour and students' performance to be processed and analysed by the prediction models.

Chapter 5, Sections 5.1, 5.2 and 5.3 presents various case studies employing the developed prediction model to monitor and evaluate students' stress and academic performance non-invasively.

The main conclusion is that prediction models can be applied in e-learning using non-invasive and non-intrusive monitoring methodologies.

To complement this section, Table 21 aligns the research objectives outlined with the respective chapters/sections where these objectives were achieved.

Table 21: Alignment of research objectives with corresponding thesis sections.

Objective	**Chapter/Section**
Obj. No. 1: *Monitor students' biometric behaviour, cognitive and activity performance during online assessments*	• **Chapter 2 'Background and Prior Art'**: Section 2.1 'Intersection of Ambient Intelligence, Education Systems and Affective Computing', Section 2.2 'Artificial Intelligence in Stress Detection and Monitoring'; • **Chapter 4 'A Stress Monitoring Tool for E-learning Environments'**: Section 4.2 'Framework Proposal to Assess and Monitor Students' Stress'; • **Chapter 5 'Experiments Performed and Analysis of Results'**: Subsection 5.1.1 'Data Collection', Subsection 5.1.2 'Data Analysis', Subsection 5.2.1 'Data Collection', Subsection 5.2.2 'Data Analysis', Subsection 5.3.1 'Data Collection', Subsection 5.3.1 'Data Collection', Subsection 5.3.2 'Data Analysis';

Continue on next page

Table 21 – *Continued from previous page*

Objective	Chapter/Section
Obj. No. 2: *Characterise students' mouse and keystroke dynamics, decision-making processes and stress profiles*	• **Chapter 2 'Background and Prior Art'**: Section 2.1 'Intersection of Ambient Intelligence, Education Systems and Affective Computing', Section 2.2 'Artificial Intelligence in Stress Detection and Monitoring'; • **Chapter 4 'A Stress Monitoring Tool for E-learning Environments'**: Subsection 4.2.4 'Data Preparation and Temporal Analysis', Subsection 4.2.5 'Behavioural Biometric Features'; • **Chapter 5 'Experiments Performed and Analysis of Results'**: Subsection 5.1.2 'Data Analysis', Subsection 5.2.2 'Data Analysis', Subsection 5.2.3 'Data Processing', Subsection 5.3.2 'Data Analysis', Subsection 5.3.3 'Data Processing';
Obj. No. 3: *Test the hypothesis that mouse dynamics, keystroke dynamics and decision-making features can predict a student's perceived stress*	• **Chapter 5 'Experiments Performed and Analysis of Results'**: Subsection 5.1.2 'Data Analysis', Subsection 5.1.3 'Prediction Across Medical Students', Subsection 5.1.4 'Prediction in Third-Year Medical Students', Subsection 5.2.4 'Prediction in Fourth-Year Informatics Engineering Students', Subsection 5.3.4 'Predicting Student Activity During Online Assessments';

Continue on next page

Table 21 – *Continued from previous page*

Objective	Chapter/Section
Obj. No. 4: *Develop a predictive model based on collected case studies*	• **Chapter 5 'Experiments Performed and Analysis of Results'**: Subsection 5.1.3 'Prediction Across Medical Students', Subsection 5.1.4 'Prediction in Third-Year Medical Students', Subsection 5.2.4 'Prediction in Fourth-Year Informatics Engineering Students', Subsection 5.3.4 'Predicting Student Activity During Online Assessments';
Obj. No. 5: *Implement the prediction model on e-learning platforms for non-invasive and non-intrusive monitoring*	• **Chapter 4 'A Stress Monitoring Tool for E-learning Environments'**: Section 4.2 'Framework Proposal to Assess and Monitor Students' Stress' • **Chapter 5 'Experiments Performed and Analysis of Results'**: Section 5.1 'Stress Assessment via E-learning Platforms for Medical Students', Section 5.2 'Stress Assessment via E-learning Platform for Informatics Students', Section 5.3 'Student Attentiveness in E-learning Activities'

6.2 Validation of the Research Hypothesis

In Section 3.2, the research hypothesis was formulated, derived from its research questions and aligned with this thesis's objectives and tasks:

Research Hypothesis

Mental stress can be monitored by analysing changes in student's cognitive and behavioural patterns through non-invasive and non-intrusive methods, to improve online assessment processes.

To validate this research hypothesis, this thesis study analysed behavioural biometric patterns, academic

performance and cognitive engagement across students from different groups/courses during online exams. By monitoring patterns of cursor speed, click rates, typing speed, decision-making intervals and correct decision ratio, the study examined the relationship between these features and stress. This evidence supported the hypothesis that monitoring these patterns can enrich the assessment processes in e-learning settings.

For this, the research employed data-driven approaches involving statistical analysis and **ML** techniques to analyse interaction data from students' use of peripheral devices like mice and keyboards during online exams. This approach involved capturing behavioural biometric, cognitive and academic performance data and applying predictive analytics to identify stress indicators.

The proposed e-learning framework is designed to be non-invasive and non-intrusive, blending into students' academic routines without disruption, intended to provide an early-warning mechanism for students' mental stress by analysing mouse and keyboard usage patterns. Furthermore, this system respects user privacy and comfort, avoids collecting users' sensitive data and offers educators and students actionable insights that allow for timely interventions and personalised stress-coping strategies, improving the education experience and student well-being.

Thus, the validation procedure and the proposed framework's characteristics support the thesis statement, proposed in Section 1.2, demonstrating that a non-invasive and non-intrusive system can effectively identify stress indicators, enabling personalised and responsive stress-coping strategies.

6.3 Discussion and Future Directions

The findings and methods presented show potential for digital education. By improving our knowledge of how non-invasive and non-intrusive monitoring can assess and address mental stress, this research sets the stage for more responsive and personalised educational environments. Continuing to explore and refine these techniques will enhance their effectiveness and applicability, benefiting students' well-being and academic success and advancing technologies in various fields.

Additionally, the insights from this doctoral research have been applied in other research projects like *EasyRide*, which focuses on **AI**-based in-vehicle sensing to assess occupants' affective states, and *Theia*, which addresses cyber-protection and anonymisation of sensitive data recorded by autonomous vehicle perception systems.

Future work should focus on collecting and including additional data from various non-invasive modalities, such as smartbands (*e.g.*, analyse user's physical activity, sleep hours, **BP**) or smartphones/tablets (*e.g.*,

touchscreen dynamics). Additionally, it is imperative to collect data from diverse student populations, considering variations in academic courses, age groups and other demographic factors. Furthermore, the inclusion of data from different e-learning exam question types (*e.g.*, multiple-choice, programming, association tasks and practical exercises) would provide a better understanding of stress in educational contexts.

Furthermore, understanding why some students perform better under stress while others do not is crucial for optimising learning outcomes. Understanding these factors will enable educational institutions to implement individualised coping strategies to mitigate the negative effects of stress.

The research of unsupervised or semi-supervised techniques should be considered to reduce the reliance on extensive amounts of annotated data. Moreover, investigating how users perceive and trust non-invasive and non-intrusive technologies is necessary for their endorsement. Finally, ensuring adherence to ethical and legal standards is a must to protect users' privacy and rights.

Lastly, the employment of these non-invasive technologies should be examined in other high-demanding environments, such as workplaces. This research could provide additional insights into managing stress and improving online/remote work performance in various settings.

6.4 Dissemination of Results

The doctoral research included plans for disseminating the developed work through publication in scientific conferences/journals and participation/organisation of scientific events.

6.4.1 Scientific Publications

This research details work disseminated across the scientific community by participating in Computer Science, **AmI**, Behavioural Analysis and Human Healthcare scientific meetings. Its findings have been disseminated via scientific journals and conference proceedings:

- Dalila Durães, Ramón Toala, Filipe Gonçalves, and Paulo Novais. Intelligent tutoring system to improve learning outcomes. *AI Communications*, 32(3):161–174, 2019. ISSN 1875-8452. doi: 10.3233/AIC-190624. URL `https://doi.org/10.3233/AIC-190624`

- Filipe Gonçalves, Davide Carneiro, José Pêgo, and Paulo Novais. Monitoring mental stress through mouse behaviour and decision-making patterns. In Paulo Novais, Jason J. Jung, Gabriel Villarrubia González, Antonio Fernández-Caballero, Elena Navarro, Pascual González, Davide Carneiro,

António Pinto, Andrew T. Campbell, and Dalila Durães, editors, *Ambient Intelligence – Software and Applications –, 9th International Symposium on Ambient Intelligence*, pages 40–47, Cham, 2019. Springer International Publishing. ISBN 978-3-030-01746-0. doi: 10.1007/978-3-030-01746-0_5. URL https://doi.org/10.1007/978-3-030-01746-0_5

Note: *Awarded "Best Application Paper" of the 9th International Symposium on Ambient Intelligence (ISAmI'18), in Toledo, Spain*

- Ramón Toala, Filipe Gonçalves, Dalila Durães, and Paulo Novais. Adaptive and intelligent mentoring to increase user attentiveness in learning activities. In Guillermo R. Simari, Eduardo Fermé, Flabio Gutiérrez Segura, and José Antonio Rodríguez Melquiades, editors, *Advances in Artificial Intelligence - IBERAMIA 2018*, pages 145–155, Cham, 2018. Springer International Publishing. ISBN 978-3-030-03928-8. doi: 10.1007/978-3-030-03928-8_12. URL https://doi.org/10.1007/978-3-030-03928-8_12

- Radu Albastroiu, Anisia Iova, Filipe Gonçalves, Marian Cristian Mihaescu, and Paulo Novais. An e-exam platform approach to enhance university academic student's learning performance. In Javier Del Ser, Eneko Osaba, Miren Nekane Bilbao, Javier J. Sanchez-Medina, Massimo Vecchio, and Xin-She Yang, editors, *Intelligent Distributed Computing XII*, pages 404–413, Cham, 2018. Springer International Publishing. ISBN 978-3-319-99626-4. doi: 10.1007/978-3-319-99626-4_35. URL https://doi.org/10.1007/978-3-319-99626-4_35

- Paulo Novais, Filipe Gonçalves, and Dalila Durães. Forecasting student's preference in e-learning systems. In Max Bramer and Miltos Petridis, editors, *Artificial Intelligence XXXV*, pages 198–203, Cham, 2018. Springer International Publishing. ISBN 978-3-030-04191-5. doi: 10.1007/978-3-030-04191-5_18. URL https://doi.org/10.1007/978-3-030-04191-5_18

- Filipe Gonçalves, Davide Carneiro, José Pêgo, and Paulo Novais. X3S: A multi-modal approach to monitor and assess stress through human-computer interaction. *Computer Science and Information Systems*, 15(3):683–703, 2018. doi: 10.2298/CSIS180115033G. URL https://doi.org/10.2298/CSIS180115033G

- Filipe Gonçalves, Davide Carneiro, Paulo Novais, and José Pêgo. *EUStress: A Human Behaviour Analysis System for Monitoring and Assessing Stress During Exams*, pages 137–147. Springer International Publishing, Cham, 2018. ISBN 978-3-319-66379-1. doi: 10.1007/978-3-319-66379-1_13. URL https://doi.org/10.1007/978-3-319-66379-1_13

- Paulo Novais, Davide Carneiro, Filipe Gonçalves, and José Pêgo. Ambient intelligent systems: The role of non-intrusive and sensitive approaches. In *Proceedings of the 9th International Joint Conference on Computational Intelligence (IJCCI 2017) - IJCCI*, pages 11–17. INSTICC, SciTePress, 2017. ISBN 978-989-758-274-5. doi: 10.5220/0006810900010001. URL `https://doi.org/10.5220/0006810900010001`

6.4.2 Lectures

The candidate delivered theoretical-practical lectures as a guest assistant professor at the Department of Informatics - University of Minho, within the curriculum units of:

- *Data and Machine Learning*, Integrated Master in Informatics Engineering, 3th Academic Year (2021-2023);
- *Learning and Intelligent Decision Making*, Integrated Master in Informatics Engineering, 4th Academic Year (2021-2023);
- *Natural Computation*, Integrated Master in Informatics Engineering, 4th Academic Year (2019-2021);
- *Intelligent Systems*, Integrated Master in Biomedical Engineering, 4th Academic Year (2018-2023);
- *Learning and Extraction of Knowledge*, Integrated Master in Informatics Engineering, 4th Academic Year (2018-2022);
- *Languages for Numerical Computing*, Integrated Masters in Physical Engineering & Bachelor in Physics, 1st Academic Year (2018-2019);
- *Logic, Knowledge and Reasoning Programming*, Integrated Master in Biomedical Engineering, 4th Academic Year (2018-2019);
- *Agents and Multiagent Systems*, Integrated Master in Informatics Engineering, 4th Academic Year (2017-2023);
- *Ambient Intelligence: Technologies and Applications*, Integrated Master in Informatics Engineering, 4th Academic Year (2017-2018);

6.5 Research Activities During the Doctoral Programme

Other research activities during the doctoral programme are described in this section, including the participation and organisation of scientific events, engagement in different research projects resulting in scientific publications, and assist mentoring Master's students' dissertations and group assignments within the curriculum of the Informatics Engineering Laboratory.

6.5.1 Participation and Organisation of Scientific Events

Throughout the doctoral programme, the candidate engaged in various scientific events. These gatherings were crucial for obtaining feedback and perspectives from field experts.

Participation of Scientific Events

During the doctoral programme, the candidate engaged in the following scientific events:

- *9th International Symposium on Environmental Intelligence (ISAmI'18), University of Castilla–La Mancha - Toledo, Spain, 2018*

  The International Symposium on Ambient Intelligence (ISAmI) is a scientific event that promotes collaboration among researchers across various disciplines within the **AmI** field, showcasing the latest findings, trends, projects and insights, including updates to previously shared work, project summaries, and doctoral thesis. The symposium highly values both fresh perspectives and significant updates to existing research;

- *Advanced School on Data Science for Big Data (EAIA 2018 - DS4BD), Faculty of Sciences of the University of Porto - Porto, Portugal, 2018*

  The summer school event showcased current trends, expert discussions and expectations in topics related to data science, aiming to enrich participants' understanding of and capabilities in these relevant fields. Furthermore, it showcased real-case examples of innovative techniques' implementation, demonstrating their impact across various sectors including economy, healthcare, agriculture, energy, media, education, industry, mobility and leisure;

Organisation of Scientific Events

The coordination of scientific events was undertaken for the following events:

- *Theia Project Open Event, Alfândega do Porto - Porto, Portugal, 2023*

  With the participation of the Minister of Science, Technology and Higher Education, Elvira Fortunato, and representatives from partner institutions, this public event consisted of the presentation of the outcomes of *Theia* (Automated Perception Driving), an innovative project aimed at enhancing vehicle safety in autonomous driving. This initiative focused on developing **AI**-based technologies and sensors to improve the perception capabilities of autonomous vehicles. These technologies use perception algorithms based on data from sensors, such as **Light Detection and Ranging (LiDAR)**, to provide precise, robust and safe environmental awareness;

- *EasyRide Project Open Event, Altice Forum Braga - Braga, Portugal, 2021*

  This public event, distinguished by the attendance of Prime Minister António Costa and Pedro Siza Vieira, Minister of State, Economy, and Digital Transition, showcased the achievements of the *EasyRide* (Intelligent Mobility), an innovation project aimed to enhance knowledge and technology of smart sensors, human-machine interfaces, vehicle communication infrastructures, in-vehicle sensing and emotional monitoring of occupants applied in the context of smart mobility, car sharing and autonomous driving;

6.5.2 Other Research Projects

During the doctoral programme, the candidate engaged in multiple innovation projects, which supported the research and application of various data collection, preprocessing and analytic methods applied in this research work. Consequently, a list and summary of these projects are provided:

- *2021 - 2023: Theia Innovation Project (co-funded by COMPETE 2020: POCI-01-0247-FEDER-047264)* resulted from the collaboration between the University of Porto and Bosch, aimed to enhance autonomous vehicles' sensory capabilities by developing and validating **AI** perception algorithms using data from integrated sensors, particularly focusing on **LiDAR** technology, seeking to respond to autonomous driving needs.

  Within this project's framework, the candidate's responsibilities included the development of perception algorithms for temporal 3D object detection and tracking. Furthermore, the candidate implemented automated data anonymisation techniques through the deployment of **AI** algorithms;

- *2018 - 2021: EasyRide Innovation Project (co-funded by COMPETE 2020: POCI-01-0247-FEDER-039334)* is the third iteration of the partnership of Bosch and University of Minho aspired to develop

technologies to respond to the future mobility paradigm, including interior vehicle sensors and the intelligent cockpit for (shared) autonomous vehicles.

In this project, the candidate's contributions included the development of in-vehicle solutions for activity and violence recognition through the analysis of audio-visual information;

- *2017 - 2018: Eustress Innovation Project (co-funded by NORTE 2020: NORTE-01-0247-FEDER-017832)* resulted from the collaboration between the OPTIMIZER and University of Minho, aimed to research and develop an information system that monitors and evaluates the user's stress levels, capable of predicting chronic stress.

  Within this project, the candidate developed non-invasive and non-intrusive intelligent solutions for assessing and monitoring students' stress levels, achieved through biometric behaviours and cognitive analysis during high-stakes online e-exams;

6.5.3 Tutoring of Students

During the doctoral research, the candidate has successfully assisted in supervising students from Informatics Engineering and Biomedical Engineering master's programs, guiding their research in related topics. Professor Paulo Jorge Freitas de Oliveira Novais supervised all these works. The list of research projects will be presented along with a summary of each work plan.

Master's Dissertations

- Raquel Sofia Miranda da Costa. Inteligência artificial para gestão de produto. Biomedical engineering master's thesis, School of Engineering of the University of Minho (EEUM), 2023

  Project Description: This dissertation aimed to research and develop an intelligent system to monitor data quality and facilitate product comparison within the food retail industry.

- Luís Pedro Barbosa Ferreira. Temporal object detection for autonomous driving. Informatics engineering master's thesis, School of Engineering of the University of Minho (EEUM), 2022. URL `https://hdl.handle.net/1822/84180`

  Project Description: This dissertation presented a temporal module designed to process se-

quential data from **LiDAR**-based 3D point clouds for autonomous driving.

- André Sousa Figueiredo. Lidar based 3d object tracking for autonomous driving. Informatics engineering master's thesis, School of Engineering of the University of Minho (EEUM), 2022. URL `https://hdl.handle.net/1822/84087`

  Project Description: This dissertation aimed to investigate the application and feasibility of implementing a 3D object tracker for autonomous driving using **LiDAR**-based 3D point clouds.

- Leonardo de Jesus Silva. Detetor de conteúdo multimédia falso gerado através de algoritmos deep fake. Informatics engineering master's thesis, School of Engineering of the University of Minho (EEUM), 2022. URL `https://hdl.handle.net/1822/84353`

  Project Description: This dissertation focused on improving the detection of *deepfake* videos using **AI** techniques.

- Filipe Pimenta Oliveira Monteiro. Application of semantic segmentation through data acquired from sensors. Informatics engineering master's thesis, School of Engineering of the University of Minho (EEUM), 2021. URL `https://hdl.handle.net/1822/80563`

  Project Description: This dissertation focused on advancing semantic segmentation techniques for classifying data from image sensors, primarily targeting outdoor scans from autonomous vehicles and supplementing these with indoor scans for a broader understanding of semantic compositions in different environments.

- Cristiana Raquel Ferreira de Carvalho. Deteção da atividade física na terceira idade através da monitorização de relógios inteligentes. Biomedical engineering master's thesis, School of Engineering of the University of Minho (EEUM), 2021

  Project Description: Using data collected from wearable devices, this dissertation explored the

monitoring of physical activity in older people.

- João Miguel Amorim Noivo. Análise de padrões biométricos para otimização do desempenho académico. Informatics engineering master's thesis, School of Engineering of the University of Minho (EEUM), 2019. URL `https://hdl.handle.net/1822/79959`

  Project Description: This dissertation aimed to research non-invasive and non-intrusive stress detection and monitoring approaches.

- José Paulo Fernandes. Automated management and validation of clinical protocols. Informatics engineering master's thesis, School of Engineering of the University of Minho (EEUM), 2018

  Project Description: This dissertation aimed to develop a user-friendly framework for automated management of clinical protocols, encoded in an **Ontology Web Language (OWL)**.

Informatics Engineering Laboratory

- João Costa, Tiago Fontes, and Tiago Sousa. Reconhecimento facial em conteúdo multimédia. Technical report, School of Engineering of the University of Minho (EEUM), 2020

  Project Description: This research project focused on developing a **DL**-based framework for identifying and locating people in images or videos using facial recognition techniques.

- Alexandre Pacheco, José Pedro Pinto, and Pedro Lima. Deployment and optimization of object detection using deep neural networks on embedded systems. Technical report, School of Engineering of the University of Minho (EEUM), 2020

  Project Description: This research project addressed the challenge of minimising the computational demands in object detection algorithms, focusing on evaluating and implementing the YOLO method [313], a state-of-the-art object detection approach, on a Raspberry Pi 3B+.

- Carla Filipa Lopes Monteiro Costa, Sandra Teixeira Marques de Sousa, and Simão Paulo Leal Barbosa. Modelo de aprendizagem para previsão de stress. Technical report, School of Engineering of the University of Minho (EEUM), 2019

  Project Description: This research project focused on intelligent algorithms capable of predicting a user's stress level and suggesting measures/actions to mitigate cases of identified high-stress levels.

- João Cunha and Nuno Moreira. Sensores mobile: Detecção de tráfego terrestre. Technical report, School of Engineering of the University of Minho (EEUM), 2018

  Project Description: This research project focused on implementing an intelligent system that collects Bluetooth signal information, focusing primarily on the **Received Signal Strength Indicator (RSSI)**, to pinpoint areas of high-ground traffic throughout the day.

- Dalila da Costa Reis, Pedro Miguel Silva Alves, and Thanira Rates. Utilização de procedimentos de mineração de dados para o tratamento de informações multimédia. Technical report, School of Engineering of the University of Minho (EEUM), 2018

  Project Description: This research work tackled the challenge of automatically classifying music genres as a way to improve music indexing and retrieval on digital platforms.

- Diogo Figueiredo Pimenta, Tiago André Alves Bouças, and Tiago Nuno Fernandes Duarte. Elaboração automática de ementas usando computação inspirada em técnicas de computer reasoning. Technical report, School of Engineering of the University of Minho (EEUM), 2018

  Project Description: This research project implemented an intelligent menu recommendation application, primarily designed for cafeterias and similar environments, seeking to simplify the process of menu creation while accommodating specific restrictions (*e.g.*, complexity and cost of dishes preparation, cultural restrictions, nutritional balance, *etc.*) and aiming to maximise user satisfaction.

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