Bachelor Thesis

The relationship between AI adoption and the character traits openness and neuroticism in healthcare students during their studies

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Abstract

This thesis explores the implications of openness and neuroticism personality traits on the adoption intentions of Artificial Intelligence (AI) technologies in a sample of healthcare students, linking these to the variables put forward by the Unified Theory of Acceptance and Use of Technology model (UTAUT). It aimed to explore through a questionnaire survey how students' direct experience with AI and perceived usefulness and ease of use relate to their intentions to use AI in their academic pursuits and practice.

Specifically, this study refers to a sample of 106 students from various healthcare fields. It aimed to explore through a questionnaire how students' direct experience with AI and perceived usefulness and ease of use in their studies relate to their intentions to use AI in their academic pursuits and future work fields.

Despite the anticipated importance of openness and neuroticism, the findings demonstrate that the main factors shaping students' attitudes to AI adoption are practical AI experience and perceived AI benefits. Contrary to previous studies, these findings suggest no significant impact of openness and neuroticism on AI adoption, requiring reconsideration of the roles these personality traits play in models of adopting educational AI technologies in healthcare.

Fusing existing research on technology adoption, learning-related personality traits, and healthcare-specific requirements, this thesis offers a multi-faceted perspective on how best to prepare healthcare students for the future where AI will be massively implemented. In particular, this study emphasizes the importance of practical AI experiences and calls attention to the need for educationally supportive policies that facilitate the integration of practical AI applications into the curricula of healthcare studies. Consequently, this research contributes to the academic discussion on technology assimilation in the educational sector. It provides a set of feasible implications for educators, policymakers, and technology innovators in the field.

Introduction

The field of healthcare education is quickly evolving. As a result, the implementation of artificial intelligence technologies is increasingly being recognized as a critical factor that can drastically improve the quality of education and the care of patients (Minerva & Giubilini, 2023; Tornero-Costa et al., 2023). AI applications, such as diagnostic algorithms and personalized learning platforms, offer unprecedented possibilities for improving education and healthcare within the field, making the study of AI's adoption in healthcare education both relevant and urgent (Luxton, 2014). Despite its potential, this adoption of AI is characterized by numerous hurdles. More specifically, the successful implementation of AI depends not only on the technology's design and functional capabilities but also on end-users intentions and the level of acceptance, as in the work fields, most healthcare professionals lack AI literacy (Charow et al., 2021). Therefore, it is very important to incorporate AI education in healthcare programs. In healthcare education, those end-users are predominantly students, so their readiness and willingness to incorporate AI tools play a critical role in using these technologies throughout educational settings.

Information relating to healthcare and how AI will be perceived in the future workforce guarantees a diversity of viewpoints among healthcare students. According to Khatrawi et al. (2023), 76% of healthcare students expressed a favorable and encouraging attitude toward AI's application in the clinical setting and its use in the future. The remaining portion of healthcare students had a negative attitude about AI and saw it as a danger to the healthcare industry. Nonetheless, most students lacked sufficient understanding and expertise in using AI. According to Teng et al. (2022), 74.5% of healthcare students expressed optimism about the growing significance of AI in their various areas, and they anticipated that AI technology would impact their careers over the next ten years. Moreover, some anti-AI students acknowledged the necessity of including a foundational grasp of AI in their courses. Furthermore, according to Labrague et al. (2023), student nurses showed readiness to embrace AI in their studies and future work fields. They perceived moderate barriers to adopting and using AI technologies, indicating a high willingness to use AI during their studies and future work fields. However, AI understanding needs to be more advanced for these students.

Therefore, understanding the factors underpinning healthcare students' acceptance and use of AI technologies holds significance for multiple reasons. These students will become future professionals working at the frontline level of medical practice, where they will most likely be expected to use AI technologies (Yu et al., 2018). These studies showcase that AI adoption in their studies and future work fields is necessary.

As previously indicated, the connection between AI developments and healthcare has grown significantly in recent years. Nieboer et al. (2014) explore how AI developments are viewed by healthcare professionals and how they relate to professional practices, values, and future healthcare direction. In order to guarantee that incorporating technologies like AI is morally and practically sound and improves the standard of healthcare delivery, the study emphasizes how crucial it is to match technical breakthroughs with professional values and practices. Through a comprehensive study, Kelly et al. (2023) showed that AI's behavioral intention, willingness, and use behavior across many industries were significantly and positively predicted by perceived utility, expected performance, attitudes, trust, and effort anticipation. The relationship between AI and adaptability in the healthcare industry has been studied using various versions of the Technology Acceptance Model (TAM), as demonstrated in Kelly et al. (2023). The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the TAM's most widely used extended versions. According to Rouidi et al. (2021), the TAM and UTAUT model can also be used for healthcare professionals to adopt certain new technologies such as in their study, remote car technologies

The Unified Theory of Acceptance and Use of Technology model developed by Venkatesh et al. (2003) is a holistic framework created to predict and justify individuals' acceptance and use of technology. This theory combines elements of different technology adoption theories into a consistent model validated in many scenarios. At the root of the UTAUT model lie four essential core constructs in deciding an individual's likelihood to use modern technology – performance expectancy, effort expectancy, social influence, and facilitating conditions. The user's belief in how much technology can assist them is known as performance expectancy. A person's ability to effectively use technology for work or learning impacts its usefulness. The more productive they can be with it, the better the outcomes they can achieve. Effort Expectancy is how easily a person can implement the technology. The greater the individual's perception of the simplicity of the technology's use and mastery, the greater the probability of acceptance. Social Influence is the individual's belief of how important other individuals, such as peers, supervisors, or society, think they should use modern technology. This construct considers how much society and social pressure affect people's decision to use, accept, or eliminate modern technology. Finally, facilitating conditions decide the individual's belief of whether the specialized infrastructure for the technology's use exists. This includes resource availability, support systems, and specific conditions conducive to the technology practice.

Additionally, there is evidence that the UTAUT paradigm can be applied to artificial intelligence. According to Dong et al. (2023), a study on acceptability obstacles for AI, widespread deployment is necessary. The study concluded that the AI sector falls under the scope of UTAUT. Furthermore, Roppelt et al. (2024) proposed that the UTAUT model, which focuses on the individual level, is the main foundation for researching artificial intelligence in the healthcare field. In addition to examining the UTAUT model's suitability for AI applications, this systematic study investigates its suitability for the healthcare industry. More papers are available that use the UTAUT paradigm in the healthcare field. In their study, Kim and Park (2017) examined how well medical professionals received a cloud-based electronic medical record interchange system. They found that social influence and expected performance were major in influencing users' behavioral intentions to utilize the system. The UTAUT model was also utilized by Gardner and Amoroso (2004) to analyze telemedicine technology adoption among healthcare providers, emphasizing the impact of EF expectation and facilitating conditions in shaping adoption behaviors. Furthermore, Malhorta et al. (2020) proposed a connection between healthcare students' intention to accept AI and its presence. These studies highlight the UTAUT model's applicability and relevance in understanding the complex factors influencing the uptake and application of cutting-edge technologies in healthcare settings, like artificial intelligence (AI). This opens the door for focused interventions and strategies to improve the uptake and application of technology in healthcare.

While these basic constructs form a good foundation for the analysis, several recent studies have shown that it is also necessary to introduce individual differences, such as personality traits, into the UTAUT model (Bano et al., 2019; Barnett et al., 2015; Lakhal & Khechine, 2017; Sharma & Citurs, 2004; Wang & Yang, 2005). These studies aim to provide a more in-depth understanding of how users' personality traits interact with the basic constructs of the model to predict their acceptance behavior regarding AI. By integrating personality traits into the framework, analysts can capture a fuller set of factors contributing to an individual's determination to accept or reject modern technologies. This comprehensive approach will offer more significant insights into the complex interplay between technology, one's personality, and the socio-technical environment and give helpful evidence for designing and implementing new strategies in various abstracts, including those in healthcare education. The analysis of the interaction between personality traits and AI technologies in healthcare education reveals the leading positions of openness and neuroticism. It identifies how these two specific characteristics affect technology acceptance in various spheres (Bano et al., 2019; Barnett et al., 2015; Lakhal & Khechine, 2017; Sharma & Citurs, 2004; Wang & Yang, 2005).

Openness, a personality trait characterized by a person's willingness to experience new things and ideas, indicates an increase in technology adoption (Hsu et al., 2019). Neuroticism, a psychological trait characterized by increased stress reactivity and a tendency to experience negative emotions often, presents a multi-faceted challenge for technology adoption (Barlow et al., 2014). According to Watjatrakul (2016), students' intentions to adopt online learning are influenced by their neuroticism and openness to new experiences through five perceived online learning values. Students who are open to new experiences, in particular, are more aware of the quality of online education. More neurotic students attempt not to get stressed when learning in an unfamiliar environment. Additionally, when students believe online learning meets their social and emotional needs, they are more likely to embrace it. The results and their consequences for theory and practice are further discussed.

Additionally, the study by Lakhal and Khechine (2017) provides empirical evidence on the effect of personality traits on technology acceptance and, more specifically, technology acceptance within an educational framework. In the context of the adoption of desktop videoconferencing in higher education, Lakhal and Khechine (2017) back their findings with survey data on the relationship between Big Five personality traits and the Unified Theory of Acceptance and Use of Technology (UTAUT) constructs and confirm their hypothesis about how personality influences these predictors. The personality traits openness, agreeableness, extraversion and contentiousness positively impacted the use of ICT. In contrast, the personality trait neuroticism had an overall negative impact on the use of ICT. Moreover, they also claim an indirect relationship between high neuroticism and lower technology adoption intentions, driven by factors such as performance and effort expectancy. More neurotic students felt that the technology was less easy to use and understand, providing evidence supporting the possibility of neuroticism as a factor dampening the eager adoption of AI technologies in healthcare education. Openness was directly related to higher technology adoption intentions, driven by performance and effort expectancy. More open students perceived the technology as easier to use, indicating that openness might promote healthcare students' adoption of AI technologies.

Barnett et al.‘s (2015) work offered one of the earliest insights into the influence of the Big Five personality traits on technology acceptance. The direct impact of openness and neuroticism on the perceived and actual use of technology has been underlined in this study. The study has found that openness had a positive association with technology adoption and neuroticism had a negative association with technology adoption, staying consistent with other findings. Therefore, the present work suggests the importance of considering personality in deciding technology adoption, claiming that individual predispositions are likely to predispose technology acceptance paths significantly.

Osei et al. (2022) conducted the most recent work that expanded the UTAUT model by integrating personality traits and motivation to understand the adoption of e-learning technology in the face of the COVID-19 pandemic. The study's results showcased the positive relationships between personality traits, motivation factors, behavioral intention, and actual usage in the context of e-learning platforms. The study reveals the importance of intrinsic motivators and personality traits in shaping the students’ attitudes and engagement with e-learning technology, which also applies to healthcare students. Thus, this research establishes a link between openness and neuroticism in the personality dimension and how they may interact with UTAUT constructs and affect the adoption of technology change—specifically, artificial intelligence among healthcare students.

Drawing on the prior research findings presented in the literature review section, the paper attempts to conduct a thorough study on the impact of openness and neuroticism on AI adoption by health students, guided by the research question: “To what extent are openness and neuroticism related to the intention of AI adoption by healthcare students during their studies and their attitude towards using it in their future work fields?” The following hypotheses have been formulated:

Hypothesis 1 (H1): There is a significant positive relationship between the personality trait of openness and the intention to adopt AI technologies among healthcare students during their studies and their attitude towards using it in their future work fields.

Hypothesis 2 (H2): There is a significant negative relationship between the personality trait of neuroticism and the intention to adopt AI technologies among healthcare students during their studies and their attitude towards using it in their future work fields.

Hypothesis 3 (H3): The intention to adopt AI technologies among healthcare students is predicted by UTAUT constructs (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions).

Methods

Research design

A survey was conducted to study the relationship between *openness and neuroticism and other UTAUT determinants and AI adoption intention in their studies, renamed to AI adoption and AI adoption intention in their future work field, and* renamed to *AI adoption future* by healthcare students. The variables were *performance expectancy, effort expectancy, social influence, facilitating conditions, openness, neuroticism, AI adoption* and *AI adoption future.* The first performed regression model utilized *performance expectancy, effort expectancy, social influence, facilitating conditions, openness* and *neuroticism* as independent variables and *AI adoption* as the dependent variable. The other regression model utilized *performance expectancy, effort expectancy, social influence, facilitating conditions, openness, and neuroticism as independent variables, and AI adoption in the future was* the dependent variable.

Participants

Multiple factors were considered for each individual, and convenience sampling was used to enroll participants. During the data collecting period, participants must be enrolled in a Bachelor's or Master's program relevant to healthcare. Additionally, since the questionnaire was only available in English and Spanish, participants had to be 18 or older and proficient in both languages. Students at the University of Twente could engage freely or in exchange for course credits (SONA). A LinkedIn post was made, the questionnaire link was shared, an online announcement on the SONA system was made, and content was disseminated on other social media platforms to reach healthcare students. Furthermore, many people were enlisted in person at various Universitat de València faculties relating to healthcare. To be clear, the previously given definition of healthcare (World Health Organization, 1948) includes students studying psychology, social work, medicine, and nursing. Therefore, the term "healthcare students" includes these students. Therefore, from November 5, 2023, to December 30, 2023, convenience sampling was used in this study, conducted on social media and via instant messaging. The study used a snowballing strategy.

The final version of the dataset did not include respondents who did not complete the survey (less than 95%). With 114 out of 130 individuals completing the questionnaire, the completion rate was 87.69%, meaning that 16 participants were eliminated from the dataset. Three people were also eliminated from the group, having disclosed that they were enrolled in a program unrelated to healthcare. Lastly, two control questions were employed to identify and weed out random responses to improve validity. These two control questions led to removing six people from the dataset. 106 of the people who finished the test could pass each checkpoint. Of the 130 who answered the questionnaire, those 106 people comprise the study's final population.

The individuals' variable age has a mean of 20.92 and a standard deviation (SD) of 1.76. Regarding sex, a higher percentage of women completed the survey (75.00%; n = 77) than men (25.00%; n = 26). When it came to nationality, Germans made up the majority of students (35.00%, n = 37), followed by Spanish (24.00%, n = 25) and Dutch (22.00%, n = 23). Since many of the programs at Universitat de València connected to healthcare are offered in Spanish, it is crucial to note that the in-person recruiting process may have impacted the nationality variable by raising the proportion of Spanish participants. According to the age-related sociodemographic data collected, more participants (64.00%, n = 32) were under 22 than individuals (36.00%, n = 18) who were 23 or older at the time of questionnaire completion. The current degree program was the final demographic to be attained. In this instance, psychology (80.00%, n = 85) was the most popular degree program among the participants, followed by social work (1.00%, n = 1), medicine/nursing (4.00%, n = 4), and others (15.00%, n = 16).

Materials

The authors created the questionnaire using several UTAUT, openness, neuroticism, and artificial intelligence studies. Venkatesh et al. (2003), the initial UTAUT study with 30 questions for each core component, is the first publication consulted. The questionnaire was modified, nevertheless, because professionals rather than students were the intended audience, and not all subcomponents were measured. According to Venkatesh et al. (2003), age is another moderator variable. However, in this instance, it was only considered in the demographic data section because the target group's age range would not be as broad as it would be if they were professionals.

Secondly, it was considered because Gansser et al.'s (2021) empirical investigation involved artificial intelligence and a variant of the UTAUT model. The selection of the essential components was impacted by the questionnaire's design. The statement "I find products in the MO/HH/HA that contain AIs easy to use" is an example of a Gansser et al. (2021) item. Relevant questions from the Big Five personality test topics were also included in the survey. To verify the validity of the test items, only those that specifically scored openness or neuroticism were employed (McCrae & Costa, 1987; Goldberg, 1992; Goldberg, 2013; Gosling et al., 2003). To view every item used in the survey, refer to Appendix 3. Qualtrics, an internet application, was utilized to develop the survey.

Procedure and measures

Participants were required to respond to an acceptance of the AI questionnaire. A Likert-type scale with five points, ranging from Strongly Disagree (1) to Strongly Agree (5), was used to assess the participants' agreement with a given statement. The target group was expanded to include Spanish-speaking people by translating the questionnaire.

The questionnaire had an estimated duration of 10 minutes and contained 79 items. It was divided into 14 sections, including an introduction (primarily made up of language selection), informed consent, demographics, several variables (described in the Measured variables section below), and two additional matrices (*Adaptability* and *Experience*). Although these additional matrices were included in the questionnaire, they were not pertinent to this study as Pablo Benito Miravete, another researcher, had used them for his research. Two checkpoints (such as "Checkpoint: Please indicate this question as Strongly Agree "5" to show that you are carefully reading the survey items") are included in the questionnaire. Participants read the following definition of artificial intelligence (AI) before responding to the questions on their experience with the technology: "The use of AI in your studies refers to the application of AI and machine learning technologies to support and enhance the learning and educational processes. It includes a range of resources and programs, such as ChatGPT and AI writing assistants that help students with many facets of their education." This explanation was given to the participants to clarify the questions before they could answer them.

Furthermore, an item in the last section of the questionnaire suggests that getting in touch with the researcher after the study could yield more specific information. After the experiment was planned, the necessary paperwork was submitted for permission to the University of Twente's BMS Faculty Ethical Committee. Ultimately, the submission was accepted by the Ethics Committee and was assigned confirmation number 231280.

Measured variables

***Performance expectancy*: ** Performance expectancy was measured using five items. An example of one of the items used is: “I believe that AI will help me accomplish tasks more efficiently.”

***Effort expectancy*:** Effort expectancy was measured using five items. An example of one of the items used is: “I find it easy to learn how to use AI tools.”

***Social influence*:** Social influence was measured using seven items. An example of one of the items used is: “I feel social pressure to use AI for academic purposes.”

***Facilitating conditions*:** Facilitating conditions were measured using five items. An example of one of the items used is: “I can easily access online help for AI.”

***AI adoption*:** AI adoption was measured using three items. An example of one of the items used is: “I intend to use AI for my studies in the upcoming month.”

***AI adoption future*:** AI adoption future was measured using six items. An example of one of the items used is: “I perceive AI as an opportunity for healthcare professionals’ future.”

***Openness*:** Openness was measured using ten items. An example of one of those items used is: “I am always eager to learn new things, even if they are challenging.”

***Neuroticism*:** Neuroticism was measured using ten items. An example of one of those items used is: “I find it difficult to relax, even when there is no apparent reason to be tense.”

Table 1.

Reliability (Cronbach’s Alpha)

Variable Name	No of Items	Cronbach Alpha
Neuroticism	10	0.867
Openness	10	0.871
AI-adoption	3	0.851
AI adoption future	6	0.501
Effort expectancy	5	0.702
Facilitating conditions	5	0.508
Social influence	7	0.730
Performance expectancy	5	0.649

Reliability analysis was performed to assess the internal consistency of the study variables using Cronbach's alpha coefficient (see Table 1). The results show satisfactory reliability for most variables, with Cronbach's alpha coefficients ranging from 0.501 to 0.871. Neuroticism, openness, and AI adoption showed an elevated level of internal consistency with Cronbach's alpha coefficient of 0.867, 0.871, and 0.851, respectively. However, the variable AI adoption future showed low reliability with a Cronbach alpha coefficient of 0.501, suggesting that items within this variable may not consistently measure the same underlying construct. In addition, Effort expectancy, social influence, and Performance expectancy showed acceptable reliability with Cronbach's alpha coefficients of 0.702 and 0.730. and 0.649, respectively. The conditions in the studies on the Facilitating conditions also showed low reliability with a Cronbach alpha coefficient of 0.508. According to general guidelines, Cronbach's alpha values above 0.700 are considered acceptable for research purposes, showing sufficient internal consistency, while values below 0.700 may require further investigation into the data structure. Articles and revisions should be done to improve reliability, but we continued using the current scales with lower reliability for the current study.

Data Analysis

To conduct statistical studies, RStudio 1.4.1103 was used with the packages "dplyr," "tidyr," "ggplot2," "plotly," "readr," and "psych." Using descriptive and inferential statistical tests improved the understanding of data patterns. To get a broad picture of the population, demographic variable frequencies (age, gender, and academic degree) and descriptive statistics (mean and standard deviation) were first measured.

Furthermore, three of the four assumptions of linear regression were examined to decide if a parametric or non-parametric analysis was appropriate for the data gathered (homoscedasticity, independence, and normality of residuals). The results of the correspondent studies (Breusch-Pagan, Ljung-Box, and Saphiro-Wilk´s tests) showed that a parametric test was the best way to measure the models (Appendix 1).

The associations between AI adoption and the chosen UTAUT components plus Openness and Neuroticism, as well as between AI adoption in the future and the chosen UTAUT components plus Openness and Neuroticism, were then examined using two regression models. The two multi-factor regression models previously discussed were used to evaluate the hypotheses. A significant threshold of p <. 05 was established. You may find the analysis script in Appendix 2.

Results

Descriptive statistics

Descriptive statistics for key variables are reported (Table 1). The variable *performance expectancy* exhibited a mean of 3.215 and a standard deviation (SD) of 0.493. *Effort expectancy* showed a slightly higher mean of 3.265 and an SD of 0.697, suggesting more consistent responses and a flatter distribution. The variables *social influence* and *facilitating conditions* had means of 3.445 and 3.088, respectively, demonstrating a mild skew towards lower scores and slightly peaked distributions. The *openness* variable indicated a wider range of responses, with a mean of 3.687 and an SD of 0.623. At the same time, *neuroticism* had a mean of 3.167 and an SD of 0.655, showing slightly skewed distributions in opposite directions, indicating a lower mean than *openness*. *AI adoption* reported a mean of 3.652 and an SD of 0.562, exhibiting a flatter distribution and slightly skewed towards lower scores. In contrast, *AI adoption future* reported a mean of 3.301 and an SD of 0.504, having a slightly lower mean than *AI adoption.*

Table 2:

Descriptive Statistics

	N	Mean	Std. Deviation
Performance expectancy	106	3.215	.493
Social influence	106	3.445	.584
Facilitating conditions	106	3.088	.554
Effort expectance	106	3.265	.697
AI adoption future	106	3.301	.504
AI-adoption	106	3.652	.568
Openness	106	3.687	.623
Neuroticism	106	3.167	.655
Valid N (listwise)	106		

Correlation Matrix

The correlation matrix (see Table 3) shows several significant relationships between the variables. First, *openness* positively correlates with *performance expectancy* (r = 0).271 p < 0.01), *social influence*, *AI adoption* and *AI adoption future*. Furthermore, there is a significant negative correlation between *neuroticism* and all other variables, although not to a significant extent. In addition, variables related to the utility and integration of AI in educational environments, such as *facilitating conditions* and *performance expectancy*, show positive correlations with each other and with other variables related to AI based on experience.

Table 3.
Correlation Matrix

	Performance expectancy	Social influence	Facilitating conditions	Effort expectancy	AI-adoption future	AI-adoption	Openness	Neuroticism
Performance expectancy	1.00							
Social influence	-0.02	1.00						
Facilitating conditions	.354**	.270**	1.00					
Effort expectancy	.310**	.279**	.224**	1.00				
AI-adoption future	0.150	.188*	.190*	.538**	1.00			
AI-adoption	.225**	.334**	0.15	.259**	.339**	1.00		
Openness	.271**	.290**	0.12	0.13	.238**	.651**	1.00	
Neuroticism	-0.15	0.14	0.01	-0.11	-0.03	-0.15	-0.09	1.00

Correlation is significant at the 0.01 level (2-tailed).
Correlation is significant at the 0.05 level (2-tailed).

Inferential statistics

A multilinear regression analysis was done with the variables *openness*, *neuroticism*, *performance expectancy*, *social influence*, *facilitating conditions*, and *effort expectancy* to see if they significantly impact the variable *AI adoption*. The findings are presented in Table 4. The model had an R-squared value of.265, indicating that it explains around 26.5% of the variation in *AI adoption*. While statistically significant (F = 5.474, p =.000), the R-squared value implies space for improvement. According to the coefficients table, only *effort expectancy* was a statistically significant predictor (t = 5.566, p =.000) with a positive beta coefficient (.551). The remaining characteristics, which included *performance expectancy*, *neuroticism*, and *openness*, had no significant individual effects on *AI adoption*.

Table 4.
Coefficients of AI adoption

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
2	(Constant)	2.216	.657		3.370	.001
	Performance expectancy	-.089	.112	-.082	-.795	.429
	Social influence	-.059	.101	-.059	-.590	.556
	Facilitating conditions	-.019	.094	-.020	-.198	.843
	Effort expectancy	.407	.073	.551	5.566	.000
	Neuroticism	.078	.082	.090	.956	.341
	Openness	.054	.095	.052	.562	.576

Furthermore, the variables *openness*, *neuroticism*, *performance expectancy*, *social influence*, *facilitating conditions*, and *effort expectancy* for *AI adoption future* were measured in a multilinear regression analysis. The results of the multiple regression analysis are visible in Table 5. The model is statistically significant ($F(6, 91) = 6.112$, $p = .000$), implying that at least one of the independent variables has a substantial impact on the dependent variable *AI adoption future*. However, the modified R-squared (.240) indicates that the model accounts for just 24% of the variance in *AI adoption future*. Only *effort expectancy* showed a statistically significant positive connection ($\beta = .550$, $p = .000$) with *AI adoption future*. The remaining variables, *openness*, *neuroticism*, *facilitating conditions*, *social influence* and *performance expectancy*, had no statistically significant influence on the dependent variable.

Table 5.
Coefficients of AI Adoption Future

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.394	.606		3.948	.000
	Performance expectancy	-.137	.104	-.135	-1.327	.188
	Social influence	-.114	.093	-.122	-1.227	.223
	Facilitating conditions	.118	.087	.134	1.353	.179
	Effort expectancy	.381	.068	.550	5.636	.000
	Neuroticism	.006	.075	.008	.082	.935
	Openness	.052	.088	.053	.587	.559

Discussion

The current thesis investigates the correlation between the personality traits *openness* and *neuroticism* and *AI adoption* and *AI adoption future* in healthcare students. This study was motivated by the research gap that could explain the role of these personality traits in moderating the acceptance of AI based on the Unified Theory of Acceptance and Use of Technology model. To achieve the research goal and explore the findings of other literature, 106 students in the field of healthcare were surveyed, and the results provided further insights into the factors that shape attitudes toward *AI adoption*. As a result, the evidence offers insights to expand the knowledge base in healthcare education and technology facilitation.

Summary and interpretation of results

Upon gathering and analyzing the results above, the following conclusions can be drawn about the hypotheses proposed in the context of AI technology adoption by healthcare students. The first hypothesis formulated a positive correlation between *openness* and *AI adoption* and *AI adoption future*. The evidence provided by this study here does not strongly support this hypothesis. Therefore, this hypothesis is rejected. Whereas openness might be expected to influence technology adoption positively based on previous studies (Costa & McCrea, 1922a; Terzis et al., 2012), *openness* does not have a significant effect according to the results. *Effort expectancy* was more highly positively related to *AI adoption* and *AI adoption future* than *openness*. While there appears to be a solid and positive relationship between *openness* and *AI adoption* based on the correlational analyses, the regression analysis implies that *Effort expectancy* and *performance expectancy* are the more important determinants. While *openness* appears to matter, it may not be the defining variable of *AI adoption* among healthcare students. A possible explanation might be that a high level of *effort expectancy* gives enough confidence to the students working with AI that the level of *openness* is no longer relevant for the willingness to use AI.

The second hypothesis formulated a negative correlation between *neuroticism* and *AI adoption* and *AI adoption future*. Similar to H1, the evidence does not support this hypothesis; therefore, this hypothesis is also rejected. Whereas *neuroticism* might be expected to influence technology adoption due to negative concerns and worry about change based on previous studies (Devaraj et al., 2008; Venkatesh et al., 2014; Zhou & Lu, 2011), *neuroticism* does not have a significant effect according to the results. *Effort expectancy* appears to function as a buffer against neuroticism's potentially negative consequences for *AI adoption* and *AI adoption future*. In other words, even students higher in *neuroticism* have no issues accepting AI if they see it as practical and easily accessible. A possible explanation might be that a high level of *effort expectancy* gives confidence to the students working with AI, potentially negating anxiety's effects from *neuroticism*.

The third hypothesis formulated that the UTAUT variables predict *AI adoption* and *AI adoption future*. The evidence does partially support this hypothesis. For both the variables *AI adoption* and *AI adoption future*, only the variable *effort expectancy* has a significant positive correlation with those variables. In contrast, the rest of the UTAUT variables, such as performance expectancy, social influence, and facilitating conditions, do not significantly affect the two variables. Contrasting already existing literature such as Lakhal and Khechine (2017) where they found that *effort expectancy* would negatively correlate with technology adoption. This could possibly be because AI is generally a new phenomenon with a seemingly large barrier of entry, discouraging many people if they perceive AI to be hard to use.

Rather than reaffirming the general assumption in the technology acceptance literature that individual personality traits, such as openness and neuroticism, are critical determinants of technology adoption (Bano et al., 2019; Barnett et al., 2015; Lakhal & Khechine, 2017; Sharma & Citurs, 2004; Wang & Yang, 2005), this study argues that these traits may play a less significant role than expected. Indeed, the observation that AI adoption is not significantly impacted by the personality traits openness and neuroticism, as suggested by this study, is not only interesting from an academic perspective. It also contrasts the existing body of literature, which indicates that, as McCrae and Costa (1987) showed, a high degree of *openness* and *neuroticism* may significantly impact the likelihood of adopting modern technologies. The current insight enables one to challenge these works and the underlying theoretical models, considering which factors influence technology adoption in particular settings, such as healthcare education. In support of the findings of this study, Khechine and Lakhal (2018) show that while individual differences matter, the perceived values of technology are more significant in influencing the intention to use online learning technologies. In addition, Nov and Ye (2008) find that personal innovativeness in IT and openness to change are crucial antecedents of technology acceptance, indicating the importance of flexibility and dedication toward technological tools in educational and professional settings. Hsu et al. (2019) further support the argument, highlighting the importance of organizational openness to technology adoption facilitated by administrative support in fostering service innovation.

The minimal influence of *neuroticism* identified in this study also aligns well with the findings of Watjatrakul (2016), who asserts that the high learning anxiety of neurotic individuals influences their caution towards unfamiliar learning situations without affecting their related adoption decisions. These concurrent results suggest that the varying personality traits at least offer an interesting lens for viewing hypothetical technology adoptions, with little or no outcomes registered among those intersecting this study. Fundamentally, these results suggest that discussing the personalities or facets becomes secondary to technology-related benefits and experiences when determining adoption intentions.

To sum up, the findings reported in this thesis offer a complex and less significant of personality traits affecting *AI adoption* in health education. Confirming the influence of benign, experiential learning outcomes at the forefront is essential, leaving personality trait sub-components like *openness* and *neuroticism* less important than other established dimensions like *effort expectancy* and *performance expectancy*. Such a reevaluation correlates well with the focus recommended for framing education professions' effective adoption, offering critical insights into the field reliant on the increased integration of AI technologies.

Implications

The study results make an imperative case for incorporating direct exposure to AI and AI-based applications in healthcare educational programs. This strategy is not limited to introducing AI in academic fields and is based on multiple principles of incorporating AI in student-oriented educational programs. These principles include the nature of experiential learning, AI in student benefits, and encouraging advancement in technological implementation. Thus, the needs of a changing healthcare sector will be met, and students will incorporate AI into their practice. Therefore, the conclusions made should be applied by educators, policymakers, and AI technology developers in healthcare education. Such a focused approach will empower healthcare education and students to remain in line with the forefront of AI technology and its utilization in real-world healthcare provision and utilization.

Limitations and Strengths

The current study's limitations, namely the generalization offered by convenience sampling, are a widespread problem among educational researchers. For example, students from several universities, such as Universitat de València and the University of Twente, comprise most of the study's population. For this reason, it cannot be used by other student populations or healthcare professionals. This restriction stands out, especially when contrasting the results with other studies conducted in various geographic or cultural contexts. While applicable and helpful in providing a confident answer, this methodology does not offer a representative overview of the experiences and perceptions of different healthcare education environments with *AI adoption.* According to Malhorta et al. (2020), 90.90% of Indian students thought that telemedicine and other remote AI techniques would be practical to include in their practice in the future. The findings of Malhorta et al. (2020) revealed that AI acceptance intention ratings were higher than the results currently being obtained, in contrast to this research.

Additionally, Nov and Ye (2008) and Watjatrakul (2016) underline the significance of individual differences and perceived value when analyzing technology acceptance. Their results suggest that more diverse and broad samples demonstrate more subtle differences between certain situational factors, such as cultural and environmental contexts, which are not the subject of this thesis.

Finally, the study's correlational design limits its capacity to determine the causes of the observed variables. Although the study examines the connection between *openness* and *neuroticism* and the intention to adopt AI, it cannot conclusively say that, according to this research, *openness* and *neuroticism* directly do not have a significant effect on *AI adoption* and *AI adoption future*. Putting more emphasis on the scale, the use of an AI acceptance intention scale in the research had only three elements, which may have affected the accuracy of the data. Some variables, such as *openness*, were tested using ten items. This information directly impacts the variables' Cronbach's alpha and increased construct validity might have resulted from standardizing the number of items.

Still, this study has a lot going for it. For example, it is among the first studies that link *openness* and *neuroticism*, as well as *AI adoption* and *AI adoption future* among healthcare students. As a result, the UTAUT model's applicability was evaluated in a setting where students are using AI. Since participants in this study come from a variety of nations and cultures, the integration of foreign participation is another noteworthy feature. Regarding survey design, adding the personality traits *openness* and *neuroticism* presents a novel element to the UTAUT model that may be repeated to create additional research on AI acceptance intention and perception.

Conclusion

The complexity of integrating AI in healthcare education was brought to light by this recent study. However, as the study's findings make clear, more comprehensive and diverse research is needed to properly understand AI's expanding role in healthcare education and practice. Going forward, while creating AI teaching initiatives for healthcare students, educators and researchers must consider these nuanced findings. To guarantee that AI technologies are successfully integrated into the future healthcare workforce, it is imperative that we continuously reevaluate our understanding and include multiple viewpoints in response to the rapidly shifting environment of AI in healthcare.

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Appendices

"During the preparation of this work, I used Google, Google Scholar, Word, Grammarly, Scribbr, ChatGPT, and Quilbot to find and cite literature, gain inspiration, knowledge, and direction to write my thesis and improve and paraphrase my written sentences, spelling, word use, and grammar. After Word, Grammarly, ChatGPT, and Quilbot, I thoroughly reviewed and edited the content as needed, taking full responsibility for the final outcome."

Appendix 1

Linear assumptions

Normality of residuals: First, a Saphiro-Wilk's normality test was performed to determine whether the residuals were normal. The Saphiro-Wilk's normality results showed that there was no violation of the assumption of normality because the data did not statistically vary from a normal distribution and the p-value is smaller than alpha (<.05) (W =.987, p =.142).

Homoscedasticity: Secondly, to verify homoscedasticity in the residuals of the suggested model, a Breusch-Pagan test was performed. The findings (BP = 8.326, df = 3, p =.237) indicated a high likelihood of detecting an extreme test statistic, indicating that the equal variances assumption is not breached.

Independence of residuals: A Ljung-Box test was performed to see if the residuals from a fitted time series model showed any autocorrelations in order to validate the independence of the residuals´ assumption. The results of the Ljung-Box test (X-squared = 14.56, df = 10, p =.152) showed that there is no substantial autocorrelation in the residuals. This indicates that the autocorrelations in the dataset have been sufficiently captured by the model up to 10 lags, and the residuals are essentially white noise.

Appendix 2

R code

```
#Import the data in Environment then follow these
attach(Data)

str(Data)
library(corrplot)

# Calculate correlation matrix
correlation_matrix <- cor(Data[c("PERSONALITY", "PNE", "ATNS",
"UOAIYFW", "UOAIYS", "CIYSTUA", "HOIYSTATUOAIYS", "EYFITUAIYS",
"EWAI")])

print("Correlation Matrix:")
print(correlation_matrix)
corrplot(correlation_matrix, method = "color")

# Calculate descriptive statistics
descriptive_stats <- summary(Data[c("PERSONALITY", "PNE", "ATNS",
"UOAIYFW", "UOAIYS", "CIYSTUA", "HOIYSTATUOAIYS", "EYFITUAIYS",
"EWAI")])

print("Descriptive Statistics:")
```

```
print(descriptive_stats)

install.packages("psych")
library(psych)

# Subset the EWAI
subset_EWAI <- Data[, c("EWAI1", "EWAI2", "EWAI3", "EWAI4",
"EWAI5", "EWAI6", "EWAI7")]

alpha_result_1 <- alpha(subset_EWAI)
print(alpha_result_1)

# Subset the EYFITUAIYS
subset_EYFITUAIYS <- Data[, c("EYFITUAIYS1", "EYFITUAIYS2",
"EYFITUAIYS3",
                      "EYFITUAIYS4", "EYFITUAIYS5",
"EYFITUAIYS6",
                      "EYFITUAIYS7")]
alpha_result2 <- alpha(subset_EYFITUAIYS)
print(alpha_result2)


# Subset the HOIYSTATUOAIYS
subset_HOIYSTATUOAIYS <- Data[, c("HOIYSTATUOAIYS1",
"HOIYSTATUOAIYS2", "HOIYSTATUOAIYS3",
                        "HOIYSTATUOAIYS4", "HOIYSTATUOAIYS5",
"HOIYSTATUOAIYS6",
                        "HOIYSTATUOAIYS7")]

alpha_result3 <- alpha(subset_HOIYSTATUOAIYS)
print(alpha_result3)


# Subset the CIYSTUA
subset_CIYSTUA <- Data[, c("CIYSTUA1", "CIYSTUA2", "CIYSTUA3",
"CIYSTUA4", "CIYSTUA5")]

alpha_result4 <- alpha(subset_CIYSTUA)
print(alpha_result4)


# Subset the UOAIYS
subset_UOAIYS <- Data[, c("UOAIYS1", "UOAIYS2", "UOAIYS3",
"UOAIYS4", "UOAIYS5")]

alpha_result5 <- alpha(subset_UOAIYS)
print(alpha_result5)
```

```
# Subset the UOAIYFW
subset_UOAIYFW <- Data[, c("UOAIYFW1", "UOAIYFW2", "UOAIYFW3",
"UOAIYFW4", "UOAIYFW5", "UOAIYFW6")]

alpha_result6 <- alpha(subset_UOAIYFW)
print(alpha_result6)

# Subset the ATNS
subset_ATNS <- Data[, c("ATNS1", "ATNS2", "ATNS3", "ATNS4",
"ATNS5", "ATNS6", "ATNS7", "ATNS8", "ATNS9", "ATNS10")]

alpha_result7 <- alpha(subset_ATNS)
print(alpha_result7)

# Subset the PNE
subset_PNE <- Data[, c("PNE1", "PNE2", "PNE3", "PNE4", "PNE5",
"PNE6", "PNE7", "PNE8", "PNE9", "PNE10")]

alpha_result8 <- alpha(subset_PNE)
print(alpha_result8)

# Subset the PERSONALITY
subset_PERSONALITY <- Data[, c("PERSONALITY1", "PERSONALITY2",
"PERSONALITY3", "PERSONALITY4", "PERSONALITY5",
                           "PERSONALITY6", "PERSONALITY7",
"PERSONALITY8", "PERSONALITY9", "PERSONALITY10")]

alpha_result9 <- alpha(subset_PERSONALITY)
print(alpha_result9)



# Load necessary library
library(ggplot2)

# correlation H2
correlation_h2 <- cor(Data[c("ATNS", "UOAIYFW", "EWAI", "PNE")])

# Print correlation matrix
print(correlation_h2)

# Scatterplot
pairs(Data[c("ATNS", "UOAIYFW", "EWAI", "PNE")],
      main = "Scatterplot")

# correlation h1
correlation_h1 <- cor(Data[c("UOAIYS", "ATNS", "EWAI",
```

```
"EYFITUAIYS", "HOIYSTATUOAIYS", "CIYSTUA")])

# Print correlation
print(correlation_h1)

# Create scatterplot matrix
pairs(~ UOAIYS + ATNS + EWAI + EYFITUAIYS + HOIYSTATUOAIYS +
CIYSTUA, data = Data)


# Perform simple linear regression
model <- lm(PERSONALITY ~ EWAI, data = Data)

# Summary of the regression model
summary(model)

# Plotting the regression line
plot(Data$EWAI, Data$PERSONALITY, main = "Scatterplot of EWAI vs
PERSONALITY",
     xlab = "EWAI", ylab = "PERSONALITY")
abline(model, col = "red")
#Import the data in Environment then follow these
attach(data)

str(data)
library(corrplot)

# Calculate the correlation matrix
correlation_matrix <- cor(data[c("EYFITUAIYS", "HOIYSTATUOAIYS",
"CIYSTUA", "UOAIYS", "AIAF", "Neuroticism", "Openness",
"UOAIYFW")])

# Print the correlation matrix
print(correlation_matrix)

corrplot(correlation_matrix, method = "color")

# Perform multiple regression
model1 <- lm(AIAF ~ EYFITUAIYS + HOIYSTATUOAIYS + CIYSTUA +
UOAIYS + Neuroticism + Openness, data=data)

# Print the summary of the regression model
summary(model1)


# Perform multiple regression
model2 <- lm(UOAIYFW ~ EYFITUAIYS + HOIYSTATUOAIYS + CIYSTUA +
UOAIYS + Neuroticism + Openness, data = data)
```

```
# View summary of the regression results
summary(model2)
```

Appendix 3

Survey questions

Introduction

Please, select your preferred language in the right upper corner.

Por favor, seleccione su idioma preferido en la esquina superior derecha.

Informed consent

Welcome!

You are being invited to participate in a research study entitled "Artificial intelligence acceptance, perception in the future workfield and adaptability for healthcare students". This study is being accomplished by Pablo Miravete Benito, Baran Çangir & Marlon Nieuwenhuis from the Faculty of Behavioural, Management and Social Sciences at the University of Twente.

The purpose of this research is to measure how students in the (mental) health field experience Artificial Intelligence (AI) in their studies. The questionnaire will take you approximately 10 minutes. The data will be used for a student thesis.

Your participation in this study is entirely voluntary and you can withdraw at any time. You are free to omit any question.

We believe there are no known risks associated with this research study. To the best of our ability your answers in this study will remain confidential. We will minimize any risks by safely storing the data on a server provided by the University of Twente and any personal information you may provide (e.g., your e-mail address) will be stored separately from your answers.

For any questions about the research you can contact Pablo Miravete Benito at p.miravetebenito@student.utwente.nl.

Demographics

1. What is your nationality?
    a. Dutch
    b. German
    c. Spanish

d. Other (determine)

2. Please, select your age (countinuous variable)
3. Please, select your gender

a. Man
b. Woman
c. Other
d. Prefer not to say

4. What is the name of your current degree program?
   Please, note this questionnaire is only intended for students who are following a degree program in (mental) health care (e.g., psychology, social work, nursing, medicine…etc. Students in studies related to the (mental) health field can also participate.
   a. Psychology
   b. Social work
   c. Nursing
   d. Medicine
   e. Other (determine)
5. Of which year in your program do you currently take most courses?
   a. Bachelor year 1
   b. Bachelor year 2
   c. Bachelor year 3
   d. Bachelor year 4
   e. Master year 1
   f. Master year 2

Experience

The following questions about your experience with artificial intelligence (AI) in your studies.

The use of AI in your studies refers to the application of artificial intelligence (AI) and machine learning technologies to support and enhance the learning and educational processes. It encompasses a wide range of tools and applications, such AI writing assistants and ChatGPT, that assist students in various aspects of education.

Please indicate how strongly you agree or disagree with the following statements using the scale: Strongly Disagree = 1, Strongly Agree = 5.

6. I would consider myself experienced in using AI.
7. I have used AI in multiple projects or tasks.
8. My experience with AI has been positive.
9. I have attended training or workshops related to AI.
10. I often experiment with new features or updates in AI.
11. My experience with AI has made me more confident in its capabilities.

12. Checkpoint: Please, indicate this question as *Strongly Agree "5"* to show that you are carefully reading the survey items.

Expected performance

The following questions are about the usefulness of AI in your studies.

Please indicate how strongly you agree or disagree with the following statements using the scale: Strongly Disagree = 1, Strongly Agree = 5.

13. I believe that AI will help me accomplish tasks more efficiently.
14. Using AI helps me understand academic concepts better.
15. AI helps me achieve better results for my group projects.
16. Using AI will improve my academic performance.
17. AI will enable me to achieve my academic goals.

Effort Expectancy

The following questions are about how easy you find it to use AI in your studies.

Please indicate how strongly you agree or disagree with the following statements using the scale: Strongly Disagree = 1, Strongly Agree = 5.

18. I find it easy to learn how to use AI tools.
19. It is easy for me to become an expert at using AI.
20. I find AI to be user-friendly.
21. I believe that using AI does not require a lot of effort.
22. I think I can become skillful in using AI quickly.
23. Even without prior experience, I find AI tools intuitive.
24. Please, indicate this question as *Strongly Disagree "1"* to show that you are carefully reading the survey items.

Social Influence

The following questions are about how others in your studies think about the use of AI in your studies.

Please indicate how strongly you agree or disagree with the following statements using the scale: Strongly Disagree = 1, Strongly Agree = 5.

25. Most students in my class use AI for academic purposes.
26. I used to have conversations with my peers about the applicability of AI in the academic domain.
27. My peers have shared positive experiences using AI for studies.

28. There is a general consensus among my peers that AI is beneficial for academic success.
29. Using AI is seen as being adapted to new technologies among my peers.
30. My teachers speak positively about AI´s potential in education.
31. I feel social pressure to use AI for academic purposes.

Facilitating Conditions

The following questions are about the conditions in your studies to use AI.

Please indicate how strongly you agree or disagree with the following statements using the scale: Strongly Disagree = 1, Strongly Agree = 5.

32. There are tutorials and guides available for AI tools we use.
33. I can easily access online help for AI tools.
34. There are student groups or clubs focused on AI that I can join.
35. The use of AI is accepted by teachers from my university.
36. I can easily collaborate with peers using the AI tools provided, enhancing group projects and discussions.

Behavioural intention

The following questions are about how likely it is you will use AI in your studies in the coming month.

Please indicate how likely or unlikely are the following statements using the scale: Strongly Disagree = 1, Strongly Agree = 5.

37. I intend to use AI for my studies in the upcoming month.
38. I expect to start using AI in the upcoming month.
39. I plan to use AI in the upcoming month.

Perception about the role of AI in the healthcare field

The following questions are about the use of AI in your future work field: (mental) healthcare.

Please indicate how strongly you agree or disagree with the following statements using the scale: Strongly Disagree = 1, Strongly Agree = 5.

40. I think AI will lead to major advances in healthcare.
41. I find the use of artificial intelligence in healthcare exciting.
42. I perceive AI as a threat to the healthcare professionals' future.
43. I perceive AI as an opportunity for healthcare professionals' future.
44. I believe that AI will be a complement for the professionals in the field of healthcare.

45. I believe that AI will be a substitute for the professionals in the field of healthcare.

Adaptability

The following questions are about the use of AI in your future work field: (mental) healthcare.

Please indicate how strongly you agree or disagree with the following statements using the scale: Strongly Disagree = 1, Strongly Agree = 5.

46. When faced with new information or unexpected situations in my studies, I can easily change my way of thinking to accommodate them.
47. I can manage my emotions effectively, even when faced with stressful situations in my academic life.
48. I can easily adapt to collaborate with different peers in group projects.
49. I actively seek feedback and use it to improve my skills and knowledge in my field of study.
50. I can come up with multiple solutions to a problem in my studies.
51. I am comfortable learning and using new technologies related to my field of study.
52. I view changes in practices in the field as opportunities for growth.
53. I am open to receiving constructive criticism and use it to enhance my performance in my studies.
54. I actively prepare for future changes in my field by updating my skills and knowledge.
55. I seek out diverse learning experiences during my studies.
56. I can easily adapt to different team dynamics and collaborate effectively in my studies.
57. I regularly reflect on my experiences and actions during my studies to identify areas for improvement.

Openness

The following questions are about how you perceive new experiences.

Please indicate how strongly you agree or disagree with the following statements using the scale: Strongly Disagree = 1, Strongly Agree = 7.

58. I am always eager to learn new things, even if they are challenging.
59. I often come up with creative ideas and solutions to problems.
60. I am open to new experiences and enjoy exploring unfamiliar places.
61. I enjoy trying new and exotic foods from different cultures.
62. I like to engage in abstract and philosophical discussions.
63. I am comfortable with ambiguity and uncertainty.
64. I enjoy reading books or watching films that challenge my thinking and perspective.
65. I often daydream and let my imagination wander.

66. I am interested in art, music, and other forms of creative expression.
67. I am open to different viewpoints and enjoy discussing controversial topics.

Neuroticism

The following questions are about you as a person.

Please indicate how strongly you agree or disagree with the following statements using the scale: Strongly Disagree = 1, Strongly Agree = 7.

68. I often worry about future events and potential problems.
69. I tend to get anxious in stressful situations.
70. I find it difficult to relax, even when there's no apparent reason to be tense.
71. I am often in a bad mood, and my emotions can change rapidly.
72. I am highly sensitive to criticism and often take it personally.
73. I tend to dwell on past mistakes and regrets.
74. I often feel overwhelmed by my emotions.
75. I experience mood swings and can go from happy to sad relatively quickly.
76. I have a tendency to catastrophize and expect the worst in various situations.
77. I frequently experience physical symptoms of stress, such as headaches or stomach aches.

Conclusion

This is the end of the survey. Thank you very much for your help!

78. Please leave your email address if you would like to receive a summary of the survey results.
79. Do you have any comments about the survey?

We thank you for your time spent taking this survey.

Your response has been recorded.