Bachelor Thesis

Artificial Intelligence Acceptance, Perception in the Future Workfield and Adaptability of Healthcare Students

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Abstract

Introduction

The integration of artificial intelligence (AI) in the healthcare field implies an adaptation process by the professionals. Numerous research was conducted about the impact of AI among healthcare professionals, but there exists a research gap in understanding healthcare students´ acceptance intention of AI in their current studies and perception of the role of AI in their future workfield. Hence, this study focused on investigating the factors influencing *AI acceptance intention* in healthcare students and their *Perception of AI in the future workfield* among healthcare students, framed within the Unified Theory of Acceptance and Use of Technology (UTAUT) model.

Methods

The participants were 60 international healthcare students, mainly from the Univeristy of Twente and Universitat de València. A few prerequisites were determined such as currently studying a healthcare related program or fluently speaking English and/or Spanish. An online questionnaire was distributed to measure different UTAUT components, namely *Effort expectancy*, *Expected performance, Facilitating conditions* and *Social influence*, an extra numerical variable namely *Adaptability* and two different variables namely *AI acceptance intention* and *Perception in the future workfield*. Since the questionnaire was divided into different variables, Cronbach's alpha was calculated to determine the validity of the collected data.

The first regression model was conducted to examine the significance between the selected UTAUT variables plus *Adaptability,* and *AI acceptance intention*. Secondly, another regression model was designed to analyse the relationship between the same dependent variables *Perception in the future workfield*. In addition, the moderation effect of *Experience* was determined in both cases.

Results

None of the UTAUT components approached significance with *AI acceptance intention*. In the second model, the relationship between *Perception in the future workfield* and *Adaptability* moderated by *Experience* (β = -.06, *SE* = .02, *p* = .03*), was determined as significant. However, the rest of the variables did not show a significant relationship with *Perception in the future workfield*.

Conclusion

The lack of significant relationships (excluding the relationship between *Adaptability* and *Perception in the future workfield,* including the moderation effect of *Experience*) suggested that the chosen variables in the UTAUT framework and *Adaptability* may not be individually strong factors of *AI acceptance intention* and *Perception in the future workfield* in the context of healthcare students.

In conclusion, educators and researchers need to consider these nuanced insights when designing AI education interventions for healthcare students. The evolving landscape of AI in

healthcare demands a continuous reevaluation of our understanding and the incorporation of diverse perspectives to ensure the effective integration of AI technologies into the future healthcare workfield.

Artificial Intelligence Acceptance, Perception in the Future Workfield and Adaptability of Healthcare Students

The integration of Artificial Intelligence (AI) into healthcare has been progressively evolving, with its potential to revolutionise various aspects of patient care and treatment management becoming increasingly apparent. Minerva & Giubilini (2023) and Tornero-Costa et al. (2023) indicated that AI has been instrumental in healthcare in various ways, such as through personal sensing and providing preliminary screening, underscoring its potential in clinical support and computer-aided systems. Luxton (2014) also elucidates the potential of AI in healthcare, highlighting the use of automated systems to provide immediate, cost-effective, and personalised interventions. These systems can be particularly beneficial in addressing the shortage of health professionals and reaching individuals in remote or underserved areas.

While there is a large amount of research exploring the implications and perceptions of AI in various professional sectors, a notable research gap exists in understanding the perceptions and AI acceptance of students, regarding the integration of AI into their future careers. Existing research has predominantly focused on current professionals, exploring adaptability and engagement with AI technologies in real-time professional settings (Nieboer et al., 2014). This gap is crucial to address, as exploring and understanding students' perspectives could provide insights into the future integration of AI in the field, ensuring that upcoming professionals are adequately prepared and adaptable to the evolving technological landscape in healthcare. The World Health Organization (WHO) defined it as "a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity". As formulated in the title, the population of this research are healthcare students, and according to WHO´s (1948) definition, students from different studies were engaged.

Relating healthcare and perception of AI in the future workfield, there exists some evidence that ensures that the healthcare students' perceptions are diverse. For example, Khatrawi et al. (2023) stated that 76% of healthcare students had a positive and promising attitude towards AI in the clinical profession and its use in the future. The remaining percentage of healthcare students perceived AI as a threat to healthcare fields and showed a negative attitude towards it. However, most students had low knowledge and limited skills in working with AI. Teng et al. (2022) found that healthcare students predicted that AI technology would affect their careers within the coming decade, and 74.5% reported a positive outlook toward the emerging role of AI in their respective fields. Furthermore, even some students opposed to AI identified the need to incorporate a basic understanding of AI into their curricula.

Regarding adaptability, this competency is often defined as the ability to effectively navigate through changes and modify one's actions, strategies, and thinking to align with emerging circumstances, which is crucial in dynamic professional and psychological contexts (Martin et al., 2018). In the era of technological advancements, adaptability necessitates a renovation of skills and approaches to align with dynamically transforming roles and workflows (Nieboer et al., 2014). In addition, McKinsey & Company (2021) defines adaptability as a key meta-skill involving the ability to learn flexibly and efficiently and apply that knowledge across situations. Martin et al. (2013) conducted a research about adaptability and students, and defined this term as individuals' adjustments of psycho-behavioral functions in response to novel and/or uncertain circumstances, conditions and situations. Thus, this skill is crucial during periods of transformation and systemic change, especially in high-tech environments such as the case of AI.

As aforementioned, the relationship between AI advancements in healthcare and adaptability has been gaining importance in recent years. Nieboer et al. (2014) delve into how AI advancements are perceived by healthcare professionals and how these technologies intersect with professional values, practices, and the future trajectory of healthcare. The study underscores the importance of aligning technological advancements with professional values and practices to ensure that the integration of technologies like AI is ethical and effective, and enhances the quality of healthcare delivery. Kelly et al. (2023) demonstrated through a systematic study that perceived usefulness, expected performance, attitudes, trust and effort expectancy significantly and positively predicted behavioual intention, willingness and use behaviour of AI across multiple industries. As shown in Kelly et al. (2023), different versions of the Technology Acceptance Model (TAM) have been utilised to investigate the relationship between AI and adaptability in the healthcare field, but one of the most popular extended versions of the TAM is the Unified Theory of Acceptance and Use of Technology (UTAUT).

UTAUT model

The UTAUT model can offer a robust framework to explore the factors influencing the acceptance and use of AI technology among students in healthcare professions. Some key constructs that determine behavioural intention and use of technology are *Expected performance*, *Effort expectancy*, *Social influence* and *Facilitating conditions* among others (Venkatesh et al., 2003). The study of determinants is crucial in exploring and understanding the factors influencing healthcare students' perceptions, intentions, and engagement with AI in their educational and future professional journeys. Thus, bridging the current research with the UTAUT model could be a key to accomplishing a comprehensive exploration of how healthcare students perceive AI for future professional purposes.

To continue, there exists some evidence of the applicability of the UTAUT model in the AI domain. Dong et al. (2023) explored barriers to AI acceptance, which stated that is a prerequisite for its widespread implementation, concluding that the applicability of UTAUT includes the AI field. Also, Roppelt et al. (2024) suggested that the predominant framework for studying artificial intelligence in the healthcare domain is the UTAUT model on the individual level. This systematic research, apart from analysing the applicability of the UTAUT model in AI, studies its applicability in the healthcare field.

Other articles that applied the UTAUT model in the healthcare domain can be found, as Kim & Park (2017) explored healthcare professionals' acceptance of a cloud-based electronic medical record exchange system, revealing the significance of *Expected performance* and *Social influence* in shaping behavioural intentions to use the system. Similarly, Gardner and Amoroso (2004) employed the UTAUT model to understand the adoption of telemedicine technology among healthcare providers, highlighting the role of *Facilitating conditions* and *Effort expectancy* in influencing adoption behaviours. Moreover, Malhorta et al. (2020) suggested that there exists a relationship between *AI acceptance intention* among healthcare students. These studies underscore the applicability and relevance of the UTAUT model in understanding the nuanced factors influencing the adoption and use of innovative technologies, such as AI, in healthcare settings, paving the way for targeted interventions and strategies to enhance technology acceptance and utilisation in healthcare.

The Current Study

This current study delves into the relationship between the *AI acceptance intention in their studies, Perception in the future workfield* and *Adaptability* among healthcare students.

The first research question concerns the extent of the relationship between *AI acceptance intention in their studies* and selected UTAUT components plus *Adaptability*. To approach it, several hypotheses were stated. First, it is hypothesized a positive significant relationship between *AI acceptance intention in their studies* and *Adaptability* (*H1*). Second, a positive relationship between the elements of the UTAUT model, namely *Effort expectancy, Social influence, Expected performance, Facilitating conditions*, and *AI acceptance intention in their studies* (*H2*)*.* Third, it is expected that the relationships between *Adaptability* and the determinants of the UTAUT model, and *AI acceptance* to be moderated by *Experience* (*H3*).

The second research question focuses on examining the relationship between *Perception in the future workfield* and selected UTAUT components plus *Adaptability*. To explore this aspect, several hypotheses have been formulated. It is hypothesized that there exists a positive and significant relationship between *Perception in the future workfield* and *Adaptability* (*H4*). Secondly, the study posits a positive relationship between the key components of the UTAUT model (namely in the prior paragraph) and *Perception in the future workfield* (*H5*). Thirdly, the research estimates that the relationships between *Adaptability* and the UTAUT model components, and *Perception in the future workfield* are subject to moderation by individuals' *Experience* (*H6*).

Methods

Research design

A survey design was utilised to measure the relation between *Adaptability* and other UTAUT determinants and *AI acceptance intention in their studies* by healthcare students. The variables were *Expected performance*, *Effort expectancy*, *Social influence*, *Facilitating conditions*, *Adaptability, AI acceptance intention in their studies* and *Perception in the future workfield*. A moderator variable is also measured, named *Experience*. The first performed regression model utilised *Expected performance*, *Effort expectancy*, *Social influence*, *Facilitating conditions*, and *Adaptability* as independent variables, *Experience* as a moderator variable and *AI acceptance intention in their studies* as the dependent variable. In the second place, the other regression model utilised *Expected performance*, *Effort expectancy*, *Social influence*, *Facilitating conditions* and *Adaptability* as independent variables, *Experience* as a moderator variable and *Perception in the future workfield* as the dependent variable.

Participants

Participants were recruited via convenience sampling since several criteria for individuals were considered. Participants had to study a Bachelor's or a Master´s program related to health care at the moment of the data collection. Furthermore, participants had to be 18 years or older and have a good command of English or Spanish language as these were the two languages in which the questionnaire was available. University of Twente students could participate in return for course credits (SONA) or voluntarily. To approach healthcare students, an online announcement on the SONA system was created, a LinkedIn post was published, the link to the questionnaire was shared and content on other social media was posted. In addition, numerous participants were recruited in-person at different healthcare related faculties from the Universitat de València. To clarify, the term "healthcare students" includes Psychology, Social Work, Medicine and Nursing students according to the priorly stated definition of healthcare (World Health Organization, 1948). Hence, this study was done with convenience sampling through a snowballing method and carried out on social networks and instant messaging from November 5th 2023 to December 30th 2023.

Participants who did not complete the survey (< 95%) were removed from the final version. The completion rate of the questionnaire was 86.67% (52 out of 60 participants), which means that 8 participants were removed from the dataset. Since 2 participants indicated that they were studying a non-healthcare related program, they were removed from the population. 50 out of the totality of participants who completed the test passed the checkpoints. Finally, those 50 individuals compose the final population of this study out of the 60 individuals who participated in the questionnaire.

The mean and standard deviation of the variable age in the set of participants is $M = 21.36$, $SD = 1.90$. Regarding sex, more women than men completed the survey (68.00%; $n = 34$ compared to males, 32.00%; $n = 16$). Regarding nationality, the majority of students were Spanish (44.00%, $n =$

22), and other common nationalities were German (26.00%, *n* = 13) and Dutch (16.00%, *n* = 13). An important factor to mention is that the in-person recruiting process could have affected the nationality variable by increasing the number of Spanish participants since a huge number of healthcare related programs at Universitat de València are Spanish. The majority of students were in the 4th year of their current degree (32.00%, *n* = 16), while other students were in the 3rd year (26.00%, *n* = 13) or in the 1st year of their Bachelor's (22.00%, *n* = 11). The obtained sociodemographic data about age showed that the majority of the participants were below 22 years old (64.00%, *n* = 32) compared to the participants who were 23 years old or older (36.00%, *n* = 18) at the moment of answering the questionnaire. The last obtained demographic was the current degree program. In this case, the most common degree program among the participants was Psychology (84.00%, *n* = 42), followed by Medicine/Nursing (14.00%, *n* = 7) and Social Work (2.00%, *n* = *1*).

Questionnaire design

The questionnaire was designed by the authors based on different UTAUT, adaptability and artificial intelligence studies. The first consulted article is Venkatesh et al. (2003), which is the original UTAUT study and consists of 30 items per core component. However, the questionnaire was adapted since its target population were professionals (instead of students) and not every subcomponent was measured. For instance, age is another moderator variable according to Venkatesh et al. (2003), but in this case was only considered in the demographic data section since the age range would not be as wide as if the target group were professionals.

Secondly, Gansser et al. (2021) were considered since this empirical study related to a version of the UTAUT model and artificial intelligence. The election of the selected key components was influenced by the composition of this questionnaire. An example of a Gansser et al. (2021) item is "I find products in the MO/HH/HA that contain AIs easy to use". Other consulted sources utilised the Adaptation to Change Quire (ADAPTA-10) to study the acceptance of technology and the attitude towards AI (Pérez-Fuentes et al., 2020; Torres et al., 2015; Collado-Mesa et al., 2019). This questionnaire evaluates the individual´s adaptability to the demands of novel situations through 17 items about disposition to achieve successful adjustment to unknown situations. "Some speciality will be replaced with AI within my lifetime" is an example of an item related to adaptability towards AI (Collado-Mesa et al., 2019). The online tool Qualtrics was used to create the survey.

Procedure and measures

Participants were asked to complete a questionnaire on AI acceptance. A five-point Likert-type scale (from *Strongly Disagree "1"* to *Strongly Agree "5"*) was utilised to measure the participants´ agreement towards a presented statement. A translation of the questionnaire was made to include Spanish-speaking individuals in the target population. Indeed, the estimated duration of the questionnaire was around 10 minutes and was composed of a total number of 79 items, which were divided into 14 sections corresponding to introduction (mainly composed by language selection), informed consent, demographics, several variables (outlined below in the Measured variables section) and two extra matrices (*Openness* and *Neuroticism*). These extra two matrices were part of the questionnaire but not relevant for this study since the questionnaire was also utilised by another author for a different research. Included in the questionnaire, there are two checkpoints (e.g. "Checkpoint: Please, indicate this question as Strongly Agree "5" to show that you are carefully reading the survey items"). Before answering the questions on AI experience, participants read a definition about AI, which was: "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 encompasses a wide range of tools and applications, such AI writing assistants and ChatGPT, that assist students in various aspects of education". This explanation was provided to clarify that participants were responding to the items after understanding the context.

Moreover, in the last part of the questionnaire, there is an item indicating the possibility of obtaining more detailed information once the study was concluded by contacting the researcher. Once the experiment was designed, the required documentation was sent to the Ethical Committee of the BMS Faculty at the University of Twente to receive approval. Finally, the Ethical Committee approved the submission with confirmation number 231280.

Measured variables

Adaptability. This variable was, in the first instance, measured with 10 items, with a Cronbach´s alpha of .69. An example item is *I can easily adapt to collaborate with different peers in group projects*. *I can manage my emotions effectively, even when faced with stressful situations in my academic life).* After analysing the outcomes, a particular item was deleted since it contradicted the positive correlation pattern among items, and then the final alpha was r = .33.

Expected performance. This variable was measured with 5 items and presents a Cronbach´s alpha of .78. An example item is*: AI helps me achieve better results for my group projects*.

***Facilitating condition*s**. This variable was measured with 5 items and presents a Cronbach´s alpha of .61. An example item is*: I can easily collaborate with peers using the AI tools provided, enhancing group projects and discussions*.

Effort expectancy. This variable was measured with 7 items and presents a Cronbach´s alpha of .71. An example item is*: I believe that using AI does not require a lot of effort.*

Social influence. This variable was measured with 7 items and presents a Cronbach´s alpha of .75. An example item is*: I feel social pressure to use AI for academic purposes*.

Experience. This variable was measured with 7 items and presents a Cronbach´s alpha of .82. An example item is*: I would consider myself experienced in using AI.*

AI acceptance intention in their studies. This variable was measured with 3 items and presents a Cronbach´s alpha of .36. An example item is*: I expect to start using AI in the upcoming month*.

Perception of AI in the future workfield. This variable was measured with 6 items and presents a Cronbach´s alpha of .76. An example item is*: I believe that AI will be a complement for the professionals in the field of healthcare*.

Data Analysis

Statistical analyses were performed using RStudio version 1.4.1103. To gain a better insight into data patterns, descriptive and inferential statistical tests were conducted.

First, descriptive statistics (mean and standard deviation) and frequencies of demographic variables (age, gender and academic degree) were measured to obtain a general view of the population. Then, an exploratory factor analysis was conducted to identify underlying relationships between *Adaptabililty* and the items that compose it to check its internal consistency. In this case, only the internal consistency of this variable was analysed since its integration in the UTAUT model was designed by the author.

To determine whether a parametric or non-parametric analysis was suited for the collected data, three out of four assumptions of linear regression were tested (homoscedasticity, independence and normality of residuals). After running the correspondent analyses (Saphiro-Wilk´s, Breusch-Pagan and Ljung-Box tests), the obtained results (Appendix 1) indicated that a parametric test was appropriate to measure the models. Then, two regression models were built to test the relationship between *AI acceptance intention in their studies* and the selected UTAUT components plus *Adaptability*, and between *Perception in the future workfield* and the selected UTAUT components plus *Adaptability.* Hypotheses were examined through both mentioned multi-factor regression models. In addition, a moderator analysis was also included in both models. The significance level was determined as p <. 05. Note that the analysis script can be found in Appendix 3.

Results

Descriptive statistics

Descriptive statistics for key variables are reported (Table 1). The variable *Expected performance* exhibited a mean of 3.49 and a standard deviation (*SD*) of 3.82, indicating moderate variability and a slight negative skew. *Effort expectancy* showed a higher mean of 3.20 and an SD of 2.94, suggesting more consistent responses and a flatter distribution. The variables *Social influence* and *Facilitating conditions* had means of 2.77 and 2.25, respectively, both demonstrating a mild skew towards lower scores and slightly peaked distributions. The *Experience* variable indicated a wider range of responses, with a mean of 2.45 and an SD of 4.87, while *Adaptability* had a mean of 3.98 and an SD of 4.31, both showing slightly skewed distributions in opposite directions. *AI acceptance intention in their studies* reported a mean of 2.94, exhibiting a flatter distribution and a slight skew towards lower scores.

Correlation analysis (Table 2) revealed varying degrees of positive and negative relationships between these variables, with coefficients ranging from -.50 to .55. Notably, strong correlations were observed between *Expected performance* and *Experience* ($r = .55$) and between *Expected performance* and *AI acceptance intention in their studies* ($r = .45$), indicating significant relationships.

Table 1

Descriptive Statistics of Variables (n = 50). var: variable, sd: standard deviation.

	Mean	sd	Skewness	Kurtosis
Expected performance	3.49	3.82	-.55	.41
Effort expectancy	3.20	2.94	.03	.08
Social influence	2.77	3.45	-.78	.35
Facilitating conditions	2.25	3.52	-.12	-.18
Experience	2.45	4.87	-.07	.05
Adaptability	3.98	4.31	-.58	1.14
AI acceptance intention in their studies	2.94	2.95	-.09	-.65
Perception of AI in the future workfield	2.52	3.85	-.42	-.73

Table 2

Correlations table of Variables (n = 50).

	EP	EE	SI	FC	A	E	AAI	PAIF
Expected performance (EP)	1.00	.17	.12	.29	.28	.55	.45	-.13

Effort expectancy (EE)	.17	1.00	.08	.38	.22	.20	.16	-.25
Social influence (SI)	.12	.08	1.00	.26	-.03	.38	.04	-.26
Facilitating conditions (FC)	.29	.26	.81	1.00	.16	.23	.18	.08
Adaptability (A)	.28	.22	-.03	.16	1.00	.38	.41	-.50
Experience (E)	.55	.20	.38	.23	.38	1.00	.20	-.42
AI acceptance intention in their studies (AAI)	.45	.16	.04	.18	.41	.20	1.00	-.30
Perception of AI in the future workfield (PAIF)	-.13	-.25	-.26	.08	-.50	-.42	-.30	1.00

Factor Analysis: ***Adaptability***

Table 3 indicates how the self-defined value *Adaptability* was composed. To validate its composition, an exploratory factor analysis was conducted. *F1* values represent factor loading for the *Adaptability*, which indicates how strongly each questionnaire item is associated with the unique *Adaptability* factor. Communalities are expressed in *h2* values, which represent the proportion of each variable´s variance that can be explained by *Adaptability*. To conclude, the explained variable in *Adaptability* is 29% and indicates that according to the standards, it does not constitute an acceptable level of explained variance. However, in Psychology a lower percentage might be obtained due to the multifaceted nature of the variables involved. Furthermore, a single factor is an input for the factor analysis.

Table 3

Factor structure, communalities and percentage of explained variance (n = 50). Extraction method: Factoring of components of Adaptability.

Items	F1	h2
Adaptability	1.07	1.14
When faced with new information or unexpected situations in my studies, I can easily change my way of thinking to accommodate them.	.56	.32
I can manage my emotions effectively, even when faced with stressful situations in my academic life.	.31	.10
I can easily adapt to collaborate with different peers in group projects.	.27	.07
I can come up with multiple solutions to a problem in my studies.	.41	.17

I view changes in practices in the field as opportunities for growth.	.51	.27
I am open to receiving constructive criticism and use it to enhance my performance in my studies.	.43	.18
I actively prepare for future changes in my field by updating my skills and knowledge.	.43	.19
I seek out diverse learning experiences during my studies.	.47	.23
I can easily adapt to different team dynamics and collaborate effectively in my studies.	.44	.20
I regularly reflect on my experiences and actions during my studies to identify areas for improvement.	.59	.35
Percentage of explained variance	.29	

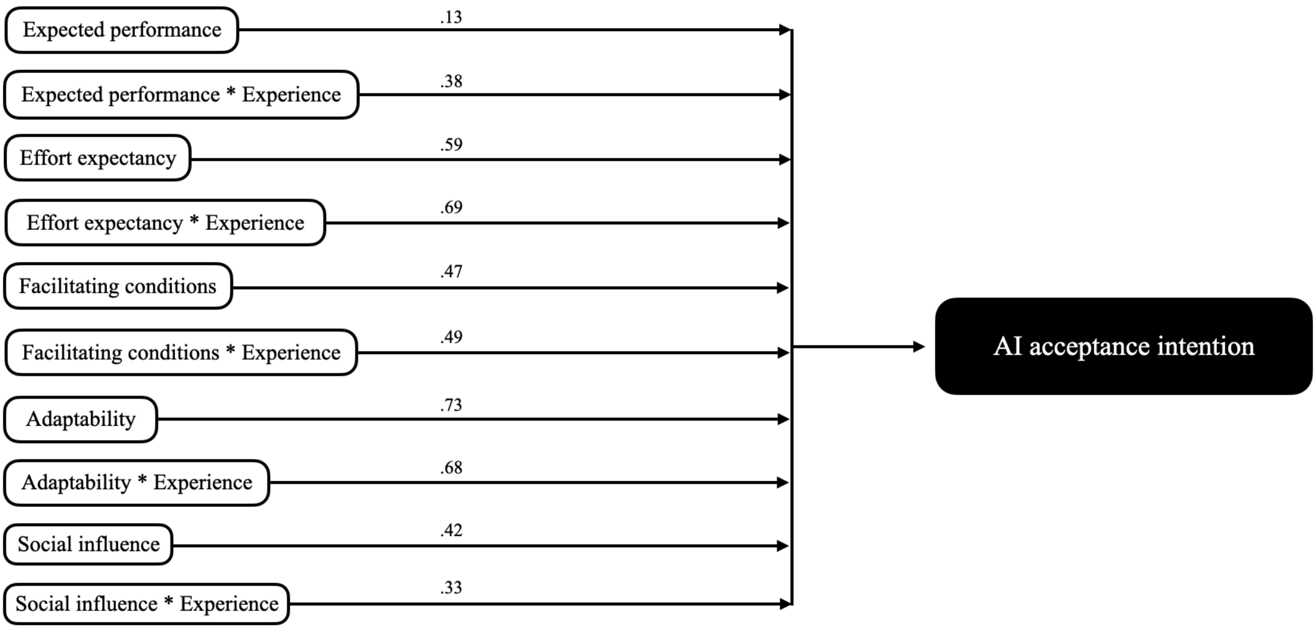
Regression models

To test the relationship between *AI acceptance intention in their studies* and the selected UTAUT components plus *Adaptability*, Figure 1 was designed. *H1, H2* and *H3* were tested through this model since the dependent variable for the three hypotheses was *AI acceptance intention in their studies.* After running the analyses, the totality of independent variables did not approach significance individually, dismissing any potential relationship with *AI acceptance intention in their studies*. The factor that was closest to approach significance was *Expected performance* (β = .77, *SE* = .50, *p* = .13). Other relationships that did not show significance were between *AI acceptance intention in their studies* and *Effort expectancy* (β = .40, *SE* = .74, *p* = .59)*, Facilitating conditions* (β = .42, *SE* = .57, *p* = .47)*, Adaptability* (β = .12, *SE* = .35, *p* = .73) and *Social influence* (β = -.48, *SE* = .58, *p* = .42). Even including the moderation effect of *Experience,* none factor showed significant relationship with *AI acceptance intention in their studies*, as *Expected performance*Experience* (β = -.03, *SE* = .03, *p* = .38)*, Effort expectancy*Experience* (β = -.02, *SE* = .04, *p* = .69)*, Facilitating conditions*Experience* (β = -.02, *SE* = .03, *p* = .49)*, Adaptability*Experience* (β = .01, *SE* = .02, *p* = .68) and *Social influence*Experience* (β = -.48, *SE* = .58, *p* = .42). In conclusion, the observed multiple R-squared in this instance was .40, signifying that the first regression model explained 40.14% of the variability in *AI acceptance intention in their studies*.

Secondly, the relationship between *Perception in the future workfield* and the selected UTAUT components plus *Adaptability* is graphically shown in Figure 2. *H4, H5* and *H6* were tested through this model since the dependent variable for the three hypotheses was the *Perception in the future workfield.* Figure 2 indicated that the moderation effect of *Experience* with *Adaptability* approached significance (*β* = -.06, *SE* = .02, *p* = .03*). However, the relationships of *Perception in the future workfield* and the rest of the factors were not significant: *Expected performance* (*β* = -.61, *SE* = .55, *p* = .27), *Effort expectancy* (*β* = .21, *SE* = .82, *p* = .80), *Facilitating conditions* (*β* = .51, *SE* = .63, *p* = .43), *Adaptability* (*β* = .45, *SE* = .39, *p* = .25) and *Social influence* (*β* = -.87, *SE* = .64, *p* = .19). The rest of relationships of *Perception in the future workfield* and the other selected variables affected by the moderation effect of *Experience* did not show significance either: *Expected performance*Experience* (*β* = .04, *SE* = .03, *p* = .19), *Effort expectancy*Experience* (*β* = -.02, *SE* = .04, *p* = .62), *Facilitating conditions*Experience* (*β* = -.01, *SE* = .04, *p* = .94), and *Social influence*Experience* (*β* = .04, *SE* = .04, *p* = .32). Finally, the multiple R-squared observed in this case was .57, which means that the second regression model accounted for 56.84% of the variance in *Perception of AI in the future workfield*.

Figure 1

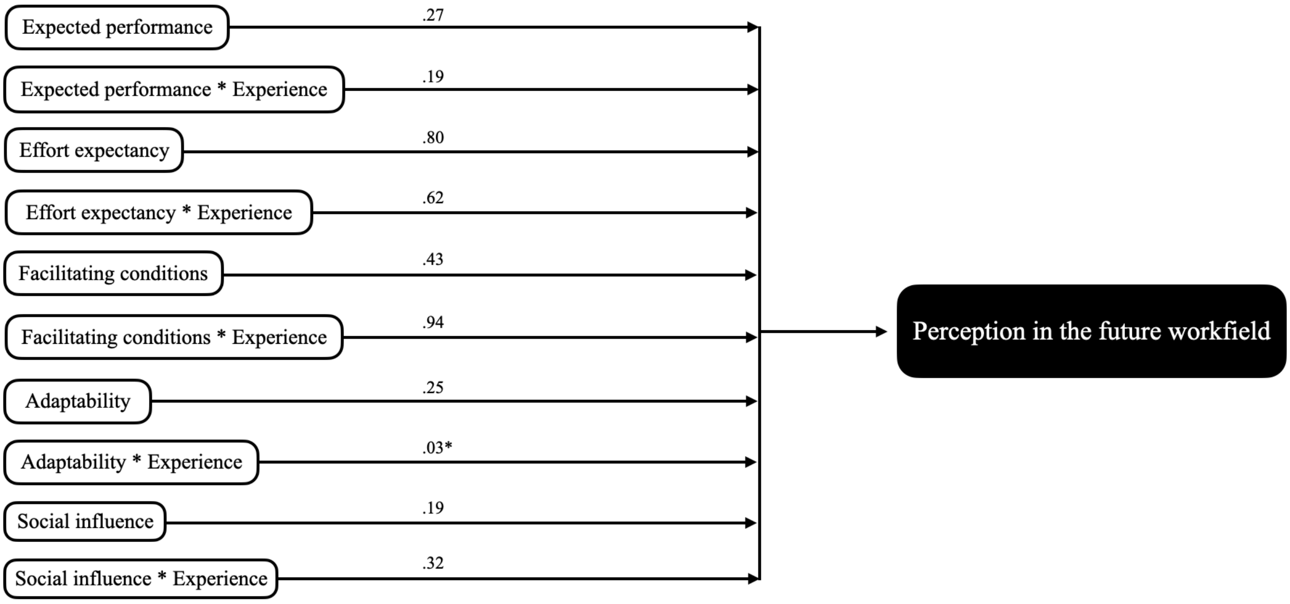
Regression model: AI acceptance intention in their studies.



Note. * *p* < .05. ** *p* < .01.

Figure 2

Regression model: Perception in the future workfield.



Note. * $p < .05$. ** $p < .01$.

Discussion

This study focused on investigating the factors influencing *AI acceptance intention* in healthcare students and their *Perception of AI in the future workfield*. To investigate this topic, the primary objective was to understand the relationships between the UTAUT selected factors plus *Adaptability* and *AI acceptance intention* in studies, as well as their impact on the *Perception of AI in the future workfield*.

Firstly, the lack of significant relationships in the *AI acceptance intention* regression model suggested that the chosen variables in the UTAUT framework and *Adaptability* may not be individually strong factors of *AI acceptance intention* in the context of healthcare students. This challenged the conventional understanding of factors influencing *AI acceptance intention* and calls for a reevaluation of the chosen variables or consideration of additional factors that may better explain *AI acceptance intention* in an educational context. Hence, the hypotheses related to *AI acceptance intention* regression model (*H1*, *H2* and *H3*) were rejected.

Regarding the *Perception in the future workfield* regression model, while the selected UTAUT components and *Adaptability* individually did not show significant direct relationships with *Perception in the future workfield*, the moderation effect suggests that the impact of *Adaptability* is context-dependent, influenced by the level of *Experience*. The implications of this significant relationship suggest that an individual who scored higher on *Adaptability* and possesses a high level of *Experience* may find their *Perceptions in the future workfield* to be more positively shaped. According to the obtained outcomes from *Perception in the future workfield* regression model, the relationship between *Adaptability* and the selected UTAUT determinants, and *Perception in the future workfield* was not significant. Therefore, *H4* and *H5* would be rejected as the relationships were not statistically significant. The moderation effect of *Experience* with *Adaptability* approached significance. However, *H6* also included the moderation effect of *Experience* with other UTAUT variables. Due to this reason, *H6* was accepted for *Adaptability*, but rejected for the rest of the analysed variables.

In comparison to Venkatesh et al. (2003), the predictive potential of the UTAUT variables was not demonstrated through the designed models. Nevertheless, other mentioned studies such as Kim & Park (2017) or Gardner and Amoroso (2004) did not obtain significant results in the totality of UTAUT variables. Kim & Park (2017) found only a significant relationship between behavioural intention, *Expected performance* and *Social influence* in healthcare professionals' acceptance of technology. Meanwhile, Gardner and Amoroso (2004) only highlighted the role of *Facilitating conditions* and *Effort expectancy* in technology adoption. Hence, the obtained outcomes in the UTAUT might suggest that the designed models might be replicated in future studies since additional research or data collection might be necessary to confirm its null impact. In addition, future research might include the moderation of other variables mentioned in the UTAUT model, such as *Gender* or *Voluntariness to use*. Research such as Malhorta et al. (2020) included these mentioned variables since the relationships between attitudes and intention to adopt AI and telemedicine tools and, as explained above, the relationship was stronger.

However, the findings about the complexity of AI acceptance align with the general theme in Nieboer et al. (2014), which discusses the intricate intersection of AI with professional values and practices. This complexity is also determined in Espejo et al. (2023), which discusses some relevant challenges and limitations facing the implementation of AI in mental healthcare such as user adaptability or ethical and legal considerations. Also, Minerva & Giubilini (2023) considered different factors that impact AI adoption such as awareness of ethical issues or AI reliability among others. Furthermore, this study also took ethical challenges into account to determine students' *Adaptability* to AI technologies through the *Effort expectancy* factor. Not only this factor is considered, but also *Social influence* was affected by the opinions and attitudes of the students' educators, peers and professional role models, which were also affected by ethical considerations from the healthcare community.

Strengths and limitations

Regarding the scope of this study, several limitations were considered. For instance, the vast majority of the population of the study are students from a few limited universities, such as the University of Twente and Universitat de València. As a justification, the SONA points system (student recruitment utilised system) approaches only students from the University of Twente since their participation was rewarded with ECTS credits. Hence, this fact restricts its generalizability to other groups of students or healthcare professionals. This limitation becomes particularly salient when comparing the findings to research involving different geographical regions or cultural backgrounds. Malhorta et al. (2020) showed that 90.90% of Indian students perceived healthcare-related AI (telemedicine and remote AI methods) as a viable integration in their practice in future. In comparison to this research, Malhorta et al. (2020) results suggested that *AI acceptance intention* scores were more positive than the currently obtained outcomes.

Furthermore, this current study did not include any comparison between students´ current program, country or gender. However, these variables were included in the demographics data, and could have had a significant impact on the final conclusions. For instance, Ala´a (2022) found that the relationship between the UTAUT variables and the adoption of artificial intelligence was significantly affected by the participant´s nationality.

Another point to consider is the voluntary nature of participation in the recruitment process, which might lead to response bias, as those who chose to engage might possess distinct views or characteristics compared to a more comprehensive cross-section of healthcare students. Al-Hadithy et al. (2023) conducted a cross-sectional study about attitudes and perceptions of artificial intelligence among healthcare students. This research found that healthcare students recognize the potential of AI in healthcare but are sceptical of its ability to replace healthcare workers in certain jobs.

To continue, the correlational nature of the study restricts its ability to establish causal relationships between the examined variables. While the study explores the relationship between *Adaptability* and *AI acceptance intention in their studies*, it cannot definitively conclude that *Adaptability* directly leads to higher *AI acceptance intention in their studies*.

Focusing more on the scale, the *AI acceptance intention in their studies in their studies* scale employed in the study consisted of a relatively small number of items (only 3), potentially impacting the reliability of the measurements. Other variables were measured with a larger number of items such as *Adaptability*, which is measured through 12 items. This fact directly affects the Cronbach's alpha of the variables, and a standardization of the number of items could have led to higher construct validity.

However, this research presents many strengths. For instance, it is one of the first studies that related *Adaptability*, *Perception of AI in the future workfield* and *AI acceptance intention* among healthcare students. Hence, the applicability of the UTAUT model was tested in a current environment as the usage of AI among students is. The integration of international participants is also a remarkable trait since this study englobes participants from different countries and cultures. Regarding the design of the survey, the inclusion of *Adaptability* as a new component of the UTAUT model could be replicated in the future to develop other studies about *AI acceptance intention* and/or *Perception of AI in the future workfield*.

Conclusion

This current study highlighted the complex nature of AI integration in healthcare education. However, the study findings underscore the need for broader, more diverse research to fully grasp AI's evolving role in healthcare education and practice. In moving forward, educators and researchers need to consider these nuanced insights when designing AI education interventions for healthcare students. The evolving landscape of AI in healthcare demands a continuous reevaluation of our understanding and the incorporation of diverse perspectives to ensure the effective integration of AI technologies into the future healthcare workfield.

References

Al-Momani, A. M. (2023). Adoption of Artificial Intelligence and Robotics in Healthcare: A Systematic Literature Review. Journal Title, 3(*4*), 1-16.

Al-Hadithy, Z. A. A., Lawati, A. A., Al-Zadjali, R., Sinawi, H. A., Lawati, A. A. & Sinawi, H. A. (2023). Knowledge, Attitudes, and Perceptions of Artificial Intelligence in Healthcare Among Medical Students at Sultan Qaboos University. *Cureus, 15*(9). https://doi.org/10.7759/cureus.44887

Charow, R., Jeyakumar, T., Younus, S., Dolatabadi, E., Salhia, M., Al-Mouaswas, D., Anderson, M., Balakumar, S., Clare, M., Dhalla, A., Gillan, C., Haghzare, S., Jackson, E., Lalani, N., Mattson, J., Peteanu, W., Tripp, T., Waldorf, J., Williams, S., Tavares, W. & Wiljer, D. (2021). Artificial Intelligence Education Programs for Health Care Professionals: Scoping Review. *JMIR medical education*, *7*(4), e31043. https://doi.org/10.2196/31043

Choudhury, A. (2022). Factors influencing clinicians' willingness to use an AI-based clinical decision support system. *Frontiers in Digital Health*, *4*. https://doi.org/10.3389/fdgth.2022.920662

Collado-Mesa, F., Alvarez, E., & Arheart, K. (2018). The Role of Artificial Intelligence in Diagnostic Radiology: A Survey at a Single Radiology Residency Training Program. *Journal of the American College of Radiology*, *15*(12), 1753–1757. https://doi.org/10.1016/j.jacr.2017.12.021

Dong, Z., Wang, J., Li, Y., Deng, Y., Zhou, W., Zeng, X. & Yu, H. (2023). Publisher Correction: Explainable artificial intelligence incorporated with domain knowledge diagnosing early gastric neoplasms under white light endoscopy. *NPJ Digital Medicine, 6*. https://doi.org/10.1038/s41746-023-00855-2

Khatrawi E. M., Prajjwal P., Farhan, M., Inban P., Gurha S., Dheyaa, M. S., Ahuja, P., Mateen, M. A., Aina F. O. & Amir, O. (2023). Evaluating the knowledge, attitudes, and practices of healthcare workers regarding high‐risk nosocomial infections: A global cross‐sectional study. *Health Science Reports*, *6*(9). https://doi.org/10.1002/hsr2.1559

Espejo, G., Reiner, W. & Wenzinger, M. (2023). Exploring the Role of Artificial Intelligence in Mental Healthcare: Progress, Pitfalls, and Promises. *Cureus*, *15*(9). https://doi.org/10.7759/cureus.44748

Gardner, R. M., & Amoroso, D. W. (2004). Development of an instrument to measure the acceptance of internet technology by consumers. *In Proceedings of the 37th Annual Hawaii International Conference on System Sciences* (pp. 10-pp). IEEE. https://doi.org/10.1109/HICSS.2004.1265623

Gansser O.A. & Reich C.S. (2021). A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technological Forecasting and Social Change*. https://doi.org/10.1016/j.techsoc.2021.101535

Kelly S., Kaye S. & Oviedo-Trespalacios O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics, 77*. https://doi.org/10.1016/j.tele.2022.101925

Kim, S. K. & Park, M. (2017). Effectiveness of person-centered care on people with dementia: a systematic review and meta-analysis. *Clinical interventions in aging*, *12*, 381–397. https://doi.org/10.2147/CIA.S117637

Luxton, D. D. (2014). Artificial intelligence in psychological practice: Current and future applications and implications. *Professional Psychology: Research and Practice, 45*(5), 332–339. https://doi.org/10.1037/a0034559

Malhotra, P., Ramachandran, A., Chauhan, R., Soni, D., & Garg, N. (2020). Assessment of Knowledge, Perception, and Willingness of using Telemedicine among Medical and Allied Healthcare Students Studying in Private Institutions. *Telehealth and Medicine Today.* https://doi.org/10.30953/tmt.v5.228

Martin, A. J., Nejad, H. G., Colmar, S., & Liem, G. A. D. (2013). Adaptability: How students' responses to uncertainty and novelty predict their academic and non-academic outcomes. *Journal of Educational Psychology*, *105*(3), 728–746. https://doi.org/10.1037/a0032794

Martin, A.J., Graniziera, H. & Collie R.J. (2018). Adaptability: A key capacity for thriving amidst complexity. *International Journal of Educational Research, 87*, 108-118.

McKinsey & Company. (2021). Everyone needs more of this one skill. McKinsey & Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/the-organization-blog/everyone-needs-more-of-this-one-skill

Minerva, F. & Giubilini, A. (2023). Is AI the Future of Mental Healthcare? *Topoi* (*Dordrecht*), *42*(3), 1-9. https://doi.org/10.1007/s11245-023-09932-3

Nieboer, A. P., Cramm, J. M., Sonneveld, H. M., Roebroeck, M. E., van Staa, A., & Strating, M. M. (2014). Professional values, technology and future of health care: The view of healthcare professionals in The Netherlands. https://doi.org/10.1016/j.techsoc.2014.05.003

Pérez-Fuentes, M. del C., Molero Jurado, M. del M., Martínez, Á. M., Fernández-Martínez, E., Franco Valenzuela, R., Herrera-Peco, I., ... & Gázquez Linares, J. J. (2020). Design and Validation of the Adaptation to Change Questionnaire: New Realities in Times of COVID-19. *International Journal of Environmental Research and Public Health, 17*(15), 5432. https://doi.org/10.3390/ijerph17155612

Roppelt, J. S., Kanbach, D. K., & Kraus, S. (2024). Artificial intelligence in healthcare institutions: A systematic literature review on influencing factors. *Technology in Society*, *76*(5), 102443. https://doi.org/10.1016/j.techsoc.2023.102443

Sit, C., Srinivasan, R., Amlani, A., Muthuswamy, K., Azam, A., Monzon, L. & Poon D.S. (2020). Attitudes and perceptions of UK medical students towards artificial intelligence and radiology: A multicentre survey. *Insights into Imaging*, *11*(14). https://doi.org/10.1186/s13244-019-0830-7

Teng, M., Singla, R., Yau, O., Lamoureux, D., Gupta, A., Hu, Z., Hu, R., Aissiou, A., Eaton, S., Hamm, C., Hu, S., Kelly, D., MacMillan, K. M., Malik, S., Mazzoli, V., Teng, Y.-W., Laricheva, M., Jarus, T., & Field, T. S. (2022). Health Care Students' Perspectives on Artificial Intelligence: Countrywide Survey in Canada. *JMIR Medical Education*, *8*(1), e33390. https://doi.org/10.2196/33390

Tornero-Costa, R., Martinez-Millana, A., Azzopardi-Muscat, N., Lazeri, L., Traver, V., & Novillo-Ortiz, D. (2023). Methodological and Quality Flaws in the Use of Artificial Intelligence in Mental Health Research: Systematic Review. *JMIR Mental Health, 10*. https://doi.org/10.2196/42045

Torres, S., Tremblay, M. C., Chiocchio, F., Litvak, É., Fortin-Pellerin, L., & Beaudet, N. (2015). An analysis of the adaptability of a professional development program in public health: results from the ALPS Study. *BMC Health Services Research, 15*(233). https://doi.org/10.1186/s12913-015-0903-3

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. JStor. https://doi.org/10.2307/30036540

World Health Organisation. (2022). *Health and well-being*. World Health Organisation; World Health Organisation. https://www.who.int/data/gho/data/major-themes/health-and-well-being

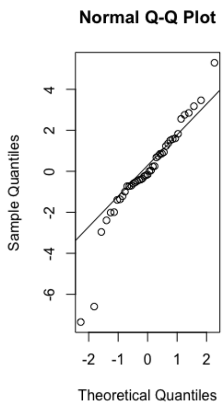
Appendices

Appendix 1: Linear assumptions

Normality of residuals. To start checking the normality of residuals, a Saphiro-Wilk´s normality test was run. The results of the Saphiro-Wilk´s normality indicated that the assumption of normality was not violated since p value is smaller than alpha (< .05) (W = .92, p = .01) since data does not significantly deviate from a normal distribution. Figure 3 graphically shows that the residuals are normally distributed.

Figure 3

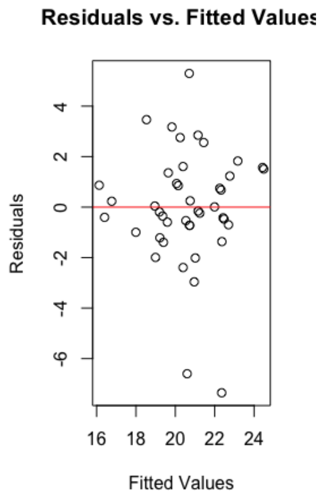
Normal Q-Q plot: normality of residuals (n = 50).



Homoscedasticity. Secondly, a Breusch-Pagan test was completed to check homoscedasticity in the residuals of the designed model. The results (BP = 4.81, df = 11, p = .94) showed that the probability of observing a test statistic as extreme is high, so equal variances assumption is not violated. Figure 4 graphically shows the residuals´ distribution.

Figure 4

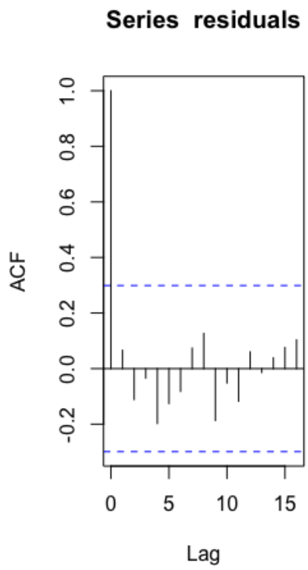
Residuals´ distribution agains fitted values (n = 50).



Independence of residuals. To confirm the independence of residuals´ assumption, a Ljung-Box test was run to check whether there are any autocorrelations in the residuals from a fitted time series model. The outcomes (*X-squared* = 12.46, *df* = 20, *p* = .90) indicated that there is not significant autocorrelation in the residuals according to the Ljung-Box test. This suggests that the model has captured the autocorrelations in the dataset adequately up to 20 lags, and the residuals can be considered as white noise. As it is shown in Figure 5, most lags are between the statistically-stated thresholds.

Figure 5

Series residuals measured in lags (n = 50).



Appendix 2: Survey composition (Venkatesh et al., 2003; Gansser et al., 2021; Torres et al., 2015)

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 Desagree "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.

Appendix 3: RStudio code script

```
install.packages("readxl")
install.packages("psych")
install.packages("dplyr")
install.packages("ggplot2")
install.packages("car")

library(readxl)
library(psych)
library(dplyr)
library(ggplot2)
library(car)

# Set the working directory to the folder where the file is located
setwd("~/Desktop")

data <- "dataset161223.xlsx"
data <- read_excel(data)

descriptive_stats <- describe(data)

# Assuming 'data' is your data frame and you want to remove rows with missing values in columns
'variable1' and 'variable2'
complete_rows <- complete.cases(data[, c("Q22_1", "Q22_2", "Q22_3", "Q22_4", "Q22_5",
"Q22_6")])
data <- data[complete_rows, ]

data <- data[-1, ]

#age measure
agedatabase <- data[, c(
  "Q11_1"
)]

agedatabase <- agedatabase %>%
  mutate(age = Q11_1)
agedatabase$Q11_1 <- as.numeric(agedatabase$Q11_1)
```

```
agedatabase <- na.omit(agedatabase)
descriptive_age <- describe(agedatabase)


# If columns are not numeric, convert them to numeric (replace 'column_name' with actual column
names)
data$Q24_1 <- as.numeric(data$Q24_1)
data$Q24_2 <- as.numeric(data$Q24_2)
data$Q24_3 <- as.numeric(data$Q24_3)
data$Q24_4 <- as.numeric(data$Q24_4)
data$Q24_5 <- as.numeric(data$Q24_5)
data$Q24_6 <- as.numeric(data$Q24_6)
data$Q24_7 <- as.numeric(data$Q24_7)
data$Q24_8 <- as.numeric(data$Q24_8)
data$Q24_9 <- as.numeric(data$Q24_9)
data$Q24_10 <- as.numeric(data$Q24_10)

data <- data %>%
  mutate(Adaptability = Q24_1 + Q24_2 + Q24_3 + Q24_4 + Q24_5 + Q24_6 + Q24_7 + Q24_8 +
Q24_9 + Q24_10)

data_adaptability <- data[, c("Adaptability", "Q24_1", "Q24_2", "Q24_3", "Q24_4", "Q24_5",
"Q24_6", "Q24_7", "Q24_8", "Q24_9", "Q24_10")]

# Checks before analysis
str(data_adaptability)
data_adaptability <- na.omit(data_adaptability)
cor_matrix <- cor(data_adaptability)

# Perform factor analysis on the cleaned "Experience" variable with varimax rotation
fa_result <- fa(data_adaptability, nfactors = 1, rotate = "promax")
print(fa_result)
data_adaptability <- na.omit(fa_result)
summary(fa_result)

# Transform variables to numerical variables
data$Q18_1 <- as.numeric(data$Q18_1)
```

```
data$Q18_2 <- as.numeric(data$Q18_2)
data$Q18_3 <- as.numeric(data$Q18_3)
data$Q18_4 <- as.numeric(data$Q18_4)
data$Q18_5 <- as.numeric(data$Q18_5)
data$Q19_1 <- as.numeric(data$Q19_1)
data$Q19_2 <- as.numeric(data$Q19_2)
data$Q19_3 <- as.numeric(data$Q19_3)
data$Q19_4 <- as.numeric(data$Q19_4)
data$Q19_5 <- as.numeric(data$Q19_5)
data$Q19_6 <- as.numeric(data$Q19_6)
data$Q20_1 <- as.numeric(data$Q20_1)
data$Q20_2 <- as.numeric(data$Q20_2)
data$Q20_3 <- as.numeric(data$Q20_3)
data$Q20_4 <- as.numeric(data$Q20_4)
data$Q20_5 <- as.numeric(data$Q20_5)
data$Q21_1 <- as.numeric(data$Q21_1)
data$Q21_2 <- as.numeric(data$Q21_2)
data$Q21_3 <- as.numeric(data$Q21_3)
data$Q21_4 <- as.numeric(data$Q21_4)
data$Q21_5 <- as.numeric(data$Q21_5)
data$Q21_1 <- as.numeric(data$Q21_1)
data$Q21_2 <- as.numeric(data$Q21_2)
data$Q21_3 <- as.numeric(data$Q21_3)
data$Q21_4 <- as.numeric(data$Q21_4)
data$Q23_1 <- as.numeric(data$Q23_1)
data$Q23_2 <- as.numeric(data$Q23_2)
data$Q23_3 <- as.numeric(data$Q23_3)
data$Q23_4 <- as.numeric(data$Q23_4)
data$Q23_5 <- as.numeric(data$Q23_5)
data$Q23_6 <- as.numeric(data$Q23_6)
data$Q22_1 <- as.numeric(data$Q22_1)
data$Q22_2 <- as.numeric(data$Q22_2)
data$Q22_3 <- as.numeric(data$Q22_3)
data$Q22_4 <- as.numeric(data$Q22_4)
data$Q22_5 <- as.numeric(data$Q22_5)
data$Q22_6 <- as.numeric(data$Q22_6)
data$Q22_7 <- as.numeric(data$Q22_7)
```

```
data$Q26_1...85 <- as.numeric(data$Q26_1...85)
data$Q26_2...86 <- as.numeric(data$Q26_2...86)
data$Q26_3...87 <- as.numeric(data$Q26_3...87)

str(data)

defined_variables <- data %>%
  mutate(ExpectedPerformance = Q18_1 + Q18_2 + Q18_3 + Q18_4 + Q18_5)

defined_variables <- defined_variables %>%
  mutate(EffortExpectancy = Q19_1 + Q19_2 + Q19_3 + Q19_4 + Q19_5 + Q19_6)

defined_variables <- defined_variables %>%
  mutate(SocialInfluence = Q20_1 + Q20_2 + Q20_3 + Q20_4 + Q20_5)

defined_variables <- defined_variables %>%
  mutate(FacilitatingConditions = Q21_1 + Q21_2 + Q21_3 + Q21_4 + Q21_5)

defined_variables <- defined_variables %>%
  mutate(AIAcceptanceIntention = Q23_1 + Q23_2 + Q23_3 + Q23_4 + Q23_5 + Q23_6)

defined_variables <- defined_variables %>%
  mutate(Experience = Q22_1 + Q22_2 + Q22_3 + Q22_4 + Q22_5 + Q22_6)

defined_variables <- defined_variables %>%
  mutate(PerceptionofAIinthefutureworkfield = Q26_1...85 + Q26_2...86 + Q26_3...87)

#Cronbach´s alpha computations
expected_performance_items <- defined_variables[, c("Q18_1", "Q18_2", "Q18_3", "Q18_4",
"Q18_5")]
effort_expectancy_items <- defined_variables[, c("Q19_1", "Q19_2", "Q19_3", "Q19_4", "Q19_5",
"Q19_6")]
social_influence_items <- defined_variables[, c("Q20_1", "Q20_2", "Q20_3", "Q20_4", "Q20_5")]
facilitating_conditions_items <- defined_variables[, c("Q21_1", "Q21_2", "Q21_3", "Q21_4",
"Q21_5")]
ai_acceptance_intention_items <- defined_variables[, c("Q23_1", "Q23_2", "Q23_3", "Q23_4",
"Q23_5", "Q23_6")]
```

```
experience_items <- defined_variables[, c("Q22_1", "Q22_2", "Q22_3", "Q22_4", "Q22_5",
"Q22_6")]
perception_of_ai_in_the_future_work_field_items <- defined_variables[, c("Q26_1...85",
"Q26_2...86", "Q26_3...87")]
adaptability_items <- defined_variables[, c("Q24_1", "Q24_3", "Q24_4", "Q24_5", "Q24_6",
"Q24_7", "Q24_8", "Q24_9", "Q24_10")]

alpha_expected_performance <- psych::alpha(expected_performance_items)
alpha_effort_expectancy <- psych::alpha(effort_expectancy_items)
alpha_social_influence <- psych::alpha(social_influence_items)
alpha_facilitating_conditions <- psych::alpha(facilitating_conditions_items)
alpha_ai_acceptance_intention <- psych::alpha(ai_acceptance_intention_items)
alpha_experience <- psych::alpha(experience_items)
alpha_perception_of_ai <- psych::alpha(perception_of_ai_in_the_future_work_field_items)
alpha_adaptability <- psych::alpha(adaptability_items)

alpha_expected_performance
alpha_effort_expectancy
alpha_social_influence
alpha_facilitating_conditions
alpha_ai_acceptance_intention
alpha_experience
alpha_perception_of_ai
alpha_adaptability

#final dataset
selected_variables <- defined_variables[, c(
  "ExpectedPerformance",
  "EffortExpectancy",
  "SocialInfluence",
  "FacilitatingConditions",
  "Experience",
  "AIAcceptanceIntention",
  "Adaptability",
  "PerceptionofAIinthefutureworkfield"
)]
```

```
selected_variables <- selected_variables[, c("ExpectedPerformance", "EffortExpectancy",
"SocialInfluence", "FacilitatingConditions", "Adaptability", "Experience", "AIAcceptanceIntention",
"PerceptionofAIinthefutureworkfield")]

selected_variables <- na.omit(selected_variables)
selected_variables_1 <- describe(selected_variables)
selected_variables <- na.omit(selected_variables)
correlation_matrix <- cor(selected_variables)


# regression analyses
model1 <- lm(AIAcceptanceIntention ~ (ExpectedPerformance + EffortExpectancy +
FacilitatingConditions + Adaptability + SocialInfluence) * Experience, data = selected_variables)
summary(model1)

model2 <- lm(PerceptionofAIinthefutureworkfield ~ (ExpectedPerformance + EffortExpectancy +
FacilitatingConditions + Adaptability + SocialInfluence) * Experience, data = selected_variables)
summary(model2)


# NORMALITY
# Assuming 'model' is your regression model
residuals <- residuals(model2)

# Histogram
hist(residuals, main = "Residuals Histogram")

# Q-Q Plot
qqnorm(residuals)
qqline(residuals)

shapiro.test(residuals)


# HOMOSCEDASTICITY
plot(fitted(model1), residuals, ylab = "Residuals", xlab = "Fitted Values",
    main = "Residuals vs. Fitted Values")
```

```
abline(h = 0, col = "red")

library(lmtest)
bptest(model2)


# INDEPENDENCE OF RESIDUALS
# Autocorrelation plot
acf(residuals)

# Ljung-Box test
library(astsa)
Box.test(residuals, lag = 20, type = "Ljung-Box")
```