EXPLORING THE ANTECEDENTS OF ARTIFICIAL INTELLIGENCE PRODUCTS' USAGE. THE CASE OF BUSINESS STUDENTS

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Abstract

This study aims to investigate to what extent facilitating conditions (those means that users consider necessary to use for a certain technology) and other predictors (perceived risk and lack of trust in technology, gender, education, income, technology proficiency and equipment used to access the Internet) influence the use of Artificial Intelligence Products (AIP) in general and for education. Using the Unified Theory of Acceptance and Use of Technology (UTAUT), the data collected, through an online questionnaire from a sample of 450 Romanian business students, were examined using principal component analysis (PCA) and logistic regression. Facilitating conditions indicated a direct effect (positive) on the dependent variables, and the combination between perceived risk and perceived lack of trust in technology displayed an opposite effect (negative) on the dependent variables. Female students showed a greater tendency to use AIPs in general and for education. Undergraduate students were more inclined to use AIPs in general. Students not using smartwatches or personal computers are inclined to use AIPs more in general and for education. This study advances the theory by exploring the actual use of AIPs for educational purposes, developing the UTAUT model by isolating facilitating conditions and using descriptive variables as predictors. At the same time, the present research contributes to enriching the empirical evidence related to UTAUT on the acceptance and use of technology in Romania. The results of the research allow for the formulation of practical recommendations for universities as current and potential providers of AIPs in order to make the educational process more efficient.

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JEL Classification: I23, M31, C51, C53

Introduction

Artificial intelligence (AI) has become a comprehensive and ubiquitous phenomenon, with its widespreadness acknowledged at individual and organisational levels, but also at the level of the European Union. Defining AI is a daunting task. The European Parliament (EP) (2020) attempted to provide a broad definition of AI by focussing on the transfer of human features and skills, such as thinking, accumulating knowledge, making decisions, or creating. AI consists of AI software (covering instruments delivering search results and recommendations, or performing voice and image analysis) and object-orientated AI, referring to objects that collect data, such as home appliances, cars, robots, or drones (European Parliament, 2020).

The educational process is under high pressure to incorporate digital culture from the early stages of the training. The incorporation of AI resources into the process of education (course content, assessment instruments, and smart learning tools), and the usage of different digital objects (e.g., smart devices) in education (Chassignol et al., 2018) will influence the future of why, how, and what students will learn (Escotet, 2023). In the near future, probably everyone will need to have a basic understanding of the technologies that support AI (Touretzky et al., 2019).

The process of integration of AI into education is increasing and diversifying. Studies display a variety of investigations related to the role of AI in improving the educational process, increasing student satisfaction and retention (Rico-Bautista et al., 2021), or providing invaluable support to learners by creating the infrastructure that makes possible flexible learning and self-education (Alzahrani, 2023). However, Raffaghelli et al. (2022) argue that the impact of AI on education should be carefully evaluated to avoid extremely optimistic or extremely pessimistic conclusions and recommend that student perceptions of the use of technology should be explored to allow higher education institutions to understand how to adapt their processes. Chatterjee and Bhattacharjee (2020) recommended that future studies on AI in higher education include 'actual use' as a dependent variable, while data should be collected from 'actual adopters' of AI.

This article looks to assess the prerequisites of AI usage in general, and for educational purposes in the case of business students from Romanian universities, by employing the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. UTAUT was intended to have a unitary framework, both theoretically and empirically, to anticipate human behaviour related to the acceptance and use of technology (Venkatesh et al., 2003). Thus, UTAUT, in addition to helping to understand the complex phenomenon of acceptance and use of technology (by identifying the influence factors: performance expectation, effort expectation, social influence, and facilitation conditions), also offers the possibility of empirical testing. In education, UTAUT is increasingly used to determine the most important factors in accepting and using technology, given the fundamental role that education plays in the behavioural modelling of future leaders, entrepreneurs, and employees (Chatterjee and Bhattacharjee, 2020; Gansser and Reich, 2021; Raffaghelli et al., 2022). By identifying the importance of factors of influence in the acceptance and use of technology, educational institutions, in general, and higher education, in particular, could develop effective strategies for the use of technology and its adaptation to the behaviour of users (both students and professors).

Focus on Generation Z is the most appropriate, as this generation is considered to be the most open to adopting AI, and studies focussing on their usage behaviour are scarce (Kelly, Kaye and Oviedo-Trespalacios, 2023). The UTAUT is one of the most commonly used models in research concerning intention, acceptance and actual usage of new technologies, due to its high explanatory power (Gansser and Reich, 2021; Rico-Bautista et al., 2021).

The article aims to investigate the potential effects of facilitating conditions (the means users would consider necessary to exist in order to be able to use the technology), perceived risk and perceived trust on the usage of AI in general and in education in the case of business students. This research is innovative both theoretically and practically. First of all, according to the experience and knowledge of the authors, there is no such study that has applied UTAUT to Romanian business students. The present study extends UTAUT by including perceived risk and the negative vision of trust in technology/AIP in the form of perceived lack of trust, as well as by transforming gender and experience with technology into independent variables and also including three other descriptive variables as explanatory variables.

From a practical perspective, the study is added to the empirical research in the field. Business students are one of the biggest categories of students in Romania. They will be tomorrow's business leaders, entrepreneurs, or employees, all acquainted with the use of Artificial Intelligence Products (AIPs). The results of the study, although qualitatively valuable (the findings could not be generalised to all business students in Romania) suggest that universities should facilitate the adoption of AIPs for educational purposes, through a stronger integration in all phases of the educational process: teaching, learning, teacher-student interaction. Thus, university strategies can be adapted to the evolution of AIPs in order to facilitate education.

The article is structured as follows: A literature review of studies supporting the role of AI in shaping new capabilities and skills for students and in acknowledging the limits and risks associated with the use of new technology, as well as a presentation of the UTAUT framework, is provided to support the research hypotheses. The article continues with research methodology, where the applied model, sampling, data collection instrument and process are explained. The data analysis and results follow, continuing with discussion, and the article ends with conclusions.

1. Literature review and the research hypotheses

1.1. Acceptance and use of AI technology and Artificial Intelligence Products (AIPs) in higher education: advantages and limits

AI is dubbed an instrument meant to improve the lives and working conditions of people from all walks of life (Gansser and Reich, 2021). For education, AI provides adaptive learning content tailored to the specificities of various groups of students, going down even to the individual level (Chatterjee and Bhattacharjee, 2020). AI is considered to have a transformational impact on collaborative education, management of teaching and learning, educational infrastructure (Papaspyridis, 2020), aiding students to scrutinise large quantities of data, and helping them to make forecasts (Hasan, Shams and Rahman, 2021). Universities recognise the competitive advantage that comes from the implementation of AI in the educational process and transform themselves into smart universities, merging classic educational content with new technology to deliver collaborative education and an adaptive learning experience (Rico-Bautista et al., 2021). Schmitt (2019) supports the idea that equipment and information cannot exist separately in the current reality. Investigating AI technology-related learning behaviour, Wang et al. (2022) termed the applications used to collect and manage data connected to terminals and storage equipment as AI techniques/products. Therefore, the current study uses their angle and calls them Artificial Intelligence products (AIPs).

It is obvious that the implementation of digital technology in the educational process involves awareness of the advantages, as well as the limits and risks of the proliferation of AIPs, from the technical limitations and ethical implications of these AIPs (Park et al., 2019) to data security and privacy. Despite the large body of literature developed in recent years, there is a lack of a systematic and rigorous framework for assessing risk and uncertainty of the diffusion of AI in education (Zhang et al., 2022, p.1). The focus is moving from the question of AI replacing humans to the question of how humans can work alongside AI, how we, as humans, can use AIPs and cooperate with AI in order to improve our welfare, and how the risks associated with the AI output are mitigated. These aspects are still less studied and understood (Markauskaite et al., 2022).

AI education provides a wide variety of advantages in the areas of self-assessment, formulation of comprehensive questions and answers, conflict management and decision-making (Roy et al., 2022). In their study, Markauskaite et al. (2022, p.4) identify the advantages brought by AI outputs, as well as the limitations and risks associated with them. There are four sources of advantages, but also limitations for the AI era and valid for students as well (Markauskaite et al., 2022). The first source looks at how to interpret and understand AI outputs. This refers to the capacity of users to understand the rapid changes of the technology, how to be prepared to internalise it in ordinary usage, and how to navigate among the multitude of applications or instruments offered by the new technology in order to capture the best of AI outputs. It also involves being aware of the risks related to the use of AI coming both from data-related risks (e.g. biased data or out of domain data) and from model-related risks (e.g. model misspecification) (Zhang et al., 2022) and continuing with the interpretation of the AI outputs in a proper way. The second source of advantages and limitations looks to integrate AI and AIPs outputs into human knowledge systems. The educational process needs to emphasise that it is the human that has the final decision about integrating AI outputs into a decision, and it is the human that has to decide how AI objects are used, and how these results need to be interpreted and applied. As studies mention, “AI is always understood within the contexts of its use” (Bearman and Ajjawi, 2023, p.16), and students must be aware that the purpose of AI must be meaningful for society. The third source of advantages, but especially challenges, looks to assess and evaluate the ethical implications of AI. The ethics of AI are one of the most important debated issues and one of the most difficult areas to address. AI can provide much wider access to knowledge, at significantly lower costs, for wider categories of people, in much less time (Huang et al., 2023; Pisică et al., 2023). However, the ethical issues that AI generates are by far the most controversial. In 2021, the Pew Research Centre addressed this topic and underlined these questions summarising the difficulties pertaining to ethics in AI: "How can ethical standards be defined and applied for a global, cross-cultural, ever-evolving, ever-expanding universe of diverse black-box systems in which bad actors and misinformation thrive?". In addition, teaching AI ethics is a big concern. It is important not only to teach about AI ethics, but also how to teach ethics related to AI (Burton et al., 2017; Zeide, 2019; Bearman and Ajjawi, 2023). Finally, the fourth source of advantages and limitations refers to how to elevate human cognitive work to creativity and meaning/sense-making domains. It involves efforts from both students and educational institutions. Students must be prepared for changes in curricula and in the way curricula are delivered, including the use of AI objects for educational purposes). Universities must be managed and resourced for a different learning environment for students and teachers, which includes technological endowments, knowledge for the use of AI, and specific content and delivery strategies for an AI-infused educational process) (Nurjanah and Pratama, 2020; Rivers, Nakamura and Vallance, 2022).

1.2 The Unified Theory of Acceptance and Use of Technology (UTAUT) framework

The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most commonly used models in research concerning the intention and actual usage of new technologies (Gansser and Reich, 2021). The UTAUT model consists of three direct antecedents of the intention to use technology, namely, performance expectation, effort expectation and social influence, and two direct prerequisites of usage behaviour, specifically intention and facilitating conditions. The model also makes use of four moderators, particularly experience, voluntariness, gender, and age (Venkatesh et al., 2003).

The UTAUT model has been used in AI research in its original format or with additional or different variables. Chatterjee and Bhattacharjee (2020), in one of the few studies investigating AI usage, employed the UTAUT model to determine the behavioural intention and adoption of AI in higher education by probing students, faculty and administrative staff. They included perceived risk and attitude, but they dropped social influence. Alzahrani (2023), aiming to determine the attitudes and behavioural intentions of students to use AI, adapted the UTAUT model by including perceived risk, awareness and attitude, and removing social influence. Raffaghelli et al. (2022) studied the acceptance of early warning systems (AI tools) by applying a longitudinal approach (pre-use versus post-use) and including trust in the model alongside the four original predictors.

Among the four predictive variables of the UTAUT model, facilitating conditions represent the only category introduced to explain usage, while the other three predictors are used to describe intention (Wu et al., 2022). Kelly, Kaye and Oviedo-Trespalacios (2023) concluded that only a small number of studies focused on studying actual use behaviour. In addition, Chatterjee and Bhattacharjee (2020) recommended that future studies on AI in higher education include *actual use* as a dependent variable, while data should be collected from actual adopters of AI. Corroborating these perspectives, the present study aims to explore the actual usage of AI in general and in education by students and, thus, preserves the facilitating conditions from the UTAUT model and removes the antecedents that describe intention, namely performance expectancy, effort expectancy, and social influence.

As proposed by Venkatesh et al. (2003), the UTAUT model includes four moderators: experience, voluntariness, gender, and age. The literature prompts situations in which the moderators were excluded from the model (Chatterjee and Bhattacharjee, 2020; Raffaghelli et al., 2022; Wu et al., 2022; Alzahrani et al., 2023). This study aims to collect data from students who are actual users of AI. For this purpose, age and voluntariness cannot provide value to the model, but this study aims to develop the UTAUT model by employing gender and experience as explanatory variables instead of moderators and including another three descriptive and behavioural variables as independent variables: education, income, and equipment used for Internet access.

Additionally, perceived privacy risk and trust are intricately connected to personal data sharing, a feature of AI objects, and are, thus, deemed important prerequisites of consumer adoption and usage of technology (Hasan, Shams and Rahman, 2021). Gansser and Reich (2021) argue that perceived risk associated with the use of AI and data processing is an important prerequisite of usage behaviour. In higher education, perceived risk is closely connected to the negative feelings users may have about AI (Chatterjee and Bhattacharjee, 2020), and thus a negative relationship is expected between perceived risk and user behaviour. The existing literature on AI shows evidence of the inclusion of perceived risk as an independent variable in the UTAUT model (Chatterjee and Bhattacharjee, 2020; Wu et al., 2022; Alzahrani, 2023). Alzahrani (2023) considers that perceived risk improves the explanatory power of the UTAUT model, especially in the case of AI. Trust is another important predictor of AI usage. Leichtmann et al. (2023) suggested that trust in AI builds over time as users better understand the technology. As users' understanding of AI improves, expectations can be developed realistically and thus users can become satisfied with the experience and trust in AIPs can be acquired (Kamila and Jasrotia, 2023). Thus, a positive relationship is expected between trust and AIPs user behaviour. Another research stream investigates lack of trust, providing an opposite view (Du and Xie, 2021; Thiebes, Lins and Sunyaev, 2021), as a negative connection is documented with AI or technology behavioural outcome. Rico-Bautista et al. (2021) recommend that trust be included as an explanatory variable of AI usage behaviour in education.

1.3 Research hypotheses

Venkatesh et al. (2003) explained that facilitating conditions would refer to the means users would consider necessary for using technology. Facilitating conditions have been analysed as an explanatory variable for the implementation of AI in education. Strzelecki (2023) determined that the facilitating conditions had a significant positive influence on the usage behaviour of ChatGPT by students. Chatterjee and Bhattacharjee (2020) discovered a significant positive effect of facilitating conditions on the intention of behaviour and the expectancy of effort in the case of adopting AI in higher education.

As facilitating conditions represent the only predictor of technology usage in the original version of the UTAUT model (Venkatesh et al., 2003) and the aim of this study is to explain the usage of AIP in general and in education, facilitating conditions could represent a strong predictor. Therefore, the first two hypotheses are as follows: *H1*. Facilitating conditions have a direct (positive) influence on the usage of AIPs in general by students; *H2*. Facilitating conditions have a direct (positive) influence on the use of AIPs for educational purposes by students.

The risk perceived by users when using AIPs is considered an important antecedent of behavioural intention or actual usage of the respective technology, with a high perceived risk being deemed a significant barrier to technology adoption (Gansser and Reich, 2021). Chatterjee and Bhattacharjee (2020) discovered a significant negative effect of perceived risk on the attitude of higher education stakeholders towards AI adoption. Alzahrani (2023) supports the idea that perceived risk should be investigated in the context of AI in education, as it strengthens the explanatory power of the UTAUT model. Considering the already established impact of perceived risk in AI in general and in education, and the call for further exploration of perceived risk in the UTAUT model, the next hypotheses were developed: *H3*. Perceived risk has an inverse (negative) effect on the usage of AIPs in general by students; *H4*. Perceived risk has an inverse (negative) effect on the usage of AIPs for educational purposes by students.

Trust in AI can be attained through consistent service delivered by the applications (Kamila and Jasrotia, 2023), but it has to be built on transparency, trustworthiness and accountability (Robinson, 2020), as lack of trust is an important obstacle in the adoption of AI (Du and Xie, 2021; Thiebes, Lins and Sunyaev, 2021). Kelly, Kaye and Oviedo-Trespalacios (2023) concluded that trust positively predicted the use behaviour of AIPs in the context of applying the UTAUT model. The trust of students in AI is essential to build credibility in AI outputs, with studies identifying a direct positive effect of perceived trust on the intention to adopt AI (Pillai et al., 2023). Considering the identified influence of trust in AI and the dual approach (trust vs. lack of trust), the present study focusses on exploring the impact of perceived lack of trust on AIP usage in general and in education by students, therefore prompting hypotheses: *H5*. Perceived lack of trust has an inverse (negative) effect on the use of AIPs in general by students; and *H6*. Perceived lack of trust has an inverse (negative) effect on the usage of AIPs for educational purposes by students.

Descriptive variables have been employed in studies on AI and/or using the UTAUT model as moderators, beginning with Venkatesh et al. (2003), who used in this regard gender, age, experience and voluntariness, but, especially, to describe the profile of the respondent. This study aims to expand the role of descriptive variables, particularly gender, education, income, technology proficiency and equipment used for Internet access, from profile descriptors or moderators to predictors.

Gender has been employed in previous studies in technology-related education and AI studies for profiling purposes (Shaya, Madani and Mohebi, 2023) and as a moderator (Khechine and Lakhal, 2018). However, there is evidence on the impact of gender on various outcomes related to AI in education. Lin et al. (2021), for example, determined that women had a lower tendency to learn AI compared to male students. On the other hand, there is a growing interest in IT education among women considering course selection, dropout rates, or IT tool usage in education (Dziuban and Moskal, 2001; Wrycza, Marcinkowski and Gajda, 2017). This study considers that gender could shed light on the use of AIPs in general and for educational purposes, and thus posits the following hypotheses: *H7*. Male students are more inclined to use AIPs in general than female students; and *H8*. Male students are more inclined to use AIPs for educational purposes than female students.

Educational level has been used in research on technology implemented in education and AI, especially to describe the respondents and the research context. The findings of studies investigating the effects of educational level on technology and/or AI use for learning purposes are divergent, as some studies prompt a clear effect (Matzavela and Alepis, 2021; Rodriguez-Hernandez et al., 2021), while others show no effect at all (Wang et al., 2023). This study aims to employ educational level as an explanatory variable for the usage of AIPs in general, and for educational purposes, and therefore postulates two hypotheses: *H9*.

Postgraduate students are more inclined to use AIPs in general than undergraduate students; and *H10*. Postgraduate students are more inclined to use AIPs for educational purposes than undergraduate students.

Income level has been employed to a lesser extent in studies on technology-related education and AI, in addition to for the description of the respondents (Shaya, Madani and Mohebi, 2023). Exceptions are the studies of Rodriguez-Hernandez et al. (2021), which used monthly family income to explain academic achievements, and of Matzavela and Alepis (2021), which employed parent income to describe the academic performance of students. As there is a lack of evidence on the impact of income level on the usage of AIPs in general and for educational purposes, this study aims to investigate its impact and, hence, suggests the following hypotheses: *H11*. Students with a higher income are more inclined to use AIPs in general than students with a lower income; and *H12*. Students with a higher income are more inclined to use AIPs for educational purposes than students with a lower income.

Experience with technology has been used in studies exploring the impact of technology in education to describe the sample and as a moderator. Shaya, Madani and Mohebi (2023) used the experience with the usage of m-learning apps (beginner, intermediate, and expert) to describe the user of mobile learning apps. Khechine and Lackhal (2018) employed experience in using computers, measured in years, as a moderator in an endeavour to assess the influence of facilitating conditions on the usage behaviour of a webinar system by students, the analysis rendering a nonsignificant result. This study aims to evaluate the impact of technology proficiency on the usage of AIPs in general and for educational purposes, and thus formulates the following two hypotheses: *H13*. Students that are more technologically proficient are more inclined to use AIPs in general than students who are less technologically proficient; and *H14*. Students that are more technologically proficient are more inclined to use AIPs for educational purposes than students who are less technologically proficient.

The equipment used for Internet access has been employed in previous research on the usage of technology in education and the usage of AIPs to not only profile the respondents, but also explain behavioural aspects. Alshammari (2021) collected data about devices used by teaching staff in a study on the use of virtual classrooms, identifying that PCs, laptops, smartphones and tablets were used by academics. Gansser and Reich (2021) argued that smartwatches were considered devices that were extensively used for convenience. The present study focusses on analysing the impact of the equipment used for Internet access on the usage of AIPs in general and for educational purposes, and therefore prompts two hypotheses: *H15*. Students who use particular equipment are more inclined to use AIPs in general than students who do not use that particular equipment: H15a. smartphone; H15b. laptop; H15c. tablet; H15d. smartwatch; H15e. personal computers; and *H16*. Students who use a particular equipment are more inclined to use AIPs for educational purposes than students who do not use that particular equipment: H16a. smartphone; H16b. laptop; H16c. tablet; H16d. smartwatch; H16e. personal computer.

The theoretical model proposed in this study is shown in Figure no. 1.

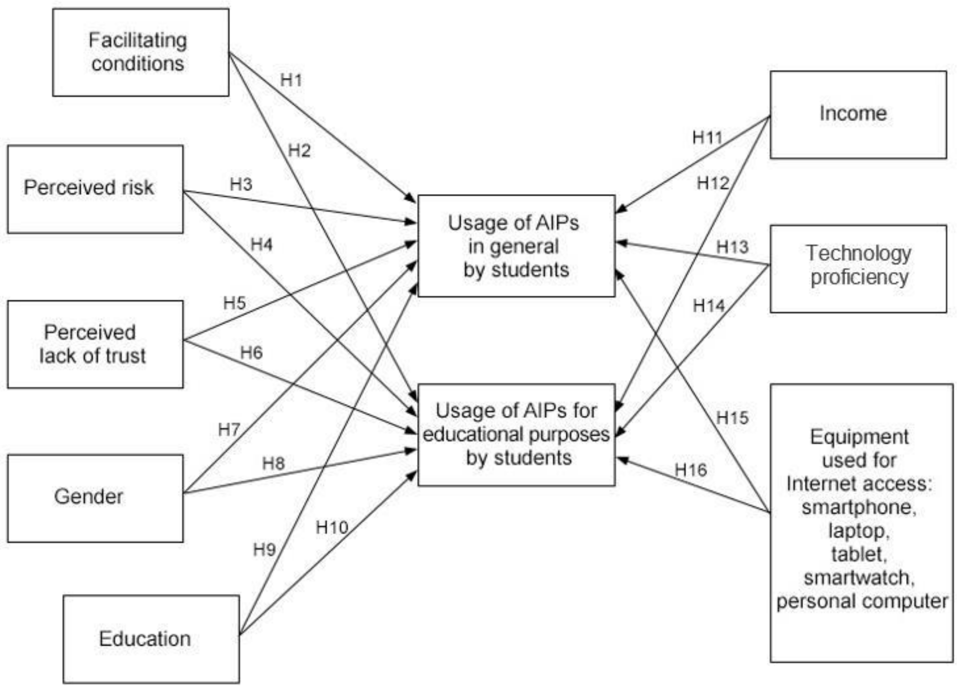

Figure no. 1. The theoretical model

2. Research methodology

This study considered the UTAUT model proposed by Venkatesh et al. (2003) and its extension employed by Arfi et al. (2021), adapting them for business students already using AI. Thus, three groups of variables were adapted from the two studies, specifically facilitating conditions of usage, perceived lack of trust and perceived risk, to determine their impact on the usage of AIPs in general and for educational purposes. Additionally, this study expanded the UTAUT model by transforming gender and experience (measured in this study through technology proficiency) from moderators into independent variables and by including other descriptive variables as independent variables, such as education, income, and equipment used for Internet access.

The sample was built through a nonprobability sampling method, the online questionnaire used to collect data (Pillai et al., 2023) being disseminated among Romanian business students. Data collection was carried out between May and June 2023, focussing on obtaining data from students of both genders enrolled in undergraduate and post-graduate academic programmes. 474 responses were collected. After reviewing them for completeness, 450 questionnaires were retained for analysis, the sample size corresponding to a 95% confidence interval and a margin of error of 4.62%. The sample size matches or exceeds the sample sizes used in previous studies on AI (Chatterjee and Bhattacharjee, 2020; Raffaghelli et al., 2022).

The questionnaire started with the definition of AI and included the seven areas of implementation of the European Parliament (2020). The questionnaire included 9 Likert scales with 5 levels (Wu et al., 2022) for assessing facilitating conditions (Venkatesh et al., 2003), perceived risk and perceived lack of trust (Arfi et al., 2021) (Table no. 1), two dichotomous scales for the dependent variables and categorical scales for the descriptive variables: gender (Raffaghelli et al., 2022), education and technology proficiency (Rodriguez-Hernandez et al., 2021; Shaya, Madani and Mohebi, 2023), income (Matzavela and Alepis, 2021) (Table no. 1), using as benchmarks the net values of the minimum and average salary in Romania at the beginning of 2023, and the equipment used for Internet access (Alshammari, 2021; Gansser and Reich, 2021). Before uploading the questionnaire to Google Forms for dissemination, 12 students enrolled in undergraduate and postgraduate academic programmes, in equal shares (adapted from Zaharia et al., 2022), with four items modified.

In this study, two methods of data analysis were used. First, principal component analysis (PCA) was used to group the items used into factors (Field, 2009). In a second phase, logistics regression was used to explain the two investigated dependent variables, the use of AIPs in general and the use of AIPs for educational purposes, according to the factors rendered by the performed PCA and the descriptive variables: gender, education, income, technology proficiency and equipment used for Internet access. Logistic regression is very useful when it is intended to determine the probability that one case is distributed in one category over another or other categories, the method presenting two advantages, the first being that the dependent variable should not comply to a normal distribution, and the second being that the model can also include categorical predictors (Wuensch and Poteat, 1998; Wuensch, 2014).

3. Data analysis and results

Data related to the descriptive variables are presented in Table no. 1. Some aspects stand out. 4.00% of the respondents preferred not to respond about gender. 72.4% of the respondents were registered in postgraduate study programmes. All respondents mentioned that they access the Internet via the smartphone.

Table no. 1. Descriptive data of the sample

Variable	Category	Frequency	Percentage	Variable	Category	Frequency	Percentage
Gender	Men	252	56.0	Do you access the Internet using your smartphone?	Yes	450	100.0
	Women	180	40.0		No	0	0
	I prefer not to respond	18	4.0	Do you access the Internet through your laptop?	Yes	420	93.3
Education	Enrolled in undergraduate programme	124	27.6		No	30	6.7
	Enrolled in undergraduate programme	326	72.4	Do you access the Internet through a tablet?	Yes	258	57.3
Income	Less than or equal to 1900 RON	192	42.7		No	192	42.7

Variable	Category	Frequency	Percentage	Variable	Category	Frequency	Percentage
	1901-3565 RON	234	52.0	Do you access the Internet through a smartwatch?	Yes	216	48.0
	3566 RON and above	24	5.3		No	234	52.0
Technologically proficient	Rather yes	270	60.0	Do you access the Internet through a personal computer?	Yes	252	56.0
	Rather not	180	40.0		No	198	44.0

Assessing the nine scales used in the questionnaire (Table no. 2) in a PCA using a Varimax rotation based on factor loadings of a minimum of 0.40, Eigenvalues higher than 1 and a Scree plot (Field, 2009), and a Cronbach Alpha higher than 0.7 (Nunnally, 1978), three factors were delineated. However, one factor included only one item. When forcing the analysis with only two factors, the item *AIPs provide a secure work environment where personal data is transmitted securely* showed a low communality, thus displaying no relations with the rest of the items of none of the two factors, being eliminated from the analysis according to the recommendations of Osborne and Costello (2009). In conclusion, two factors were retained (Table no. 2). The procedure was repeated by using Principal Axis Factoring as suggested by Osborne and Costello (2009), as this extraction method displays the covariance of items, the conclusion being the same regarding the two factors. The two factors were named *F1 (Risk and lack of trust associated with AIPs) and F2 (Facilitating conditions for AIPs).*

Table no. 2. Principal Component Analysis - items covering user experience with AIPs

Rotated Component Matrix[a]		
	Component	
	1	2
I have the resources to use AIPs		.834
I have the knowledge to use AIPs		.874
I have access to the support I need to use AIPs		.878
It is risky to use AIPs	.821	
Using AIPs comes with more risks than benefits	.816	
It is a mistake to use AIPs	.874	
I am afraid to use AIPs because of the possibility of losing personal data and privacy	.829	
AIPs provide a secure work environment where personal data are transmitted securely		
I find it risky to disclose personal data and information to use AIPs	.742	
Cronbach Alpha	.884	.857
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalisation.		
Note A. Rotation converged in 3 iterations. **Note B:** Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.744; Bartlett's Test of Sphericity-Sig.: 0.00 **Note C:** Cronbach Alpha: >0.70 for all factors and between factors.		

In a second step, the two factors were regressed together with gender, education, income, technology proficiency and equipment used for Internet access (smartphone, laptop, tablet, personal computer, smartwatch) against the usage of AIPs in general and the usage of AIPs for educational purposes. The evaluation of the use of each equipment to access the Internet was performed on a different scale (Table no. 1). Smartphone usage was not introduced in the regression models because this option was selected by all respondents, thus rendering zero non-users. About the performed logistical regression, using a stepwise approach and a non-significant value of the Hosmer and Lemeshow goodness-of-fit test (Wuensch, 2014), the model with the most significant independent variables, explaining the use of AIPs in general, initially included six variables, namely F1, F2, gender, education, smartwatch use for accessing the Internet and technology proficiency. However, when checking the data against the logistic regression assumptions, technology proficiency was significantly highly correlated with gender, so it was removed from the model in order to meet the assumptions (Zaharia et al., 2022). The final model for explaining the usage of AIPs in general is displayed in Table no. 3.

Table no. 3. Logistic regression- the usage of AIPs in general as dependent variable

Variables in the Equation								
							95% C.I. for EXP(B)	
	B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**Lower**	**Upper**
F1 (Risk and lack of trust associated with AIPs)	-.348	.134	6.730	1	.009	.706	.543	.919
F2 (Facilitating conditions for AIPs)	.560	.133	17.657	1	.000	1.751	1.348	2.273
Gender (Prefer not to respond)			55.787	2	.000			
(Women)	3.742	.534	49.149	1	.000	42.174	14.816	120.048
(Men)	2.617	.544	23.112	1	.000	13.690	4.711	39.785
Education (Undergraduate vs. Postgraduate)	-1.247	.465	7.192	1	.007	.287	.115	.715
Equipment used for Internet access (Smartwatch- No vs. Yes)	-.740	.270	7.491	1	.006	.477	.281	.811

Note A: Hosmer and Lemeshow Test- non-significant value (p>0.05)-adequate level of data fitting; Chi-square = 202.892 (p<0.001); Nagelkerke R Square = 0.484; correctly classifying 80% of the cases; Note B- Logistic regression assumptions met (according to Zaharia et al., 2022)

Variables not included in the equation due to a significance level below .05	**Score**	**df**	**Sig.**
Income (less than or equal to 1900 RON)	5.405	2	.067
Income (1901-3565 RON)	.633	1	.426
Income (3566 and above)	3.346	1	.067
Equipment used for Internet access (Laptop) (No vs. Yes)	.465	1	.495
Equipment used for Internet access (Tablet) (No vs. Yes)	.538	1	.463
Equipment used for Internet access (Personal computer) (No vs. Yes)	.012	1	.914

The model includes five significant variables (Wald tests, $p<0.001$ for the second and third variables and $p<0.01$ for the first, fourth and fifth variables) (Table no. 2). The impact of each variable on the usage of AIPs in general is explained based on the odds ratio. *F1 (Risk and lack of trust associated with AIPs)*, with an odds ratio of 0.706, displays that a decrease of one unit on the measurement scale of the predictor increases the odds of using AIPs in general by a multiplicative factor of 1.416. *F2 (Facilitating conditions for* AIPs*),* with an odds ratio of 1.751, shows that an increase of one unit on the measurement scale of the predictor increases the odds of using AIPs in general by a multiplicative factor of 1.751. *Gender* (significant overall at p<0.001), with odds ratios of 42.174 (p<0.001) and 13.690 (p<0.001), displays that female students are 42.174, while male students are 13.690 times more inclined to use AIPs in general than people who preferred not to respond to their gender. *Education,* with an odds ratio of 0.287, shows that students enrolled in undergraduate programmes are 3.484 times more inclined to use AIPs in general than those enrolled in postgraduate programmes. The *equipment used for Internet access (Smartwatch),* with an odds ratio of 0.477, shows that students not using this equipment to access the Internet are 2.096 times more inclined to use AIPs in general than those using smart watches.

The most comprehensive model explaining the usage of AIPs for educational purposes includes four variables, namely F1, F2 gender, and the use of personal computers to access the Internet. These variables are retained after checking the data against the logistic regression assumptions (Zaharia et al., 2022). The final model for explaining the usage of AIPs for educational purposes is shown in Table no. 4.

Table no. 4. Logistic regression - the usage of AIPs for educational purposes as dependent variable

Variables in the Equation							95% C.I. for EXP(B)	
	B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**Lower**	**Upper**
F1 (Risk and lack of trust associated with AIPs)	-.498	.124	16.048	1	.000	.608	.477	.776
F2 (Facilitating conditions for AIPs)	.745	.127	34.405	1	.000	2.106	1.642	2.700
Gender (Prefer not to respond)			67.850	2	.000			
(Women)	1.823	.225	65.717	1	.000	6.188	3.982	9.614
(Men)	1.252	.250	25.169	1	.000	3.498	2.145	5.704
Equipment used for Internet access (Personal computer- No vs. Yes)	-.494	.254	3.789	1	.052	.610	.371	1.003
Note A: Hosmer and Lemeshow Test- non-significant value (p>0.05)-adequate level of data fitting; Chi-square = 189.387 (p<0.001); Nagelkerke R Square = 0.458; correctly classifying 81.3% of the cases; Note B- Logistic regression assumptions met (according to Zaharia et al., 2022)								

Variables not included in the equation due to a significance level below .05	**Score**	**df**	**Sig.**
Income (less than or equal to 1900 RON)	12.712	2	.302
Income (1901-3565 RON)	12.709	1	.302
Income (3566 and above)	1.415	1	.234
Education (Undergraduate vs. Postgraduate)	2.892	1	.089
Technology proficiency (Rather technologically proficient vs. Rather not technologically proficient)	.672	1	.412
Equipment used for Internet access (Smartwatch) (No vs. Yes)	.115	1	.735
Equipment used for Internet access (Laptop) (No vs. Yes)	3.841	1	.150
Equipment used for Internet access (Tablet) (No vs. Yes)	0.484	1	0.486

The model includes four significant variables (Wald tests, $p<0.001$ for the first three variables and $p<0.1$ for the fourth variables) (Table no. 3). The impact of each variable on the usage of AIPs for educational purposes is explained based on odds ratio. *F1 (Risk and lack of trust associated with AIPs)*, with an odds ratio of 0.608, displays that a decrease of one unit on the measurement scale of the predictor increases the odds of the usage of AIPs for educational purposes by a multiplicative factor of 1.645. *F2 (Facilitating conditions for AIPs),* with an odds ratio of 2.106, shows that an increase of one unit on the measurement scale of the predictor increases the odds of the usage of AIPs for educational purposes by a multiplicative factor of 2.106. *Gender* (significant overall at $p<0.001$), with odds ratios of 6.188 ($p<0.001$) and 3.498 ($p<0.001$), displays that female students are 6.188, while male students are 3.498 times more inclined to use AIPs for educational purposes than people who preferred not to respond regarding their gender. The *equipment used for Internet access (Personal computer),* with an odds ratio of 0.610, shows that students not using personal computers are 1.639 times more inclined to use AIPs for educational purposes than those using personal computers.

In conclusion, hypotheses H1 to H6 were supported, while hypotheses H7 to H16 were not supported by the findings. Furthermore, the two dependent variables, using AIPs in general and AIPs for educational purposes, are strongly correlated based on Phi coefficient value (0.789, $p<0.001$). Furthermore, the other can be explained in a similar proportion based on Lambda coefficients (0.684, $p<0.001$).

4. Discussion

In both situations, the use of AIPs in general and the use of AIPs for educational purposes show that facilitating conditions are a stronger predictor compared to the risk and lack of trust associated with AIPs. The significant positive effect of facilitating conditions is in line with previous works in AI adoption in general (Gansser and Reich, 2021) and in higher education (Chatterjee and Bhattacharjee, 2020) or ChatGPT usage by students (Strzelecki, 2023), and extends the existing literature on their stimulating impact on AI acceptance by consolidating the actual usage perspective. Thus, universities should focus their strategies on displaying the resources linked to the infrastructure and on the support offered to efficiently make use of AI and on building knowledge on how to use it.

The risk and lack of trust associated with AIPs have a significant influence on the usage of AIPs in general and for educational purposes. The PCA performed in this research grouped perceived risk and perceived lack of trust, offering a new angle to explore and understand AI usage. The significant negative effect of this variable on AI usage in both research streams is in sync with previous works on this issue (Chatterjee and Bhattacharjee, 2020; Du and Xie, 2021; Gansser and Reich, 2021; Thiebes, Lins and Sunyaev, 2021). Universities must respond by better communicating the benefits of AI, thoroughly explaining the risks associated with them, and focussing on safety by clarifying personal data and privacy issues.

Gender turned out to be a significant predictor in both cases. However, it is interesting that female students turned out to be more inclined to use AIPs than male students, with the reference base in the performed logistic regressions being those who did not want to declare their gender. The finding contradicts even the view of Venkatesh et al. (2003) that supports that men were more inclined towards technology. Furthermore, the result disproves the findings of Lin et al. (2021), who concluded that male students were more inclined to learn AI. However, the result of this study expands on AI the views of Dziuban and Moskal (2001) and Wrycza, Marcinkowski and Gajda (2017) who point to a growing interest among women in IT education and in technology, in general. An explanation for this result could be that AIPs are becoming more user-friendly, and thus more accessible. Moreover, many AIPs, in general and more clearly for educational purposes, target both genders.

Education was a significant predictor in the case of the use of AIPs in general. Undergraduate students showed a higher tendency to use AIPs in general compared to those enrolled in postgraduate programmes. This result could be explained based on the perspective that students enrolled in undergraduate programmes find themselves in a knowledge-building stage, thus, looking for ways and methods to acquire knowledge, while the others are in a refinement phase in which people try to specialise in various fields. The findings of this study support the divergence found in the literature, with the significant effect found on AIP usage in general that matches the conclusions of studies that determined the impact of education on technology and/or AI use for learning purposes (Matzavela and Alepis, 2021; Rodriguez-Hernandez et al., 2021), while the no-effect result on AIP use for education converging with the conclusions of studies that found no effect of education on AI applications used in teaching (Wang et al., 2023). However, through the results obtained, this study highlights that the academic level deserves to be taken into consideration as a predictor in analyses related to understanding the behavioural aspects of AI and technology.

Two types of equipment used for Internet access turned out to be significant predictors, interestingly, both displaying an inverse relationship with the dependent variables. Thus, people not using smartwatches tend to use AIPs in general more, while those not using personal computers show a higher tendency to use AIPs for education. In the first instance, an explanation could come from the fact that the screen of smartwatches is too small for a proper experience, although they are deemed highly convenient devices (Gansser and Reich, 2021), while in the second instance, individuals found in this age bracket tend to like to access the Internet through mobile devices, such as smartphones, laptops, or tablets (Petrosyan, 2023; Taylor, 2023). The results are even more interesting as tablets and laptops did not show no effect on AIP usage, although 93.3% of the respondents mentioned using laptops and 57.3% tablets (Table no. 1). However, all respondents mentioned that they used smartphones for connectivity purposes, hence for AIPs too.

Conclusions

The scientific contributions of this study could be found on multiple levels. This study expands the AI user behaviour literature by probing into the actual usage of AIPs, offering a new perspective on the UTAUT model by retaining the only predictor that directly explained usage, and including perceived risk and the negative view of trust in the form of lack of trust. Additionally, the UTAUT model has been developed in this study by converting gender and experience into independent variables, upgrading their role from the moderating one in the original model (Venkatesh et al., 2003), and by including another three descriptive variables to explain AIPs usage in general, and for educational purposes, namely income, education and equipment used for Internet access. In this study, based on the principal component analysis (PCA), perceived risk and perceived lack of trust were combined into one variable (Risk and lack of trust associated with AIPs), thus prompting a new theoretical perspective in the field. Moreover, as a result of using logistic regression, the significant direct (positive) effect of facilitating conditions and the inverse (negative) one of risk and lack of trust display a different view that can be applied to understanding AI adoption or technology adoption in general. The significant results obtained in the case of gender, education and types of equipment used for accessing the Internet indicate that these variables could bring clarifications regarding the use of technology in general and AI, in particular. Furthermore, the high correlation displayed between the two dependent variables adds to the literature on AI in education, with this strong connection being rendered by three common antecedents with similar impact, namely facilitating conditions, risk and lack of trust related to AIPs and gender.

For managerial implications, the findings of this study show that universities must facilitate the necessary means for users to exploit AIPs for educational purposes effectively. Thus, higher education institutions should consider a comprehensive integration of AIPs to cover teaching, learning, and faculty-student interaction (Wu et al., 2022), as well as assessment and administrative tasks. Faculty and students have been accustomed to working remotely since the time of the pandemic (Istudor et al., 2020). AIP providers should also attempt to alleviate perceived risk and lack of trust in technology by providing comprehensive information on the actual usage of AIPs and data protection and privacy. The providers should create adequate instructional materials, provide support services and encourage interaction with and between users about processes and outcomes of the implementation of this procedure. Furthermore, AIPs and supportive resources should be tailored based on the educational level of the target audience and the mobile equipment, as the results of this study show that all respondents used smartphones to access the Internet. Regarding public policies, the authorities should consider allocating funds for the purchase of equipment and AIPs, but also for training academics on the usage of AIPs. In addition, as a country strategy, funding of scientific research must be prioritised in this extremely dynamic field.

The study presents some limitations that could be addressed as directions in future research. Firstly, the study focused on business students from Romania. Future research can employ the model to investigate students from other fields, as well as for multi-country analysis. Secondly, the research made use of a nonprobability sampling procedure, which makes the generalisation of the findings difficult. Future studies should employ a probability sampling approach. Third, the sample used presented an imbalance between students enrolled in undergraduate study programmes and those enrolled in postgraduate programmes. Future studies could seek to ensure representativeness from the perspective of distributing students between university and postgraduate programmes. Fourthly, the nonsignificant results rendered by the usage of tablets and laptops, as well as the inverse effects recorded by smartwatches and personal computers, should be further analysed. Future studies should investigate the effect of the equipment used for Internet access using Likert scales. Fourth, the model can be developed by including other descriptive variables, such as AI usage purposes or AI usage frequency.

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