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Discriminant power of socio-demographic characteristics and mood in distinguishing cognitive performance clusters in older individuals: a cross-sectional analysis

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ABSTRACT

Objectives: Identification of predictors of cognitive trajectories has been a matter of concern on aging research. For this reason, it is of relevance to infer cognitive profiles based on rapid screening variables in order to determine which individuals will be more predisposed to cognitive decline.
Method: In this work, a linear discriminant analysis (LDA) was conducted with socio-demographic variables and mood status as predictors of cognitive profiles, computed in a previous sample, based on different cognitive dimensions. Data were randomly split in two samples. Both samples were representative of the Portuguese population in terms of gender, age and education. The LDA was performed with one sample ($n = 506$, mean age 65.7 ± 8.98 years) and tested in the second sample ($n = 548$, mean age 68.5 ± 9.3 years).
Results: With these variables, we were able to achieve an overall hit rate of 65.9%, which corresponds to a significant increment in comparison to classification by chance.
Conclusion: Although not ideal, this model may serve as a relevant tool to identify cognitive profiles based on a rapid screening when few variables are available.

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Linear discriminant analysis; mood; neurocognitive function; aging

1. Introduction

Aging is associated with a continuing deterioration in several cognitive dimensions. Although the factors and mechanisms that promote this decline are not completely known, it is well established that education (Ardila, Ostrosky-Solis, Rosselli, & Gómez, 2000; Santos et al., 2014), social status and cognitive engagement (Paulo et al., 2011; Stine-Morrow, Parisi, Morrow, & Park, 2008), motivation and mood (Forstmeier & Maercker, 2008; Harvey, Reichenberg, & Bowie, 2006) are important modulators of cognitive aging. In fact, differential interactions between these may underlie and/or contribute to intra- and inter-individual differences in cognitive performance/reserve over the lifespan (Hilborn, Strauss, Hultsch, & Hunter, 2009; Stern, 2009; Steffener & Stern, 2011). In particular, it has been demonstrated that specific characteristics predispose individuals to be protected against age-related cognitive deteriorations. This is described in the theory of cognitive reserve, which refers to individual differences in the susceptibility to age-related declines. In this theory, two different types of reserve are described: brain reserve and cognitive reserve. The first is proposed as a passive model of reserve, which states that individuals with larger brains present a reduced likelihood of developing dementia when comparing to individuals with smaller brains. On the other hand, cognitive reserve is an active form of reserve, by which brain functioning rather than brain size is the relevant variable for explaining cognitive differences. Cognitive reserve enables the individual to successfully cope with pathology by using pre-existing cognitive compensatory mechanisms. Individual characteristics, including higher education and occupational attainment, contribute to the development of these mechanisms, allowing individuals to be less susceptible to age-related declines (Stern, 2009).

Linear discriminant analysis (LDA) is a statistical predictive procedure used with the purpose of distinguishing among groups of a dependent variable based on independent variables. LDA can be used when the dependent variable is categorical with two or more groups. In LDA, discriminant functions (DFs) are calculated to maximize the difference between groups. The number of DFs produced is equal to $k - 1$, with k corresponding to the number of groups included in the analysis. Thus, when the dependent variable has three groups, two DFs are calculated. This allows the profiling of characteristics of the subjects and the assignment of subjects to the most suitable group. The discriminant power of the DF depends on the overlap of the distributions of the groups, such that a small overlap between distributions yields a good discrimination, whereas higher overlaps produce poorer discrimination ability. Overall, the main advantage of LDA is that it allows the derivation of classification models so that the group membership can be predicted from new observations (Hair, Black, Babin, & Anderson, 2010).

The present work from the SwitchBox Consortium (http://www.switchbox-online.eu/) is based on findings in older, community-dwelling individuals living in the Minho region of Portugal. The results may have broader implications given that, on measures of literacy, (un)employment rates, positive experience/mental health and other demographic characteristics,

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Portugal ranks close to the Organization for Economic Co-operation and Development (OECD; www.oecd.org/) average (OECD, 2013). In particular, education is of interest as it is considered a major factor explaining cognitive trajectories throughout aging (Ardila, Ostrosky-Solis, Rosselli, & Gómez, 2000; Santos et al., 2014; Wilson et al., 2009). On this, Portugal is an interesting population-based case study. Its current middle-aged and older population overall has less school years than those in Western European and North-American countries, with most having only completed the four school years that comprise basic grade school; however, it is similar to most of the other more newly developed and/or developing countries which also present low percent scores of higher education levels. Herein, we aim to develop a function to characterize individuals' cognitive performance based on socio-demographic characteristics (e.g. gender, age, level of education and occupational status) and mood.

2. Material and methods

2.1. Ethics statement

The study was conducted in accordance with the Declaration of Helsinki (59th Amendment) and was approved by national (Comissão Nacional de Protecção de Dados) and local (Hospital de Braga, Braga; Centro Hospitalar do Alto Ave, Guimarães and Unidade Local de Saúde do Alto Minho, Viana-do-Castelo/Ponte-de-Lima) ethics review boards. As required by the national ethics committee, psychologists and the other research professionals involved in the study signed a Statement of Responsibility and Confidentiality. Potential participants were explained the study goals and the nature of the tests, and all volunteers provided informed written consent. Selection criteria are described elsewhere (Santos et al., 2014). Briefly, the primary exclusion criteria included participant choice to withdraw from the study, incapacity and/or inability to attend the neuropsychological assessment session(s), diagnosed neuropsychiatric disorder (medical records) and/or inability to understand informed consent. A team of experienced clinicians performed a standardized clinical interview that also addressed current medication and allowed to further detect and exclude disorders of the central nervous system (epilepsy and neurodegenerative disorders) as well as overt thyroid pathology.

2.2. Sample characteristics

In order to create calibration and validation models, two cohorts (Cohorts A and B) were recruited from the local health registries (Guimarães and Vizela). Cohort A ($n = 506$) has been previously described (Costa, Santos, Cunha, Palha, & Sous, 2013). All participants still lived in the community (community-dwellers), with equal distribution between urban and rural areas. The majority of individuals (70.4%, females 51.9%) were in the medium socio-economic stratum (Class III, Graffar measure (Graffar, 1956)) and retired ($n = 344$, females 48.3%). The cohort was representative of the general Portuguese population with respect to: (1) gender (females, $n = 264$ or 52.2%); (2) age (range: 50−89 years; $M = 65.7$, SD = 8.98; age categories: [50−60], 30.2% (females, 55.6%); [60−70], 33.2% (females, 54.8%); [70+], 36.6% (females, 47.0%)) and (3) education (median years of schooling = 4; 1.2%, 5.9%, 73.9%, 7.7%, 9.1% and 2.2% of the cohort attended school for 0, 1−2, 3−4, 5−8, 9−12 and 13+ years, respectively; literacy rate 99.4%, able to read and write). Cohort B ($n = 548$) was also representative of the Portuguese population with respect to (1) gender (females, $n = 298$ or 54.4%); (2) age (range: 50−97 years; $M = 68.5$, SD = 9.30; age categories: [50−60], 21.0% (females, 49.6%); [60−70], 29.4% (females, 52.2%); [70+], 49.6% (females, 57.7%)) and (3) education (median years of schooling = 4; 24.5%, 13.1%, 49.1%, 6.2%, 6.0% and 1.1% of the cohort attended school for 0, 1−2, 3−4, 5−8, 9−12 and 13+ years, respectively; literacy rate 74.8%, able to read and write) and all were community-dwellers. The majority of individuals (55.1%, females 54.4%) were in the medium socio-economic stratum and retired ($n = 419$, females 54.7%); noting that Cohort B covered older age categories, compared to Cohort A, extending on previous findings particularly regarding lower cognitive performance groups (Paulo et al., 2011; Santos et al., 2013).

2.3. Cognitive and psychological evaluation

Tests were selected to provide mood and general cognitive profiles, and memory and executive function profiles, as previously reported (Costa, Santos, Cunha, Palha, & Sous, 2013; Santos et al., 2013; Santos et al., 2014 and references therein). Briefly, global cognitive status was assessed with the mini-mental state examination (MMSE) and mood with the geriatric depression scale (GDS, long-version). Working memory was assessed with the digit span forward and backward tests (subtest of the Wechsler adult intelligence test, WAIS III); digits forward is generally regarded as more of an auditory immediate working memory probe, while the digit backward span is considered as the more challenging probe and where there is at least some executive load. Verbal fluency was evaluated with the controlled oral word association test (COWAT, F-A-S; parameters: admissible and non-admissible). Response inhibition/cognitive flexibility was assessed via the Stroop color and word test (Stroop; parameters: words, colors and words/colors) and multiple trial verbal learning and memory with the selective reminding test (SRT; parameters: consistent long-term retrieval (CLTR), long-term storage (LTS), delayed recall (DR) and intrusions). A team of experienced psychologists conducted the neuropsychological evaluation.

2.4. Statistical analysis

The study is aimed to determine whether the socio-demographic characteristics (gender, age, school years and occupational status) and mood could predict cognitive performance. Data analysis was structured as follows:

(1) Conversion of all cognitive/psychological test scores into *z scores* to express all variables in the same scale.
(2) Exclusion of participants that met previously established MMSE criteria for cognitive impairment ($n = 45$ from both cohorts). The MMSE exclusion criteria were adjusted for education level according to previous suggestions (Busch & Chapin, 2008; Folstein, Folstein, & McHugh, 1975; Grigoletto, Zappala, Anderson, & Lebowitz, 1999). Thus, different thresholds were used: a total MMSE score <17 if individual with ≤ 4 years of formal school education and/or ≥ 72 years of age or a total score of <23 if individual with ≥ 5 years of formal school education and/or ≤ 71 years of age (Paulo et al., 2011; Santos et al., 2014). This also follows the validation study for the Portuguese population (Guerreiro et al., 1994).

(3) Calculation of individuals' performance score in each cognitive and mood dimension, following the cognitive and mood dimensions previously identified (MMSE, general cognition; GDS, mood; MEM, memory; EXEC, executive function) using factor analysis for allocation of multiple cognitive/psychological test parameters into single (composed of one test variable/parameter) or composite (composed of multiple test variables/parameters) dimensions, allowing to reduce information of the multiple parameters into a minimal number of dimensions and the identification of the 'weight' of each of its components.
(4) LDA considering as dependent variables the Bayesian latent class (LC) analysis cognitive clusters[1] previously determined for Cohort A (cognitive performance: LC1, 'high'; LC2, 'medium'; LC3, 'low') (Costa et al., 2013).
(5) Computation for cognitive group membership ('high,' 'medium' or 'low') for Cohort B based on the classification function coefficients calculated for Cohort A.
(6) Eta squared for determination of effect size of LDA predicted group on cognitive performance score.

The SPSS package v22 (IBM SPSS Statistics) was used to perform the statistical analysis.

3. Results

3.1. Comparison of the cognitive performance groups regarding socio-demographic and mood characteristics

The characteristics of the cognitive performance clusters are described in Table 1. For all considered variables, the Bayesian LC cognitive groups presented statistical significant differences. Overall, higher to lower performers (LC1 to LC3) were progressively constituted of more females, older individuals, less school years, retired status and higher GDS scores (that is, more depressed mood). Subsequently, LDA was conducted considering using first only socio-demographic variables (Model M1) and, thereafter, adding GDS total score (Model M2) and, thus, including all the significant variables. Since three LC groups were considered, two DFs were obtained (Functions 1 and 2) for each model. Considering Model M1, the first function (eigenvalue = 0.366) explained 26.8% of the variance in the grouping variable (i.e. whether an individual belongs to LC1, LC2 or LC3); whereas the second function did not reveal to be statistically significant ($\Lambda = 0.987$, $\chi^2_{(4)} = 6.49$, $p = 0.165$), adding less than 0.01% of explained variance in this model. Regarding Model M2, the first function (eigenvalue = 0.46) explained 30.3% of the variance (canonical correlation coefficient = .551) in the grouping variable and for Function 2 the eigenvalue was 0.013 with a canonical correlation of .114 and the model explained 1.3%. The overall Wilks' lambda for Function 1 was significant ($\Lambda = 0.687$, $\chi^2_{(10)} = 186.2$, $p < 0.001$) indicating that the overall predictors differentiated between the cognitive groups; while Function 2 was not significant ($\Lambda = 0.987$, $\chi^2_{(4)} = 6.49$, $p = 0.165$).

Table 2. Correlation and standardized coefficients for LDA functions (Functions 1 and 2) for Cohort A.

	Structure coefficients (r_s)		Standardized coefficients	
	Function 1	Function 2	Function 1	Function 2
School years	−.647[a]	.426	−.617	.554
Age	.610[a]	−.080	.633	.157
Occupational status (1, retired)	.410[a]	−.207	.074	−.202
GDS	.423	.747[a]	.430	.670
Gender (1, male)	−.150	−.571[a]	−.014	−.411

Note: Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions; variables ordered by absolute size of correlation within function.
[a]Largest absolute correlation between each variable and any discriminant function.

Table 2 presents the within-groups correlations between the predictors and the DF as well as the standardized weights. Based on these coefficients, 'School years' and 'Age' demonstrated the strongest relationship with the discriminant Function 1; whereas 'GDS' and 'Occupational status' demonstrated a moderate relationship and 'Gender' showed the weakest relationship. Furthermore, 'GDS' demonstrated the strongest relationship with Function 2, 'Gender' and 'School years' a moderate relationship, and 'Occupational status' and 'Age' the weakest. As such, the discriminant Function 1 was labeled 'School years and age' and Function 2 'GDS and gender.' That is, the Function 1 separates LC1 from LC2 and LC3, and Function 2 separates between LC2 and LC3 (although the variance explained by this variable is low, it indicates the role of mood in identifying weaker performers). The correlation coefficients reflect Pearson correlations between the predictors and the DF; here, all were above .30 for each function (the reference value to consider all variables in the analysis as relevant to the DF (Burns & Burns, 2008)). Higher ages are related with lower number of school years and with higher Function 1 values; while higher Function 2 values reflect higher GDS and female gender.

The overall hit rate (corrected classification) was 65.9%, corresponding to an increase of 20.7% compared to the proportional percentage of correct classification by chance ($(148/502)^2 + (298/502)^2 + (56/502)^2 \times 100\% = 45.2\%$). Since the overall percentage of cases correctly classified is affected by chance agreement, the Kappa coefficient (and index that

Table 1. Characterization for each Bayesian latent class analysis cognitive performance group (LC1−LC3) for Cohort A.

		LC1 'High'	LC2 'Medium'	LC3 'Low'	
Gender (%)	Male	52.7	48.5	32.1[a]	$\chi^2_{(2)} = 6.98$, $p = 0.030$
	Female	47.3	51.5	67.9[a]	
Age (mean (SD))		60.9 (3.49)[b]	66.9 (8.43)[c]	71.4 (8.71)[d]	$F_{(2,500)} = 40.7$, $p < 0.001$, $\eta^2 = 0.14$
School years (mean (SD))		6.2 (3.49)[d]	4.2 (2.06)[c]	3.1 (1.05)[b]	$F_{Welch(2,144.7)} = 41.4$, $p < 0.001$, $\eta^2 = 0.16$
Occupational status (%)	Non-retired	49.3	26.4	12.5[a]	$\chi^2_{(2)} = 34.7$, $p < 0.001$
	Retired	50.7	73.6	87.5[a]	
GDS (mean (SD))		8.3 (5.54)[b]	10.5 (6.08)[c]	14.4 (7.05)[d]	$F_{Welch(2,141.0)} = 18.9$, $p < 0.001$, $\eta^2 = 0.08$

Note: LC = Bayesian latent class; SD = standard deviation.
[a]Adjusted standardized residual above |1.96|, more females in LC3 and more retired individuals in LC2 and LC3, [b,c,d]different letters represent significant differences (*post hoc* Bonferroni for equal variances assumed and Games−Howell for equal variances not assumed).

Table 3. Classification results using 'leave one-out' cross-validation method for Cohort A.

			Predicted group membership			
		LC3	LC1 'High'	LC2 'Medium'	LC3 'Low'	Total
Original[a]	Count %	LC1 'High'	63	85	0	148
		LC2 'Medium'	33	261	4	298
		LC3 'Low'	1	48	7	56
		LC1 'High'	42.6	57.4	0	100
		LC2 'Medium'	11.1	87.6	1.3	100
		LC3 'Low'	1.8	85.7	12.5	100
Cross-validated[b,c]	Count %	LC1 'High'	62	86	0	148
		LC2 'Medium'	35	259	4	298
		LC3 'Low'	1	48	7	56
		LC1 'High'	41.9	58.1	0	100
		LC2 'Medium'	11.7	86.9	1.3	100
		LC3 'Low'	1.8	85.7	12.5	100

Note: LC = Bayesian latent class.
[a]65.9% of original grouped cases correctly classified.
[b]Cross-validation is done only for those cases in the analysis. In cross-validation, each case is classified by the functions derived from all cases other than that case.
[c]65.3% of cross-validated grouped cases correctly classified.

corrects for chance agreements) was computed. Results indicate a moderate agreement (Kappa = .282, $p < 0.001$; Kappa ranges from -1 to $+1$, where 1 indicates perfect prediction and 0 indicates chance level prediction). By cognitive classes, the correct prediction rates were 42.6%, 87.6% and 12.5% for the LC1, LC2 and LC3 groups, respectively (Table 3). Since it is sought a discriminant model that has external and internal validities, the technique of 'leave-one-out classification' as a form of cross-validation was used (Table 3). The classification accuracy on the discriminant analysis is similar to the classification accuracy from the cross-validation which refers to the quality, stability and generalization of DFs used. The results regarding the relevance of the predictors used in the analysis by reference to the DFs are presented in Table 4. The Fisher's linear discriminant classification functions translate into coefficients that are multiplied by the result obtained for each individual allowing to predict the cognitive group to which the individual belongs. Thus, the results are calculated taking into account the three Fisher DFs and the individual will be assigned to the group/function that has the highest score.

3.2. *Predictive power of the discriminant functions in the validation sample*

Based on Table 4, the following Fisher DFs were applied for the validation sample (Cohort B):

$$\begin{aligned}\text{LDA High} = {} & (2.18\times\text{Gender}) + (1.3\times\text{Age}) \\ & + (0.997\times\text{School years}) + (-12.219\times\text{Retired}) \\ & + (0.462\times\text{GDS}) - 43.333\end{aligned}$$

$$\begin{aligned}\text{LDA Medium} = {} & (2.281\times\text{Gender}) + (1.385\times\text{Age}) \\ & + (-0.675\times\text{School years}) \\ & + (-11.958\times\text{Retired}) + (0.526\times\text{GDS}) \\ & - 47.197\end{aligned}$$

$$\begin{aligned}\text{LDA Low} = {} & (1.977\times\text{Gender}) + (1.462\times\text{Age}) \\ & + (0.52\times\text{School years}) + (-11.956\times\text{Retired}) \\ & + (0.63\times\text{GDS}) - 54.802\end{aligned}$$

Table 4. Fisher's linear discriminant classification functions coefficients for Cohort A.

	LC1 'High'	LC3 LC2 'Medium'	LC3 'Low'
Gender (1, male)	2.180	2.281	1.977
Age	1.300	1.385	1.462
School years	0.997	0.675	0.520
Occupational status (1, retired)	−12.219	−11.958	−11.956
GDS	0.462	0.526	0.630
Constant	−43.333	−47.197	−54.802

Note: LC = Bayesian latent class.

where female gender = 0, male = 1; age = age in years; school years = number of school years; retired = 0, non-retired = 1; GDS = GDS score. All LDA scores were calculated for each individual. The maximum score corresponded to the cognitive performance group to which the individual was attributed to ('high' $n = 72$, 14%; 'medium' $n = 400$, 79%; 'low' $n = 34$, 7%). Cognitive performance scores based on LDA predicted cognitive group membership are shown in Figure 1. The Eta squared (η^2) was calculated for each cognitive dimension: EXEC = 0.227, MMSE = 0.165 and MEM = 0.148, representing a large effect size according to Cohen (1988).

4. Discussion

Using LDA, the present cross-sectional analysis was designed, without an a-priori hypothesis, to determine whether the socio-demographic characteristics gender, age, school years and occupational status, together with mood, could predict cognitive performance in an aging cohort mainly characterized by low educational levels. The overall hit rate (corrected classification) was 65.9%, representing an increase of 20.7% compared to the proportional percentage of correct classification by chance. It is plausible to argue that the classification in the extreme groups is far from ideal (higher: 42.6% and lower: 12.5%). However, it is relevant to take into account that the majority of the sample was in the intermediate cluster. For this reason, it is more likely that more individuals are misclassified in this cluster. In addition, it is also possible to hypothesize that in the extreme groups, other variables not considered here are crucial to individuals' classification. Besides these limitations, it is also relevant to note that none

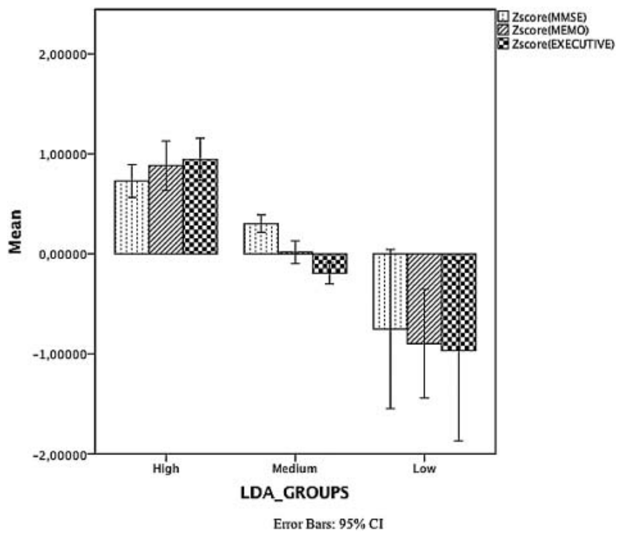

Figure 1. Means and 95% confidence intervals for the cognitive performance scores for the LDA predicted groups for Cohort B.

of the participants from the highest cluster was classified in the bottom one; similarly, only one participant of the bottom cluster was misclassified in the top one. Based on these results, we consider that a simple model containing only few socio-demographic characteristics and mood status may constitute a relevant advance for researchers to identify weaker and stronger cognitive performers. In addition, it may also be questioned, the use of LDA over other statistical procedures such as logistic regression (LR). In fact, several simulation studies reveal that LR often excels over LDA. However, it is well established that when the assumptions are not violated, it is expected that LDA will perform better than LR (Pohar, Blas, & Turk, 2004). In fact, Pohar and colleagues were able to show that, when the assumption of normality is respected, LDA yields better results than LR, although when analyzing very large samples, the results become close.

Although LDA has been applied in aging research, most of these rely on classifying individuals based on more complex parameters, such as brain network connectivity, hormonal levels and anatomical declines (e.g. Fornari, Maeder, Meuli, Ghika, & Knyazeva, 2012; Qiu, Younes, Miller, & Csernansky, 2008 ; Zhou et al., 2010). To our knowledge, there are no works using basic socio-demographic variables as predictors and few exceptions using LDA in order to classify groups using cognitive functioning parameters. Holtzer, Goldin, and Donovick (2009) were able to predict group membership (individuals with cognitive impairments and controls) using a verbal fluency test. Also, using multiple neuropsychological tests, it was shown that semantic fluency, working memory, episodic memory and education were significant predictors in the classification of group membership: mild cognitive impairment, Alzheimer's disease and controls (Quintana et al., 2012). Moreover, as far as we know, there are currently no studies using LDA to classify healthy individuals based on cognitive variables.

These results highlight the relevance of socio-demographic variables, such as age, gender, socio-economic and occupational characteristics, on the prediction of cognitive status, corroborating the existing literature on cognitive research. Moreover, the addition of mood status to the model, allowed us to correctly classify participants of the cluster with the weakest cognitive profile, which highlights the inclusion of this variable in the model. Still, to the best of our knowledge, the ability to classify cognitive performance based only on these variables was not previously reported. This may constitute an important step towards the correct classification of individuals' cognition. Altogether, the study adds to the literature by providing a relevant tool to identify cognitive profiles based on a rapid screening with few aspects available, which may complement already vastly used rapid-screening cognitive tools such as the MMSE.

Note

1. The latent classes were derived from a Bayesian latent class analysis (LCA). LCA is a model-based approach that produces a probability-based classification. It relies on the use of starting values to ensure that the best solution is achieved. In contrast with other clustering approaches, LCA does not rely on traditional modeling assumptions, such as linear relationship or normal distribution of the variables.

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Disclosure Statement

The authors declare no conflicts of interest. The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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