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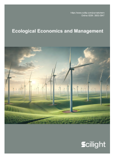

Article

Modeling Financial AI Adoption: A Comparative Decision Tree Analysis of Demographic Profiles in Personal and Organizational Contexts

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Abstract: This research investigates the socio-demographic determinants of the use and acceptance of artificial intelligence, by comparatively analyzing the context of personal financial decisions and organizational financial decisions. In this sense, the purpose of the study is to identify how the profile of the respondents influences their openness to algorithmic solutions in the two distinct spheres of their lives. The methodology used is based on machine learning, namely on decision trees, and the profiles of the respondents are segmented according to age, level of education and professional experience. The main results indicate a significant divergence between the two settings analyzed. Thus, in the sphere of personal finance, professional experience is the main factor, while in the organizational environment, age becomes the central variable. The study's conclusions highlight the contextual nature of AI acceptance in financial decisions. While in private life respondents exhibit proactive behavior, based on the accumulation of skills and the need to optimize financial resources, in the workplace context, compliance with artificial intelligence is mediated differently. However, it should be emphasized that the model explains only a marginal share of the variance in financial decision-making, more exactly 3.4% for individual decisions and almost 0 for organizational financial decisions. Therefore, the paper offers important and valuable insights for managers but also for Fintech solution developers, suggesting the need to adapt the implementation strategies for algorithm-based tools in accordance with the conditions of use and the user profile.

Keywords: AI adoption; financial decisions; demographic profiles; decision tree

1. Introduction

The integration of digital technologies into decision-making has seen an extraordinary increase over the past 5 years, especially in terms of the use of artificial intelligence as a basic tool in the decision-making process. However, the expansion of AI integration into everyday life has created a real dichotomy between the use of technologies for personal efficiency and their acceptance in organizational decision-making processes. In contrast, although the benefits of algorithms are often documented, the true success of their implementation is highly dependent on the human factor and its acceptability when it comes to making algorithmically based decisions. In this sense, a first tendency would be to consider that demographic factors play a fundamental role in shaping people's critical thinking and in determining their openness to AI-assisted decisions. More so with regard to decisions that have a much higher degree of sensitivity, namely financial decisions. Accordingly, the motivation underlying the present study is one that resides in the need to understand whether the demographic profile of individuals is the one that shapes a uniform attitude towards AI. Or whether acceptance thresholds change drastically when the algorithm goes from being a personal assistant in everyday financial decisions to being a professional career arbiter. More specifically, it is necessary to determine whether these features govern the adoption of AI in settings where the stakes are different. Namely in private life where the risk assumed by the human is individual and paradoxical in the organizational context, where the algorithmic decision will have profound implications and independent of the individual's wishes. It can thus be said that the relevance of the present topic derives precisely from this contrast born between personal financial decisions and organizational financial decisions. In accordance with these, 2 major research questions were generated and which are intended to concretely synthesize the results sought by the present study.

- RSQ1: How does the influence of demographic variables on the acceptance of artificial intelligence differ when individuals are direct users of the technology compared to the situation where they are beneficiaries of financial decisions assisted by AI within organizations?
- RSQ2: Which demographic variable exerts the strongest influence within each of the 2 contexts?

Although the specialized literature often explores the acceptance of technology among employees or even in a general way, among the population, it does not often delve into the critical thresholds that define the profile of the modern employee. Of course, there are studies that touch on the sensitivity of AI in financial decisions and that also discuss the modeling of consumer traits through AI. In accordance, a good example in this regard is found in a work carried out on the construction of a theoretical model called AI-IMPACT, research through which it was considered that AI also influences psychological processes [1]. Nonetheless, the influence that is exerted on the openness to technologies in financial decisions does not cover the entire dimension of the willingness to use and accept financial decisions based on algorithms. As the human critical thinking represents a complex mechanism that cannot be shaped solely by the influences exerted by these modern technologies.

Analyzing the specialized literature, two clear trends were identified: the first is the one focused on studying the benefits of using AI in financial decisions, with many of the studies targeting issues such as making much better-founded financial decisions [2]. The second being a direction for identifying and presenting potential ethical risks [3,4]. Nevertheless, the literature most often follows either a strictly organizational direction, with a focus on the implications of AI in organizational decisions, or an individual direction, focused on the individual. A fact which essentially implies that there is a significant gap in comparative research that captures both points of view. Moreover, there is also a lack of studies that explore whether the demographic characteristics of individuals act similarly when they move from managing their own finances to accepting a "boss" who makes financial decisions that directly concern them. Therefore, there is a real need to identify whether characteristics such as age or education have the role of a universal predictor or whether, when faced with decisions whose financial and ethical stakes are higher, they transform into much deeper factors. In this regard, the present work aims to bring a new and substantial contribution by using decision tree analysis. A method chosen precisely with the aim of identifying clear hierarchies of influence as well as behavioral inflection points, which conventional statistics fail to capture in the same detail.

Accordingly, the general hypothesis of the study is based on the idea that the determinants of AI acceptance and adoption are not universal, but rather very strongly contextualized. It is thus anticipated that in personal financial management, expertise accumulated in the work environment and educational capital are the main vectors of AI integration in decisions. While in the organizational environment, where it can be said that a certain perception of algorithmic ethics and fairness intervenes, maturity and life experience become more robust predictors than academic training. Thus, by outlining these profiles, the paper provides a scientific basis for human resources departments and, at the same time, for financial institutions, so that they can better determine what the most effective strategies for implementing AI solutions would be. Taking into account the rigorous indicators on the error and validity side, the study clearly assesses the limits of demographic predictability. In this sense, it can be said that the main objective is to identify the decisional roots that section the sample. Moreover, the research aims to evaluate the limits of demographic predictability in relation to a multidimensional phenomenon such as the acceptance of artificial intelligence.

2. Materials and Methods

2.1. Study Design and Participants

The present paper has an observational and predictive research approach, thus making it possible to identify the influence that socio-demographic factors have on the proposed analysis. In this sense, the research is qualitative, built on data collected through a questionnaire disseminated among the active population in Romania. Regarding the actual collection, the questionnaire was created and disseminated online and the period for collecting responses was relatively short, namely under a month. In this regard, the sampling approach was a hybrid one, using one of the most popular methods in studies that analyze the psychological side, more precisely convenience sampling [5]. Additionally, and the snowball sampling method as one of the most popular methods used in quantitative studies [6]. This dual approach is mainly due to the sensitivity of the analyzed context, namely that of the financial part, making it important to consider both the type of study and the psychological implications of the questions in this area. At the same time, it can be said that this approach allowed the formation of a diverse sample, totaling 235 people. Sample on which no predefined professional or demographic restrictions were applied. That being said, the socio-demographic characteristics of the sample are presented below in Table 1.

Table 1. Socio-demographic characteristics of the sample.

Highest Completed Level of Education		Age		Professional Experience	
Highschool	15.3%	18–24	19.6%	Under 1 year	10.6%
Post-high school studies	8.5%	25–34	34.5%	1–3 years	22.6%
Bachelor’s studies	30.6%	35–44	25.5%	4–7 years	17.9%
Master’s studies	37%	45–54	14.5%	8–15 years	17.9%
PhD	8.5%	55–64	5.1%	More than 15 years	31.1%
		65 and above	0.9%		

Source: Own processing.

In order to ensure the accuracy of the predictive models and to make it possible to identify a measure of uncertainty, the data set generated following the use of the questionnaire was segmented using the so-called hold-out method. An approach often encountered in statistics for the purpose of estimating the risks of estimators [7]. Method following which 80% of the responses were allocated to the training set, i.e., a total number of 188, while 20%, i.e., 47, were used as the test set.

2.2. Tools Used and the Definition of Indicators

The questionnaire used for data collection was structured into distinct sections with two of them being the ones reflecting the dual context of the study, thus playing the role of the dependent variables

The three socio-demographic questions used in the study were initially coded on a numerical scale and then automatically standardized by the analysis program. Standardization was thus performed to ensure data compatibility, which led to the conversion of raw values into standard deviation units from the mean, i.e., *Z*-scores. Therefore, the first analysis focused on the part of AI-assisted financial decisions in the personal context, having in its structure three key indicators, namely: using AI to compare prices, consulting AI to choose the payment method and using AI to plan one’s own investments. All items were rated on a Likert scale from 1–5, where 1 represented Total disagreement and 5 Total agreement. As a result, the direct and immediate purpose of this section was to observe financial decision-making behavior “at home”. In this sense the first dependent variable of the study was constructed by achieving an average score of the three, coded in the research as Personal_Financial_Digital_Behavior.

The second analysis focused on the part of AI-assisted financial decisions in the organizational context, independent of the will of individuals. It had in its structure 5 items that targeted the use of AI in sensitive organizational decisions, such as those related to salary increases, restructurings and bonus awards. As in the case of the first part, this one also had a Likert scale assessment. As such, the direct and immediate purpose of this part was to observe the behavior towards financial decisions at work, due to which the second dependent variable was constructed through an average score of the 5 indicators, coded as Organizational_AI_Finance.

2.3. Data Analysis Procedure through Machine Learning

The processing of the data collected through the questionnaire was carried out using the JASP software, version 0.95.4.0, using the Machine Learning module of the rpart package. More specifically, in order to identify non-linear interactions between demographic variables, the Decision Tree Regression technique was chosen and applied to both dependent variables. The motivation behind the choice to use the decision tree is motivated by its ability to better capture the contextual differences of the research. Additionally, providing a much clearer visual interpretation of the influences exerted by demographic factors as compared to traditional statistical methods. Regarding the algorithm configuration, it can be noted that it was carried out in order to balance precision and generalization capacity. Thus, imposing a complexity threshold equal to 0, as well as a limitation of the depth of interactions on 3 levels. Also, in order to ensure the significance of each branch, the model used was programmed to require a minimum of 15 observations to generate a new branch and. While at the same time, a minimum of 7 observations was required to generate a terminal node. Regarding the ranking of the importance of the study predictors, this was established by the so-called permutation method, namely 50 permutations, using RMSE (mean dropout loss) as a reference metric.

2.4. Data Validation and Statistical Quality of the Model

In accordance with the journal's transparency requirements, a multidimensional evaluation of the performance of the test set is reported for the present study. Thus, the following error indicators are calculated: MSE (mean square error), RMSE (root mean square error), MAE (mean absolute error) and MAPE (mean absolute percentage error).

3. Results

3.1. AI User Profile for Individual Financial Decisions

The first decision tree regression model was configured to assess the influence of demographic variables on the average score regarding the use of AI in financial decisions at home. In this sense, the model was trained on a data set (n = 188) and validated with a test sample (n = 47), thus using the hold-out method (Table 2).

Table 2. Hold-up method for the first model.

Model Summary: Decision Tree Regression				
Complexity Penalty	**Splits**	**n (Train)**	**n (Test)**	**Test MSE**
0.000	19	188	47	0.943

Source: Own processing.

Further, to maintain high transparency, a table of performance indicators was created (Table 3); an MSE of 0.943 and an RMSE of 0.971 were identified. It also included the coefficient of determination R^2, which took into account the fact that the model explains only 3.4% of the variance of financial decision-making behavior at home through demographic predictors. At the same time, given the standardization of the data, the model also reported a scaled MSE of 2.318.

Table 3. Performance indicators for regression model 1.

Model Performance Metrics	
	Values
MSE	0.943
MSE (scaled)	2.318
RMSE	0.971
MAE/MAD	0.816
MAPE	49.92 %
R^2	0.034

Source: Own processing.

Next, before presenting the final tree, the importance of the variables was also established through Table 4, this being based on the 50 permutations of the RMSE error. It was identified in this way that work experience is the most influential factor (42.25%), followed by the level of education (29.02%) together with age (28.73%), both having more secondary weights.

Table 4. Analysis of the importance of demographic factors for regression model 1.

Feature Importance Metrics		
	Relative Importance	**Mean Dropout Loss**
Work experience	42.25	1.018
Education level	29.02	1.009
Age	28.73	0.991

Note. Mean dropout loss (defined as root mean squared error (RMSE)) is based on 50 permutations. Source: Own processing.

So, finally the generated decision tree (Figure 1) confirms the central role of work experience, having a standardized threshold of 0.815 for the first branch of the model. Hence, for the 131 respondents who have less experience (below 0.815), education becomes a major differentiating factor. Essentially, those with lower levels of education (scores below −1.4) tend to report AI usage scores between 2.33 and 2.86. While for those with education above the −1.4 threshold, the averages are lower, between 2.11 and 2.39. On the other hand, in the segment with high experience (57), lower education generates an average of 2.33, while higher education is identified within a more mature age group, obtaining an average score of 2.85.

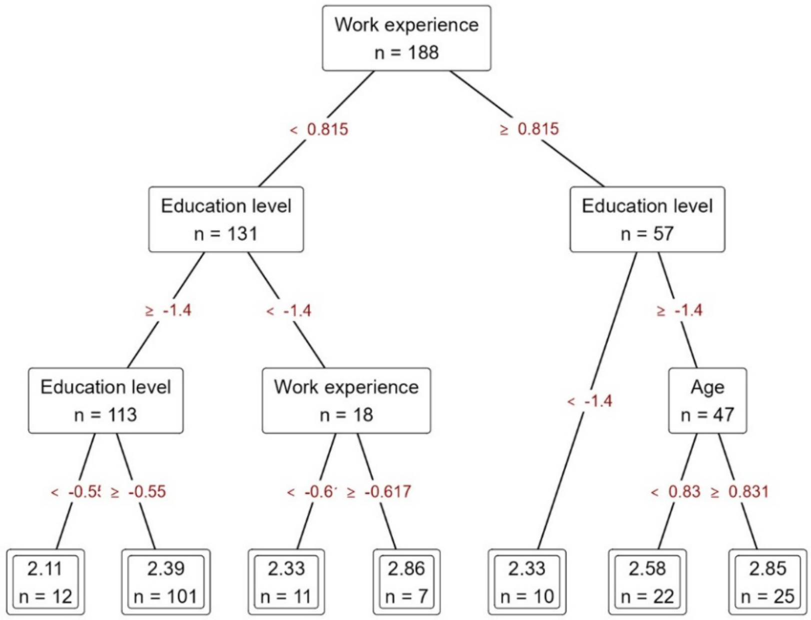

Figure 1. Decision tree plot for personal financial decisions. Source: Own processing.

3.2. Profile of Employee Receptivity to AI in Organizational Financial Decisions

The second regression model was developed to assess the influence of demographic variables on the mean score regarding the acceptance of the use of AI in organizational financial decisions. Having the same data set for training and testing as in the first one (Table 5).

Table 5. Hold-up method for the second model.

Model Summary: Decision Tree Regression				
Complexity penalty	**Splits**	**n (Train)**	**n (Test)**	**Test MSE**
0.000	15	188	47	0.912

Source: Own processing.

Regarding the performance indicators (Table 6), the recorded MSE was lower than in the case of the first model (0.912), as was the RMSE which was 0.955. Although the MAE (0.776) is also lower compared to the previously analyzed context, the coefficient of determination shows an extremely low explanatory power of the demographic factors.

Table 6. Performance indicators for regression model 2.

Model Performance Metrics	
	Values
MSE	0.912
MSE (scaled)	1.974
RMSE	0.955
MAE/MAD	0.776
MAPE	37.95 %
R^2	7.553×10^{-5}

Source: Own processing.

In the case of the hierarchy of importance of the variables by permutation, a hierarchical change is highlighted compared to the previous model (Table 7). In this situation, age becomes the most influential factor, having a relative importance of 47.35%. Professional experience is now in second place (29.55%), followed by education level (23.10%), so both have a similar impact.

Table 7. Analysis of the importance of demographic factors for regression model 2.

	Feature Importance Metrics	
	Relative Importance	**Mean Dropout Loss**
Age	47.35	0.976
Work experience	29.55	0.972
Education level	23.10	0.977

Note. Mean dropout loss (defined as root mean squared error (RMSE)) is based on 50 permutations. Source: Own processing.

Finally, the decision tree that was generated (Figure 2) confirms the main role played by age, with the first branching node being presented at a standardized threshold of 1.69. Thus, for the majority segment (179 respondents), respectively for the younger segment, the acceptance of AI in organizational financial decisions is mediated by education. In this regard, those with below-average education (<−0.55) also have the lowest acceptance scores, between 2.14 and 2.38. While people with above-average education tend to be more open if they also have less work experience (<0.099), the average being 2.76. While those with the same level of education but more professional experience have a lower average acceptance. In the case of the segment with a higher receptivity (small group of 9), a much higher level of acceptance is recorded, the average being 3.20.

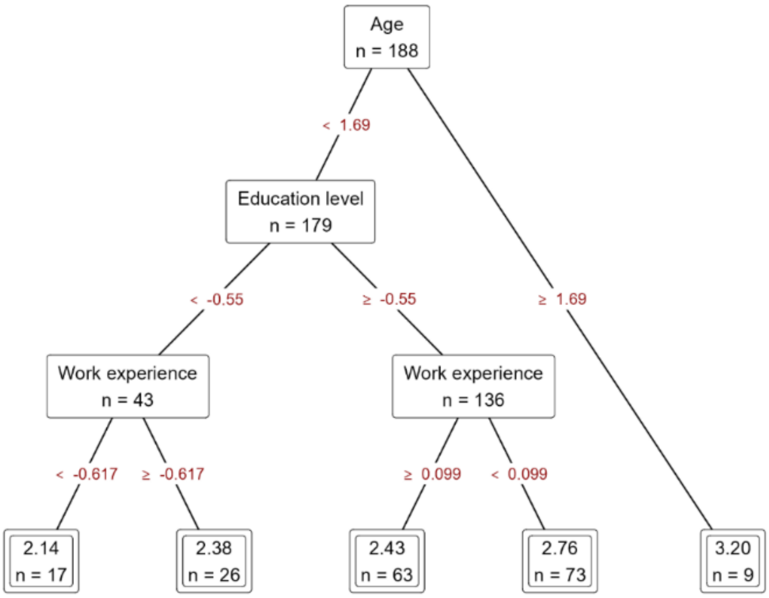

Figure 2. Decision tree plot for organization financial decisions. Source: Own processing.

In order to provide a more coherent view of the differences between the two analyses, a comparative summary table of the results was created (Table 8).

Table 8. Comparative summary of decision tree models.

Feature	First Tree	Second Tree
Root node	Work experience	Age
Tree depth	4 levels	3 levels
Leaf nodes	7	5
Primary splitter	Work experience	Age
Secondary predictor	Education level	Education level
Maximum predicted value	2.86	3.20
Minimum predicted value	2.11	2.14

Source: Own processing.

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4. Discussion

The results of the decision tree analysis presented in Figure 1. present a clear hierarchy of socio-demographic factors. In this sense, work experience is the one that mainly segmented the sample, thus suggesting that longer exposure to the professional environment may make individuals more confident in using AI in financial decisions at home. The inflection point discovered by the algorithm is around a threshold of approximately 8 years of professional experience, which implies that those who exceed this level will have higher scores. Comparatively, in a similar study investigating the influence of demographic characteristics on the acceptance and adoption of AI-based products, the results suggest that age and financial status are the ones that shape openness to these intelligent tools [8]. Meanwhile, in a research that deepens trust in intelligent systems, it was determined once again that age plays an influential role [9]. In the case of the present research, the decision tree considers that for those with less than 8 years of professional experience, education comes second as a critical control variable, which means that those with higher education will have a higher average score compared to those with only high school or post-high school education. Similarly, in research focusing on identifying demographic factors that predict the use of AI among teachers, the results identified that education level is the strongest predictor of the adoption of artificial intelligence tools [10].

Although age does not seem to be an important predictor, the model in this section presents a remarkable issue. Namely that in the case of respondents with solid professional experience, who have higher education, age becomes a pillar of final refinement of their behavior. If the common prejudice propagates the idea that young people are the main users of AI, the tree contradicts this statement. Showing that the maximum score for the use of AI at home is reached by the group of people over 45 years old (2.85). Of course, this paradox can be explained by the fact that older age also implies a much higher financial complexity at home.

Even so, viewed from a statistical validity point of view, performance indicators provide a much more realistic perspective on the complexity of this phenomenon. Thus, the R^2 value of 0.035 means that the model in the first decision tree explains only 3.4% of the variation in digital financial behavior in personal life. However, even if the percentage is relatively low, it is somewhat specific to behavioral studies, since it can be said that such sensitive decisions are affected by many more influences, including algorithmic literacy and financial literacy. Essentially, the MAE value confirms that the tree identifies valid trends.

The second model presents a nuanced perspective on how demographic characteristics influence the sample's opinions. Thus, according to Table 7, it was highlighted that age clearly dominates the predictive hierarchy of the three analyzed characteristics, having an importance of 47.35. Comparatively, in a study analyzing employees' attitudes towards AI in the work environment, age was not identified as having a major effect in relation to socio-demographic characteristics such as country of residence and gender [11]. According to the significant differences between age and work experience (29.55) and education level (23.10), it can be said that openness seems to be shaped by the respondents' general life experience and generational affiliation, rather than by a specific academic background. Which is extremely interesting, given that in another study that delved deeper into the issue of AI acceptance among the workforce, it was highlighted that there is a negative correlation between age and AI acceptance. More exactly, the older the people are, the more reluctant they are [12]. Nevertheless, when it comes to employees, issues such as AI anxiety must often be considered as a factor impacting their well-being [13] as well as matters concerning the contribution it makes to job satisfaction [14]. Both of them having a strong impact on psychological acceptance of decisions that are supported by intelligent systems.

Regarding the performance of the second model, indicators such as MAE (0.776) and RMSE (0.955) point to reasonable prediction accuracy, being certainly better than in the case of the first analysis. Hence, the decrease in the mean error is able to suggest that employees' opinions are somewhat more homogeneous and relatively easier to fit into patterns. However, as in the previous case, R^2 has a very low value. This implicitly indicates that although specific groups have been identified through the tree, such as seniors who show a higher degree of acceptance, the demographic characteristics analyzed can only explain a very small fraction of the variability of the responses. Given the even higher sensitivity of the indicators that built the dependent variable of the last analysis, it can be considered that the acceptance of AI in the workplace is a multidimensional phenomenon. Additionally, that also goes beyond the simple demographic characteristics of employees. This issue can also be observed in the literature, where other characteristics were identified as important, such as high negative emotionality and high conscientiousness [15]. A fact which means that psychological characteristics play an important role in employee behavior towards AI-assisted decisions. Moreover, in a study conducted over AI adoption in family firms, it was noted that social capital can also play a crucial role in this direction [16]. A fact which indicates that there are a lot more determinants that could explain the studied phenomenon, and also that concerns such as organizations type should be included as well.

5. Conclusions

The present research marked with the help of Machine Learning algorithms, distinct profiles of use and acceptance of artificial intelligence depending on the context in which it was found. Accordingly, in the personal financial sphere, the model highlighted the fact that work experience is the dominant predictor, thus dominating education and age. Moreover, the maximum score in this section was achieved by older respondents who had both greater professional experience and a greater level of higher education.

In parallel, the second analysis, revealed a paradigm shift, a context in which age became the most important variable. A situation where the senior segment showed the highest degree of acceptance of AI, with the majority of respondents who were below their age threshold having a profile determined by higher education but with less work experience.

In line with this, it can be argued that the divergence between the two settings is able to suggest that if in the personal environment, the use of AI is based on expertise, in the organizational environment its acceptance is age-related. In this way, the results of the study demonstrate that resistance to change is certainly not a universal trait, but rather a contextual one in which the user as the architect of his own finances becomes a user mediated by the organizational culture.

In conclusion, the success of AI integration and acceptance depends greatly on its alignment with the specific profile of employees, and although R^2 is low, the research is able to provide a solid basis for differentiated management strategies. In addition, surprisingly suggesting that organizational seniors could be the most stable pillars when it comes to the adoption of these technologies. In this sense, it can be concluded that future research should explore additional psychological variables or even other demographic variables. It should also be noted that, this is due to the fact that the models presented in this paper only manages to describe to some extent who would be the people that accept AI more easily. However, it also emphasizes that their reasons are much deeper and more complex than their age, education and professional experience.

Study Limitations

The study also had certain limitations in terms of data collection from respondents, as the openness to completing the questionnaires is sometimes lower. At the same time, the sensitivity of the topic addressed could have had a negative impact on the decision to take part in the study. Equally, limitations also occurred in terms of the results, as the introduction of more demographic variables could have given the models greater explanatory power. However, if the size of the questionnaire had been larger, there could have been a reluctance to complete it in relation to the time required.

Author Contributions

V.-L.S., R.-S.B. and T.-F.C.: conceptualization, methodology, questionnaire design, investigation, data curation, formal analysis (decision tree), visualization, writing: original draft preparation, writing: review and editing. All authors contributed equally to this work and have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

The completion of the questionnaire was anonymous and informed consent was obtained from all subjects involved in the study.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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