Artificial Intelligence in Higher Education: a UTAUT-based Approach to Modelling Student Acceptance

The present research analyses the key factors that determine the acceptance of artificial intelligence and related technologies among university students. This study employs the Unified Theory of Acceptance and Use of Technology (UTAUT) as its theoretical framework. An online cross-sectional survey was conducted among students currently enrolled in higher education. The proposed hypotheses were tested using CB-SEM on the final dataset (n=438). Our results confirmed that performance expectancy and effort expectancy are crucial in forming behavioural intention to use AI, while social influences exert a moderate effect. However, facilitating conditions showed a weak link with both usage intention and actual usage, suggesting that infrastructural factors play a secondary role in shaping technology acceptance. Results imply that the availability of resources alone is insufficient to drive AI adoption and highlight the strategic importance of targeted educational programmes and awareness campaigns to shape students' expectations and attitudes towards AI.

Keywords: *artificial intelligence, AI acceptance, higher education, technology adoption, UTAUT, structural equation modelling*

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1. Introduction

Since its early emergence in the mid-20th century, artificial intelligence (AI) has evolved through cyclical waves of enthusiasm and disappointment, including two major 'AI winters' characterised by declining funding and reduced expectations (Russell and Norvig 2022). Despite these discontinuities, recent decades have witnessed an accelerated resurgence and widespread adoption of AI technologies across industries (Grabowski 2024). The concept of artificial intelligence can be defined in multiple ways, encompassing various aspects and dimensions of the technology and its applications. Based on Zhang et al. (2021) AI is a subfield of computer science aimed at developing systems capable of performing tasks that traditionally require human intelligence, such as learning, reasoning, decision making and comprehension. In the present study, AI is conceptualised as a broad category of data-driven algorithmic systems capable of performing these cognitive tasks. Accordingly, our analysis does not focus exclusively on generative AI applications, but rather on AI-based technologies used in higher education more generally, including adaptive learning systems, intelligent tutoring systems, automated assessment tools and generative AI applications. This broader operationalisation allows the investigated determinants of acceptance to reflect individual-level cognitive evaluations and behavioural intentions toward AI as a technological class rather than toward a single application type.

The profound socio-economic impact of AI has been analysed from multiple perspectives (Capraro et al. 2024; Lukianenko and Simakhova 2024; Pintér 2022; Lőrincz 2015), consistently highlighting the need for comprehensive social transformation processes (Sosaya-Rodríguez et al. 2024). From a broader innovation perspective, the societal diffusion of new technologies has traditionally been explained by the Innovation Diffusion Theory (Rogers 1983), which emphasises the role of communication channels, social systems and adopter categories in shaping the spread of innovations. While diffusion theory captures macro-level adoption dynamics, the present study focuses on the micro-level psychological mechanisms underlying individual acceptance behaviour. To operationalise the concept of acceptance behaviour, we can draw on numerous well-established models of social psychology (see Ajzen 1985; Ajzen and Fishbein 1980; Bandura 1986; Davis 1986; Deci and Ryan 1985; Triandis 1979; Venkatesh et al. 2012a, 2003, 2016; Venkatesh and Bala 2008), of which the Unified Theory of Acceptance and Use of Technology (UTAUT) is considered to be the most sophisticated construct, providing a concise and thorough depiction of the complexity of factors that have parallel effects on the formation of acceptance behaviour in consumers (Venkatesh et al. 2003).

To establish a solid foundation and define scientifically relevant objectives for our empirical research, we conducted a systematic literature review, analysing scientific papers published between 2018 and 2023. The meta-analysis of 44 relevant studies shows that the topic of AI adoption has been widely studied in various fields such as business, finance and healthcare (Norzelan, Mohamed and Mohamad 2024; Schulz et al. 2023), yet limited research has explored its acceptance in higher education in the given time period. This study aims to address this gap by examining the key factors influencing university students' adoption of AI-based technologies, as it is a sector that directly impacts societal transformation, influencing the general acceptance and spread of the technology. By fostering AI literacy and advocating ethical use, universities contribute to preparing society for the implications of AI, ensuring that the benefits of this transformation are accessible to all segments of the population (Ferk Savec and Jedrinović 2024). Furthermore, integrating AI into education equips students with relevant digital skills and knowledge, preparing them for evolving labour market demands (Makarenko et al. 2024). Encouraging university students to leverage AI for personal development and to develop practical AI skills is crucial, as AI proficiency is becoming a key requirement across different professions. In light of these considerations, higher education is not only a societal entry point for AI adoption but also emerges as a crucial facilitator in the targeted development of skills that determine the process. Given the expanding role of AI in higher education (Alateyyat and Soltan 2024), understanding student acceptance is becoming critical. Accordingly, this study aims to analyse AI acceptance and its influencing factors among university students. To achieve this objective, an online questionnaire was conducted among Hungarian university students, following the UTAUT model as a theoretical framework. The acquired data was analysed using the CB-SEM method.

This study follows the structure outlined below. Section 2 provides a literature review, summarising previous findings on AI acceptance and explains the theoretical framework used during the research. This section presents our hypotheses and conceptual model as well. Section 3 describes the methodology applied in the survey. Section 4 presents the results of our analysis, which are subsequently discussed in Section 5. Finally, Section 6 summarises the key conclusions of the study.

2. Literature review

2.1. AI in Higher Education

Artificial intelligence is already embedded in higher education, revolutionising traditional academic practices and offering significant advancements in both teaching and institutional management. Based on the available literature, we have identified five main dimensions of AI adoption: (1) personalised education (Jing and Boyi 2023; Murdan and Halkhoree 2024; Naseer et al. 2024; Sajja et al. 2024); (2) support for innovative educational practices (Alrayes, Henari and Ahmed 2024; Saleem et al. 2024); (3) optimisation of institutional operations (Nurhasanah et al. 2024; Téllez, Ortiz and Domínguez 2024; Cholyshkina et al. 2024); (4) facilitation of data-driven managerial decision-making (Fok et al. 2018; Téllez, Ortiz and Domínguez 2024); and (5) transformation of knowledge acquisition and academic research (Dwivedi et al. 2023; Cotton, Cotton and Shipway 2023). Consequently, AI-based solutions guide educational institutions towards more effective, evidence-based practices. Despite the unquestionable advantages that artificial intelligence offers to higher education institutions, its integration poses significant challenges related to ethical considerations (Alrayes, Henari and Ahmed 2024; Héder 2020, 2021), the preservation of educational integrity

(Murdan and Halkhoree 2024) and the digital divide among stakeholders (Murdan and Halkhoree 2024; Téllez, Ortiz and Domínguez 2024). In particular, the emergence of generative AI tools such as large language models has generated extensive debate regarding authorship, academic integrity, and the epistemic role of AI in higher education (Kasneci et al. 2023; Cotton, Cotton and Shipway 2023).

2.2. AI acceptance

Investigating personal or organisational acceptance of emerging technologies has been the focus of several studies. The acceptance of AI and the factors that influence its popularity among individuals have been increasingly discussed in a wide array of publications, covering different sectors and applications from medicine (Schulz et al. 2023), finance (Norzelan, Mohamed and Mohamad 2024) to construction (Na et al. 2022). Artificial intelligence (AI) acceptance can be defined as the willingness and readiness of individuals or organisations to adopt and use AI-based technologies (Kelly, Kaye and Oviedo-Trespalacios 2023). To begin with, perceived usefulness and ease of use are consistently identified as critical determinants of AI acceptance (Aldraiweesh and Alturki 2025; Ibrahim et al. 2024). These factors are often assessed using models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (Kelly, Kaye and Oviedo-Trespalacios 2023). Ismatullaev and Kim (2024) concluded that increased transparency and reliability of AI can induce greater trust and acceptance among users. Cornelissen et al. (2022) found that the technical performance and the functionality of AI-based systems can influence user acceptance in the healthcare sector. Apart from technological factors, individual determinants also play a crucial role in the formation of technology adoption. Based on Schiavo, Businaro and Zancanaro (2024), higher AI literacy, i.e. the understanding and ability to use AI technology, reduces anxiety in individuals and fosters a positive attitude towards AI, hence exerting a positive influence on acceptance. Furthermore, certain personality traits, such as openness and an innovative inclination can enhance the perceived ease of use and usefulness of AI, thus prompting acceptance (Hao, Miao and Yan 2021). Trust and anxiety have also proved to be cardinal in the formation of acceptance. The first has a positive effect on AI acceptance, while the latter has a negative impact (Cornelissen et al. 2022; Schiavo, Businaro and Zancanaro 2024). Moreover, organisational factors, such as a supportive culture, participation (Bengel 2020) and a competitive climate (Fousiani et al. 2024) are also vital in the implementation and acceptance of AI technologies. Furthermore, several studies have concluded that social influences, such as social norms, social influence, word of mouth and societal attitudes towards AI can alter the general acceptance of technology (Chen et al. 2024; Fares et al. 2024; Mutlu 2024). Banytė, Lindžiuvienė and Dargytė (2024) proved that privacy and data management concerns can also hinder AI acceptance and emphasised the need for addressing these concerns directly in order to gain trust of users. Finally, emotional and cognitive factors are also significant determinants of AI adoption. In their study, Mutlu (2024) found that the emotions and intrinsic motivations of individuals have a significant impact on their readiness to use AI-driven technologies and underlined that generally positive responses can enhance acceptance. Based on Chen et al. (2024) and Hao, Miao and Yan (2021), perceived risk associated with AI can have a negative impact on acceptance. Mitigating these risks through guidelines and literacy programs is essential to ensure the success of AI-driven institutional innovations. Nevertheless, the factors influencing AI adoption and the nature of their impact can show a great variance based on the different contexts the tool is being used (Aldraiweesh and Alturki 2025; Nazri et al. 2023).

2.3. Unified Theory of Acceptance and Use of Technology

The present study is based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The UTAUT model was developed by integrating and revising eight different models and theories that primarily originate from behavioural sciences. It incorporates certain elements of the Technology Acceptance Model (TAM) while building on the Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB) as well (Venkatesh et al. 2003). The core variables that UTAUT focuses on are usage intention and actual usage of the technology. Based on the framework, the independent and moderating variables that influence these outcomes can be examined as well. The model developed by Venkatesh et al. (2003) explains consumer technology acceptance through four input variables and one mediator variable, which ultimately reflect in actual usage behaviour. The input variables include individual expectations regarding technology performance (performance expectancy, PE), consumer perceptions of the difficulty associated with using the technology (effort expectancy, EE), the social influence or potential pressure to adopt the technology (social influence, SI), and certain facilitating conditions, such as the infrastructural and other necessary requirements for technology use (facilitating conditions, FC). These factors directly influence usage intention (behavioural intention, BI), which serves as a mediating variable within the model. Additionally, the model establishes a direct relationship between facilitating conditions and the outcome variable, actual usage of technology (use behaviour, UB) (Venkatesh et al. 2003). Among these factors, performance expectancy and effort expectancy have been identified as the strongest predictors of usage intention (Gupta et al. 2019; Simeonova, Bogolyubov and Blagov 2013; Sobti 2019). However, in certain cases, the effect of effort expectancy has been found to be non-significant (Sánchez-Holgado and Arcila-Calderón 2024). By contrast, the impact of social influence and facilitating conditions on usage intention appears to be more variable, with their significance showing variance across different research contexts (Bhati, Sharma and Gola 2023; Jewer 2018; Soomro 2019).

Venkatesh et al. (2016) proposed a revised model (UTAUT 2) that supports a more consumer-oriented approach. The model introduces new variables, i.e. hedonic motivation, price value and habit, providing a more complex theoretical framework for the analysis of technology acceptance. Our choice between the two models is guided by several recommendations in the literature. First, the fact that the UTAUT model is a simpler approach compared to UTAUT 2 can be advantageous in contexts where the analysis aims to uncover fundamental relationships. Tamilmani et al. (2021) highlight that from a parsimony perspective, the application of UTAUT 2 may sometimes be less favourable. Moreover, UTAUT 2 was primarily developed for analysing situations where consumer and consumption-related aspects are prominent. As a result, the model incorporates factors such as hedonic motivation and price value, whose relevance in non-commercial contexts may be questionable. This is supported by the findings of Syamsudin et al. (2018), who investigated public service technologies. Their results indicate that certain model elements introduced to diversify the original framework, such as hedonic motivation, are less applicable to technologies used in public services and often require modification. Given that the higher education sector can also be considered as a non-commercial context, it can be assumed that certain constructs of UTAUT 2 may not be relevant in studies examining technology acceptance in this domain. Furthermore, Or (2023) highlights that in many cases, the application of UTAUT 2 in educational settings does not yield significantly better results than the original model, particularly in explaining the variance between usage intention and actual use. This suggests that in specific educational contexts, the effectiveness of UTAUT is comparable to, or may even surpass that of UTAUT 2. Based on the findings discussed above, we conclude that the original model is more suitable with respect to the objectives of this research.

2.4. Hypotheses and conceptual model

Within the framework of the present research, the hypotheses examined are grounded in the findings of several studies that have investigated the acceptance of various technologies (e.g., e-learning systems, mobile-based learning, interactive whiteboards) used in different educational contexts.

(H1) Performance Expectancy (PE) positively influences university students' Behavioural Intention (BI) to use Artificial Intelligence (AI).

We posit that students' expectations regarding the performance of artificial intelligence have a favourable impact on their intention to use AI technologies. Specifically, the more useful students perceive AI tools and the services they provide, the more open they will be to adopting and utilizing them in their studies. The strong positive relationship between performance expectancy and behavioural intention in the context of higher education technologies has been confirmed by several previous studies (Xue, Rashid and Ouyang 2024). For instance, in the cases of interactive whiteboards (Wong, Teo and Russo 2013) and mobile-based learning (Khan et al. 2022), it has been explicitly demonstrated that performance-related expectations significantly influence both student and teacher intentions to adopt these technologies.

(H2) The Effort Expectancy (EE) positively influences students' Behavioural Intention (BI) to use AI tools.

In general, a positive relationship can be observed between effort expectancy and behavioural intention. However, the strength of this relationship is highly context-dependent. While some studies have identified a moderately significant effect (Ali, Warraich and Butt 2024), others have found a negligible impact of expected effort on behavioural intention (Bacuna and Castro 2023).

(H3) Social Influence (SI) positively affects students' Behavioural Intention (BI) to use Artificial Intelligence.

We hypothesize that students' social environment, including prevailing perceptions and expectations regarding artificial intelligence, positively influences their intention to use AI technologies. This assumption is supported by several studies on technology acceptance in education. However, prior research has reported varying effects of social influence on behavioural intention. For instance, Haripin and Warsono (2024) examined the adoption of an e-learning platform and found a significant relationship between social influence and behavioural intention. In contrast, the study of Bacuna and Castro (2023) on Google Classroom adoption indicated that the effect of social influence on behavioural intention was negligible. These findings suggest that the impact of social networks depends not only on the specific educational context but also on the technology in question.

(H4) Facilitating Conditions (FC) positively influence students' Behavioural Intention (BI) to use Artificial Intelligence.

The availability of necessary resources, knowledge and potential support for using artificial intelligence directly enhances students' intention to adopt AI technologies. This assumption is supported by several studies emphasizing that access to essential resources and assistance plays a crucial role in the acceptance of certain technologies (Bacuna and Castro 2023). However, in some cases, this positive effect is not found to be statistically significant (Ali, Warraich and Butt 2024).

(H5) Facilitating Conditions (FC) Have a Direct Positive Effect on Students' Actual AI Use (UB).

The presence of facilitating conditions supports students' actual use of artificial intelligence. This implies that when students perceive that they have access to the necessary resources and required support, they are more likely to engage in active AI usage. This relationship has been consistently observed in numerous studies (Awwad and Al-Majali 2015; Khechine and Augier 2019). Interestingly, opposing findings have also emerged. For instance, Alblooshi and Hamid (2021) identified a negative relationship between students' use of an e-learning system and facilitating conditions. Their results suggest that merely providing operational and technical resources is insufficient for fostering actual usage behaviour if these conditions do not align with students' specific needs, existing competencies, and prior experiences.

(H6) Students' Behavioural Intention (BI) to use AI positively influences Actual Use (UB).

Numerous studies have confirmed a strong positive relationship between behavioural intention and actual use. For instance, in the context of learning management systems (LMS) during the COVID-19 pandemic, behavioural intention significantly influenced the actual adoption of the technology (Ahmed, Štreimikienė and Štreimikis 2021). Similarly, students' intention to use ICT tools was found to strongly impact their actual usage behaviour (Attuquayefio 2022). This relationship has also been evident in research on online education and e-learning, where studies consistently identified the positive effect of behavioural intention on actual use (Tahir 2023; Zulfakar et al. 2023).

In summary, the theoretical model developed for this study is presented in Figure 1. The model illustrates the measurement models included in the study (manifest and latent variables) as well as the relationships between the various constructs. Latent variables are represented by ovals, while their corresponding manifest variables or measurement indicators are depicted as rectangles. The relationships between the constructs, along with the associated hypotheses, are illustrated through arrows connecting the variables.

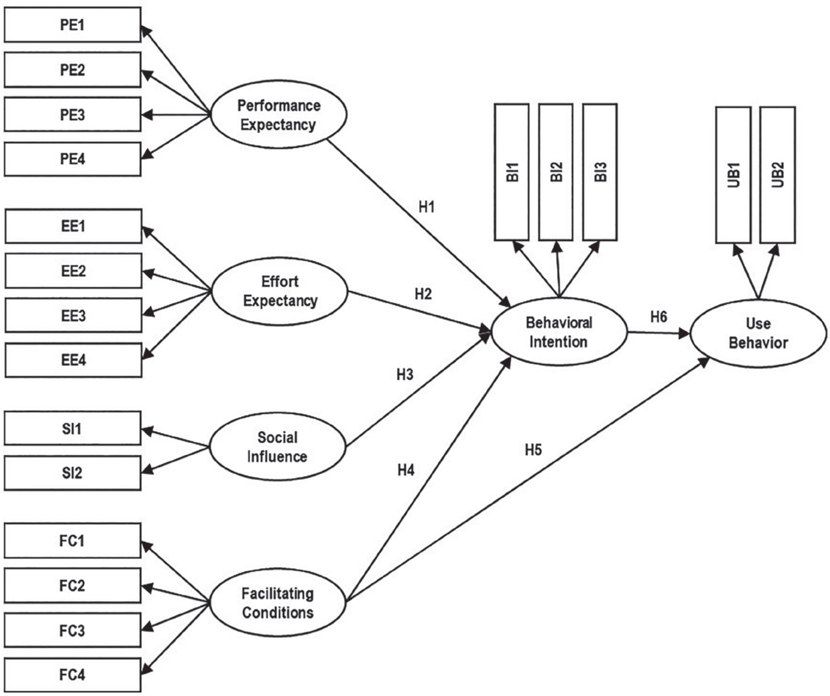

Figure 1. Conceptual model
(Source: edited by the authors)

The proposed model is structured in accordance with the framework of the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003). The dependent variable in the model is actual use (UB), which is directly influenced by the mediating variable (behavioural intention, BI) and the independent variable (facilitating conditions, FC). Four independent variables affect the consumer acceptance of artificial intelligence and the formation of behavioural intention. These include functional elements (performance expectancy, PE, and effort expectancy, EE) as well as contextual factors (social influence, SI, and facilitating conditions, FC). The model is expected to analyse students' intention to use AI along the delineated model variables, identify the mechanisms of influence among the constructs, and determine their significance.

3. Methodology

3.1. Applied Research Method and Sample

This study employed a cross-sectional survey targeting Hungarian students currently enrolled in higher education. Respondents were contacted and invited to participate in the questionnaire-based survey through various social media platforms. Data collection took place between September and November 2024, during which a total of 511 individuals completed the questionnaire. As no predefined sampling frame was available, a non-probability, quota-based sampling technique was applied. Quotas were defined primarily along gender and age dimensions in order to approximate the known demographic composition of Hungarian higher education students. However, due to the social media-based recruitment and the non-random nature of the sampling procedure, the sample cannot be considered statistically representative of the overall population of Hungarian higher education students. Consequently, the findings should be interpreted as applicable to the studied sample, and generalizations to the broader population should be made with caution.

The data cleaning process was carried out in multiple stages. First, responses containing invalid or out-of-range values (e.g., scale responses outside the predefined response categories) were removed (18 records). In addition, responses that failed the embedded attention check item were excluded (2 records). To identify insufficient effort responding, we calculated the within-respondent standard deviation (s) across the scale-based items for each participant. This indicator captures response patterns such as straightlining (very low variance) and excessively inconsistent or erratic responding (very high variance). Cases with $s = 0$ (indicative of complete straightlining) were removed (16 records). In addition, lower and upper threshold values were determined using the Outlier Labeling Rule based on the interquartile range (IQR) of the respondent-level standard deviations. Accordingly, cases with unusually low variability ($s < 0.45$; 10 records) and unusually high variability ($s > 1.55$; 17 records) were excluded from further analyses. Next, we identified logical inconsistencies that could indicate invalid responses. One record was flagged as inconsistent due to a contradiction between the reported age (18–19 years) and the level of study (PhD), and it was removed (it had already been identified for deletiondue to low variance). Duplicate responses were identified using SPSS (3 records), while outliers were analysed using the approach proposed byOlkin and Sampson (2001) approach, employing the Mahalanobis distance test for robust multivariate analysis (7 records). Following the data cleaning process, the final dataset comprised 438 valid responses, which were used for subsequent analyses. Statistical analyses were conducted using SPSS, while the study's hypotheses were tested using covariance-based structural equation modelling (CB-SEM) in SmartPLS 4. The choice of CB-SEM over PLS-SEM was justified by the large sample size, the assumption of multivariate normality, the factor-based modelling approach, and the study's theory-testing focus.

The demographic characteristics of the respondents can be summarized as follows. 51.4% of the respondents were female, while 48.6% were male. All respondents were within the 18-25 age group (mean age: 21 years, standard deviation: 1.68). Regarding place of residence, 21.5% of the respondents lived in rural areas, 18.9% in small towns, 32.6% in cities, and 26.9% in county seats (no responses were received from residents of the capital). In terms of educational programs, the distribution was as follows: 82.6% were enrolled in undergraduate programs, 11.4% in undivided programs, 1.1% in master's programs, 4.1% in higher education vocational training, and 0.7% in specialized postgraduate programs (no responses were received from doctoral students). Regarding prior experience with artificial intelligence tools, 75.6% of the respondents had previously used AI-based tools, while only 24.4% responded negatively to a question regarding their past experience. Given this, we deemed it appropriate to retain the actual usage model construct, as the majority of responses identified this variable as relevant.

3.2. Measurement Methodology

The constructs (latent variables) included in the study, along with the corresponding measurement indicators (manifest variables) and the applied codes, are summarized in Table 1. When defining the individual measurement indicators, we took into account the model elements published by Venkatesh et al. (2003), aiming to create the appropriate higher education context for each indicator. During data collection, respondents were asked to evaluate 19 statements, listed in the following table, using a five-point Likert scale based on their level of agreement. The scale ranged from "1 = Strongly disagree" to "5 = Strongly agree."

Construct	Measurement item	Code
Performance Expectancy (PE)	Artificial intelligence is an effective aid for my studies.	PE1
	With the help of AI, I can complete tasks more quickly.	PE2
	The use of artificial intelligence can enhance my performance.	PE3
	Using AI increases my chances of achieving better academic results.	PE4

Effort Expectancy (EE)	Interactions with artificial intelligence are simple and clear for me.	EE1
	It is easy for me to learn how to use AI and become proficient in its application.	EE2
	I find the use of AI to be straightforward.	EE3
	Mastering the use of AI is not problematic for me.	EE4
Social Influence (SI)	Individuals who influence me and my behaviour believe that I should use artificial intelligence.	SI1
	The people who are important to me believe that I should use artificial intelligence.	SI2
Facilitating Conditions (FC	I have the resources necessary for using artificial intelligence.	FC1
	I possess the knowledge required for using artificial intelligence.	FC2
	Artificial intelligence is not compatible with the other tools I use.	FC3*
	I have acquaintances who could assist me if I encounter difficulties with using AI.	FC4
Behavioural Intention (BI)	If AI were available to me, I would definitely use it.	BI1
	If AI were available to me, I believe I would use it.	BI2
	I plan to use artificial intelligence in the future.	BI3
Use Behaviour (UB)	I frequently use artificial intelligence for my studies and completing academic assignments.	UB1
	I feel that it is essential for me to use AI in my studies.	UB2

*Negatively worded item was reverse-coded

Table 1. Constructs and measurement items
(Source: edited by the authors)

Prior to the CB-SEM analysis, we validated the structure of the individual constructs through an exploratory factor analysis. As a result of this validation, two indicators (EE1 and FC4) were removed. In the case of EE1, a cross-loading was identified, meaning that the variable was not clearly associated with only one factor but showed relationships with two factors, which significantly undermines the clarity of the factor structure. The reason for removing the FC4 indicator was its low factor loading (0.327). Based on these findings, the final analysis and evaluation involved 17 indicators.

4. Research results

4.1. Convergent and Discriminant Validation

The validation of our model began by evaluating the criteria of convergence and discriminant validity. In this evaluation, we applied the Fornell-Larcker criterion (Fornell and Larcker 1981), which posits that the condition for convergence is that the average variance extracted (AVE) exceeds a value of 0.5. Furthermore, following Hair's (2006) recommendations, it is also required for convergence validity that, in addition to AVE, the standardized factor loadings should exceed 0.5 and the composite reliability (CR) should surpass the threshold of 0.7. As reflected in Table 2, our constructed theoretical model meets all these criteria.

Construct	**Item**	**M**	**SD**	**Factor-loading**	**Cronbach α**	**AVE**	**CR**
Performance Expectancy (PE	PE1	3.68	1.142	0.784	0.899	0.689	0.896
	PE2	3.71	1.241	0.891			
	PE3	3.37	1.247	0.825			
	PE4	3.19	1.293	0.681			
Effort Expectancy (EE)	EE2	3.73	1.101	0.823	0.892	0.737	0.892
	EE3	3.76	1.042	0.921			
	EE4	3.68	1.088	0.728			
Social Influence (SI)	SI1	2.22	1.127	0.821	0.844	0.733	0.847
	SI2	2.28	1.162	0.899			
Facilitating Conditions (FC)	FC1	3.87	1.133	0.830	0.742	0.521	0.742
	FC2	3.39	1.139	0.715			
	FC3*	3.38	1.304	0.586			
Behavioural Intention (BI)	BI1	3.50	1.271	1.038	0.917	0.883	0.715
	BI2	3.63	1.268	0.842			
	BI3	3.76	1.267	0.592			
Use Behaviour (UB)	UB1	2.89	1.327	0.837	0.785	0.686	0.804
	UB2	2.31	1.267	0.688			

*Negatively worded item was reverse-coded

Table 2. Summary table of averages, standard deviations, convergence, and discriminant validity indicators (Source: edited by the authors)

The discriminant validity of the established model is satisfactory, as none of the correlation values exceeded the 0.85 threshold, which, according to Henseler et al. (2015), would suggest weak discriminant validity. The correlations identified between the constructs are illustrated in Table 3.

	BI	EE	FC	PE	SI	UB
BI						
EE	0.677					
FC	0.559	0.767				
PE	0.778	0.607	0.469			
SI	0.439	0.272	0.244	0.336		
UB	0.654	0.473	0.394	0.758	0.463	

Table 3. Heterotrait-monotrait (HTMT) ratio matrix
(Source: edited by the authors)

4.2. Reliability

The reliability of the model's constructs can be assessed using three tests: Cronbach's alpha (α), average variance extracted (AVE), and composite reliability (CR). A measurement model is considered acceptable if the three criteria mentioned above are met, i.e., $\alpha > 0.5$ (or ideally 0.7), AVE > 0.5 (Fornell and Larcker 1981), and CR > 0.7 (Malkanthie 2015). As shown in Table 2, for each construct, a Cronbach's α value of 0.742 or higher is observed, the AVE consistently exceeds 0.521, and the composite reliability (CR) is greater than 0.715 in all cases. These results suggest that the measurement model achieves an optimal level of reliability.

4.3. Model Fit

In addition to the aforementioned, we also examined the absolute and relative fit of the model. For the absolute fit, the chi-square test yielded a value of 771.941 (df=113) with a probability level of 0.000. Furthermore, the χ^2/df ratio was 6.831. The additional absolute fit indices showed the following values: GFI: 0.825; AGFI: 0.763; RMSEA: 0.115; SRMR: 0.256. When evaluating relative fit, the NFI, TLI, and CFI indices were considered. The NFI was 0.85, the TLI was 0.841, and the CFI was 0.868. Overall, based on the recommendations in the literature (Byrne and St 2022; Doğan 2022; Heene et al. 2011; Lide, Mat Daud and Shidrah 2013; Mohammad and Yusoff 2018), the model fit is considered acceptable. Furthermore, it can be stated that the model is suitable for parameter estimation and interpretation.

4.4. Hypothesis Testing and Estimations

The covariance-based structural model was applied with the aim of investigating the previously outlined hypotheses and gaining a deeper understanding of university students' intentions to use artificial intelligence. The results of the hypothesis testing are summarized in Table 4, along with the unstandardized and standardized regression weights measured in the model. In cases where a statistically significant relationship ($p<0.05$) was confirmed in the predicted direction, the corresponding hypothesis was accepted.

Hypothesis	Relationship	Regression weights				Standardized regression weights	Result
		Est.	S.E.	C.R. (T)	P		
H1	PE → BI	0.640	0.047	13.504	0.000	0.679	*accepted*
H2	EE → BI	0.308	0.056	5.501	0.000	0.306	*accepted*
H3	SI → BI	0.238	0.045	5.260	0.000	0.229	*accepted*
H4	FC → BI	0.113	0.057	1.972	0.051	0.110	*rejected*
H5	FC → UB	0.132	0.077	1.725	0.085	0.101	*rejected*
H6	BI → UB	0.724	0.058	12.419	0.000	0.570	*accepted*

Table 4. Unstandardized and Standardized Regression Weights and Hypothesis Testing (Source: edited by the authors)

To ensure the stability of the obtained parameters, we employed the bootstrapping procedure, which generates random samples from the original dataset, allowing us to verify how stable or sensitive the parameter estimates are to slight changes in the data. In the case of hypothesis H5, both the primary and secondary evaluations (bootstrapping procedure) revealed a significantly high p-value, leading to the clear rejection of hypothesis H5. In the primary analysis, hypothesis H4 yielded a p-value very close to the 0.05 threshold, which led to the rejection of hypothesis H4. After applying the bootstrapping procedure, it was confirmed that the relationship outlined in hypothesis H4 was not significant, as the secondary analysis produced a p-value of 0.123 (H5: $p=0.206$, while H1; H2; H3; H6: $p=0.000$).

Figure 2 displays the standardized estimates and factor weights, illustrating the relationships between the model constructs and the observed indicators, as well as the model's correction factors.

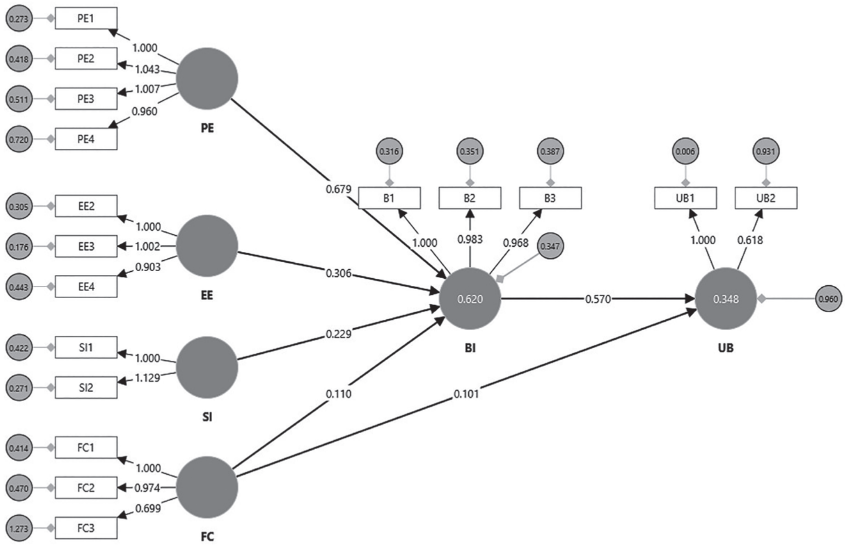

Figure 2. Model results
(Source: edited by the authors)

5. Discussion

In the following sections, we summarise and evaluate the results of our empirical research based on the hypothesis formulated in advance.

First, we suggested that students' performance expectancy regarding artificial intelligence would have a positive impact on their intention to use the technology (H1). This hypothesis was supported (β=0.679, p=0.000), confirming that the anticipated performance benefits of AI play a significant role in shaping university students' usage intentions. In other words, the more useful students perceive a given AI tool to be, the more likely they are to adopt it in their studies. This underscores the importance of explicit communication highlighting the advantages of AI to enhance technology acceptance. The findings are broadly consistent with previous research outcomes. Studies conducted in various educational contexts have consistently identified performance expectancy as a significant predictor of technology usage intention, either in relation to interactive whiteboards or online learning platforms (Wong, Teo and Russo 2013; Yudiatmaja et al. 2022). Furthermore, multiple studies have underscored a positive correlation between performance expectancy and usage intention (Basak, Wotto and Belanger 2018; Xue, Rashid and Ouyang 2024).

Our second hypothesis (H2) proposed a positive relationship between effort expectancy and behavioural intention. The results support this hypothesis (β=0.306, p=0.000). Accordingly, the easier students find operating AI tools or acquiring necessary knowledge to use such technologies, the more likely they are to use them. This finding highlights the importance of user-friendly interfaces and simplified access to AI-based technologies. The positive relationship between effort expectancy and usage intention has been confirmed in multiple studies examining technologies used in education. For instance, Chao (2019) and Shaya, Madani and Mohebi (2023) investigated the acceptance of mobile-based learning and identified a significant positive correlation between effort expectancy and usage intention. Similar findings have been reported in adaptation studies focusing on ICT tools and virtual reality (VR) headsets (Shen et al. 2017).

Our third hypothesis (H3) proposed a positive relationship between social influence and behavioural intention. Following the analysis, this hypothesis can also be accepted ($\beta=0.229$, $p=0.000$). This suggests that feedback from key reference groups – such as family, friends, and acquaintances – positively influences students' intention to use artificial intelligence for study-related tasks. It also implies that social support and reinforcing peer influence can facilitate AI adoption. The majority of studies in this field reach similar conclusions regarding the relationship between social influence and usage intention in the context of educational technology adoption. For example, a study conducted in Taiwan examined students' behaviours and habits related to an e-learning system and identified a positive relationship between social influence and behavioural intention (Liao, Yu and Yi 2011). This correlation is further reinforced by Haripin and Warsono (2024), who also investigated the acceptance of e-learning systems using the UTAUT model.

The fourth hypothesis (H4) proposed a positive relationship between facilitating conditions and behavioural intention. However, the results did not support this hypothesis ($\beta=0.110$, $p=0.051$). The weak correlation and the p-value approaching the significance threshold indicate that facilitating conditions – such as infrastructure and institutional support – do not have a statistically significant effect on students' intention to use AI. While facilitating conditions are generally considered an important factor in technology adoption, they do not appear to play a decisive role in shaping AI-related usage intentions among university students enrolled in this study. These findings contrast with the prevailing literature, where facilitating conditions have frequently been identified as strong predictors of behavioural intention in educational technology adoption. Studies on e-learning systems in higher education have consistently demonstrated a significant positive relationship between facilitating conditions – such as access to technological infrastructure and human support – and students' willingness to engage with these technologies (Alblooshi and Abdul Hamid 2021; Nain 2021). Nonetheless, there are some empirical findings that support our results, as previous research has also identified instances where facilitating conditions exhibit only a marginal positive effect on technology acceptance. Maita et al. (2018), for instance, found a weak relationship between facilitating conditions and usage intention in the context of academic information systems. Shah et al. (2024) reached similar conclusions. Three potential explanations may account for the negligible relationship observed between facilitating conditions and AI usage intention in this study. One plausible explanation is that the technological infrastructure necessary for AI usage – such as Wi-Fi access, computing resources, and relevant software – may already be widely available at the university. If students take these resources for granted, they are unlikely to perceive them influential in their decision to engage with AI. This aligns with previous research suggesting that when technological prerequisites are already met, the effect of facilitating conditions on adoption intentions diminishes. Another possible explanation is students' lack of awareness regarding the AI-related resources and support systems provided by the university. If students are unaware of available AI tools, specialised software licenses or dedicated AI learning spaces, they may not factor these resources into their decision-making process. This suggests that insufficient institutional communication about available AI resources could be a contributing factor to the weak relationship observed in this study. A third explanation relates to students' perceived lack of technical preparedness for AI use. If students do not feel sufficiently skilled or trained to use AI effectively, the presence of facilitating conditions alone may not be enough to influence their adoption intention. This perspective is consistent with prior studies highlighting that users' self-efficacy and prior technological experience shape the influence of facilitating conditions on technology acceptance (Venkatesh et al. 2012b; Wang et al. 2020; Al-Maroof et al. 2021).

The fifth hypothesis (H5) proposed a direct positive relationship between facilitating conditions and actual use. Based on our results, the hypothesis was rejected ($\beta=0.101$, $p=0.085$). This suggests that in higher education contexts, the availability of infrastructure and other critical intellectual and technical resources necessary for operating artificial intelligence does not significantly influence students' technology usage intention or their actual usage behaviour. These findings diverge from the general conclusions of previous research in the field. Most studies suggest that facilitating conditions exhibit a significant positive relationship with actual technology use. For instance, prior research has demonstrated that supporting conditions positively influence the adoption of online learning practices (Tahir 2023). However, Handoko (2019) found that among students participating in online learning programmes, facilitating conditions did not have a direct effect on actual use. Similarly, another study by Kuciapski (2016) concluded that facilitating conditions influence actual usage only indirectly, through behavioural intention, rather than via a direct relationship. The weak relationship identified between facilitating conditions and actual use in this study may be explained by several factors. The findings suggest that the formation of actual usage behaviour is primarily driven by motivational factors – such as psychological and social influences – rather than by infrastructural conditions. This implies that students' decisions are largely shaped by their perceptions of the technology's usefulness (performance expectancy, H1) and ease of use (effort expectancy, H2) rather than by the mere availability of supporting conditions. Another possible explanation is that although the necessary technological resources are accessible to students, they may not be optimally utilised. Students may not take full advantage of these resources, especially if they do not perceive immediate and tangible benefits from using them. This scenario is probable when students receive insufficient guidance or practical support in understanding the explicit advantages of AI adoption in their studies. A further factor that may contribute to the weak relationship is the level of independence students maintain from university-provided infrastructure. Many students develop their own learning strategies and may not feel the need to rely on institutional resources. This aligns with the observation that AI tools are increasingly accessible on personal devices such as laptops and smartphones, reducing students' dependence on university infrastructure. As a result, institutional facilitating conditions may not play a crucial role in shaping students' actual AI usage.

Finally, the sixth hypothesis (H6) proposed a positive relationship between students' intention to use artificial intelligence and their actual AI usage. The results support this hypothesis ($\beta=0.570$, $p=0.000$), reinforcing the notion that university students who are open to AI adoption are more likely to integrate AI into their academic activities. The positive association between behavioural intention and actual technology use in educational contexts has been well documented in prior research. Studies on technology acceptance in online education consistently indicate a strong positive correlation between usage intention and actual adoption (Tahir 2023). Similarly, Awwad and Al-Majali (2015) examined electronic library services at Jordanian universities and concluded that alongside facilitating conditions, usage intention plays a decisive role in determining actual use. These findings align with the broader technology acceptance literature, suggesting that fostering a strong intention to use AI is a critical factor in ensuring its widespread adoption.

6. Conclusions

The empirical research carried out among Hungarian university students has successfully identified the factors that influence the acceptance and adoption of artificial intelligence. In summary, the most significant predictors of artificial intelligence usage are personal perceptions, specifically performance expectancy and effort expectancy. Additionally, social influence contributes to shaping actual usage behaviour, although its impact is comparatively low. By contrast, facilitating conditions, including both human and material infrastructure, did not emerge as key determinants of students' AI usage intention or actual adoption. This finding suggests that while infrastructural availability is important, it does not play a decisive role in driving AI adoption in higher education when students already have access to necessary resources.

Despite its contributions, the study has certain limitations. It focused solely on Hungarian university students, limiting generalisability. Future research should explore diverse educational and cultural contexts. The quantitative approach offered robust insights, but qualitative methods – such as interviews or focus groups – could reveal deeper motivations and barriers to adoption. Moreover, this study examined individual-level factors only, hence future work should also consider institutional elements like faculty support, curriculum design, digital literacy initiatives and formal regulations governing AI use in teaching and assessment. Institutional policies and educators' decisions regarding the permitted or restricted use of AI tools may substantially shape students' actual usage behaviour. Examining such contextual and regulatory factors would provide a more comprehensive understanding of AI adoption in higher education.

The findings offer practical guidance for universities, policymakers, and developers. Higher education institutions should enhance awareness of AI's benefits and offer training to improve students' perceived ease of use. Encouraging peer collaboration and integrating AI into learning tasks can amplify social influence, which ultimately promotes the formation of acceptive behaviour. Policymakers should support AI literacy, while developers should design intuitive, education-focused AI tools to drive broader adoption.

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