Entrepreneurial Business and Economics Review

2025, Vol. 13, No. 3

10.15678/EBER.2025.130308

Understanding artificial intelligence chatbot quality and experience: A higher education student perspective

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A B S T R A C T

Objective: The article aims to identify the key aspects that define service quality for artificial intelligence chatbots (AICB) in higher education, based on insights from students. The second objective is to put AICB quality into the broader context of other key variables associated with student experience of AICB, such as AICB adoption, AICB usability, AICB engagement, and AICB mistrust.

Research Design & Methods: Based on extant service quality research and established scale development techniques, the study constructs, refines, and validates a multidimensional AICB service quality scale through a series of pilot and validation studies. The article includes both qualitative and quantitative technics, as we developed a questionnaire based on a literature review and 48 mini focus group interviews. In total, 308 participants filled out the questionnaire. For the analyses, we applied both exploratory and confirmatory factor analysis together with scale validation and correlation analysis.

Findings: We began the AICB service quality scale with 27 items across five dimensions: AICB quality, AICB mistrust, AICB usability, AICB adoption, and AICB engagement. The final scale consisted of 15 items across four dimensions with only AI engagement left out. Data analysis emphasised the critical role of AI quality in AI usability and AI adoption. The research also confirmed AI mistrust is an important aspect with a negative connection to AI quality.

Implications & Recommendations: The study results have several theoretical and practical implications. From the theoretical standpoint, we confirmed that the quality of artificial intelligence (AI) plays a central role in forming student experience. Quality of AICB received the highest score in this analysis (5.03) while AICB mistrust scored lowest (3.58). On the other hand, when it comes to individual correlations between student experience elements and AICB quality, mistrust in AICB shows a negative correlation with the highest score (-0.48). Use and adoption are both connected to AICB quality in a positive way. Results show us there is room for improvement in both AICB quality and student experience since average scores were in the range of 4.5-5.0. The results also emphasised the importance of reducing AICB mistrust for improving AICB quality and overall experience.

Contribution & Value Added: The AICB quality scale facilitates theory development by providing a reliable scale to improve the current understanding of student perceptions regarding different aspects of AICB quality. Higher education institutions (HEI) can use the study results to understand the impact of new technologies such as AICB on student experiences.

Article type:	research article
Keywords:	artificial intelligence (AI); chatbots; artificial intelligence chatbots (AICB); AICB experience; AICB quality; higher education
JEL codes:	C38, I23

Received: 16 October 2024 Revised: 17 February 2025 Accepted: 31 March 2025

Suggested citation:

Dužević, I., Baković, T., & Surman, V. (2025). Understanding artificial intelligence chatbot quality and experience: A higher education student perspective. *Entrepreneurial Business and Economics Review,* 13(3), 151-170. https://doi.org/10.15678/EBER.2025.130308

INTRODUCTION

Higher education institutions (HEIs) function as service providers, they are under extensive pressure to satisfy the needs and expectations of various stakeholders, mainly customers. In the higher education system, students are the primary customers, as they directly engage with educational services, invest in their learning, and ultimately benefit from the acquired knowledge and skills (Eagle & Brennan, 2007). Therefore, this article examines students as customers. Higher education institutions look for opportunities that allow for an increase in institutional performance and related satisfaction. The growing competition at both the national and international levels, the increase in the number of HEIs, the growing demand for domestic institutions to appear on the international scene, as well as the need to increase their competitiveness, require institutional management to pay more attention to the education services quality and the students' expectations. The application of AI into education processes has a significant influence on both institutional performance and student satisfaction. However, there is limited literature on measuring AICB service quality and experience in HEIs.

With the widespread adoption of AI services in every aspect of business and life, it is important to explore its quality aspects and monitor its performance by developing valid measurement scales. According to the quality management literature, understanding the voice of the customers is the basis for quality enhancement. Therefore, the state-of-the-art has already started to pay attention to the implementation of different methods to explore customer experiences with AI services (Marimon *et al*., 2024; Noor *et al.*, 2022; Prentice, 2023; Qian *et al.*, 2022). However, there is a need for further research and development of comprehensive instruments focusing on this field (Cox, 2021).

The implementation of AI in higher education (HE) is spreading immensely, highlighting many new challenges (biases in datasets and algorithms, plagiarism, and privacy concerns) and opportunities (increasing stakeholder satisfaction). According to Hannan and Liu (2023), AI has the potential to reshape HEIs in various ways. It changes the roles of students and teachers in the education system (Blau & Shamir-Inbal, 2018; Niemi, 2020; Ali *et al.*, 2021). Perception of students' role in HE evolved from passive consumers to the users whose needs must be identified and satisfied, and finally to the active participants in the teaching and learning process who equally participate in all processes (Dužević *et al.*, 2018). The new role of students is even more important considering the technology development and evolution of new teaching and learning models, based on AI. Students are offered different AI-based services for learning and research purposes, and with good preparation and guidelines this could increase the effectiveness and productivity of the educational processes (Liu *et al.*, 2022). Therefore, understanding the student experience is crucial for enhancing HE service quality.

One of the areas in which AI services are used is certainly AI chat tools or chatbots. The use of AI in HE is becoming increasingly popular (Dempere *et al.*, 2023; Rudolph *et al.*, 2023; Neuman *et al.*, 2023), but it is not yet possible to speak of mass application. Chat tools for individual courses and some universities as a whole are still a long way from being an industry standard (Heryandi, 2020). Many studies look at the implementation process and related experiences with AI chat tools in HE and show that students adopt them very quickly (Crawford *et al.*, 2023). For this reason, we focused on the broader question of how students perceive the quality of services offered by AICB (AI-based chatbots, especially Chat GPT) and their current experiences.

This article aims to examine services, including AICBs, as conventional services and assess their quality comprehensively. As students increasingly demand higher standards and play a more active role in shaping HE services, it becomes essential for HEIs to align their processes with student expectations. Noteworthy, AICB services are now integral to the teaching and learning experience, necessitating rigorous evaluation and quality measurement. To this end, we employed mixed-method approaches to develop and validate a reliable scale for assessing AICB service quality. This scale offers valuable insights for HE professionals in evaluating AICB performance and assists developers in identifying and addressing specific user needs and expectations.

Our research questions were the following:

RQ1: What are the key dimensions for assessing the quality of AICB for students in HE?

RQ2: What is the connection between AICB quality and other key aspects of AICB experience?

The article is structured as follows. The subsequent section presents a review of the relevant literature, emphasizing key aspects of service quality in higher education from the customer perspective, the integration of artificial intelligence in HE services, and the associated dimensions of AI-enabled service quality. The following section outlines the research methodology, detailing the development of the survey instrument and the procedures employed for data collection. Thereafter, we present the principal findings, followed by a critical discussion that contextualizes the results within the existing body of literature. Finally, the article concludes by summarizing the key outcomes of the research and outlining implications for future studies.

LITERATURE REVIEW

This part of the article discusses the key concepts namely: customer experience, AI services and the problem of measuring their quality.

Customer Experience and Service Quality in HE

With the development of HE, the focus is on the needs and expectations of students and other direct stakeholders. The increasingly intense competition for potential students makes it necessary to measure, evaluate, and provide feedback on the appropriate aspects of student experiences, perceptions, and satisfaction with adequate methods (Elsharnouby, 2015; Tóth & Surman, 2019). Scholars study students' experience within different fields and determine it as a very complex area connected to service quality. From the student life cycle perspective, it can be explored based on the freshman experiences (Kahu & Nelson, 2018), career development (Stiwne & Jungert, 2010), student engagement (Close, 2018; Kuh, 1995), student development (Surman *et al.*, 2022) and participation in extracurricular activities (Dean & Gibbs, 2015; Bakoban & Aljarallah, 2015).

In the last 25 years, the research focus in the quality management field moved towards customer experiences (Tan *et al.*, 2016). The primary focus is to identify the areas and processes in HE that affect students' development and growth and to define the institutional practices that can improve study experiences (Hong *et al.*, 2020). Considering the topic's complexity and different perspectives, research can explore the student experiences through three dimensions: the social dimension which includes the relationship between students and different subjects they meet during student life, the educational dimension containing all the factors related to the teaching and learning, and personal dimension which focuses on different aspects of student life. To summarise, we may define student experience as the physical and emotional perceptions that students feel during the interactions with products, systems or services provided by the HEIs and interactions with persons that are related to the academic environment (Matus *et al.*, 2021).

The modern HE system is based on innovative teaching and learning techniques and the use of technology to enhance student experiences and provide student support. AI-based support systems have the potential to significantly improve the productivity and effectiveness of all educational processes. Therefore, it is of utmost importance to explore student perceptions and experiences. Our study contributes to a nuanced understanding of student perspectives, serving as a foundational resource for further explorations and strategic integrations of AI within HE systems.

The Use of AI Services in HE

Artificial intelligence is a technology that enables systems or machines to imitate the behaviour of intelligent beings (Poole & Mackworth, 2010). It is a multidisciplinary field that aims to understand the functioning of human minds and apply the same principles in technology design. We may expect many changes in HE based on AI implementation, as today, the use of AI in the classroom is becoming an integral part of the learning process (Goralski & Tan, 2020). Scholars explore the application of modern technology in HE mainly through the new role of the students, as they increasingly become active and independent participants in educational processes (Bedzsula & Tóth, 2019). They became partners in these processes with their participation in designing content, teaching-learning experiences and outcomes, and assessing the learning outcomes (Blau & Shamir-Inbal, 2018). Accordingly, the teacher's role is also changing in such a way that in digital pedagogy the emphasis is on facilitating and guiding students (Niemi, 2021). These changes bring new opportunities for enhancing educational processes. The use of AI tools has the potential to increase teaching effectiveness, optimise the curriculum, and encourage students to deep learning (Liu *et al.*, 2022). Moreover, AI can imitate the role of both the teacher and the student (Dodigovic, 2007) and possibly replace the teacher (Goralski & Tan, 2020). Chen *et al.* (2020) highlight that the implementation of AI in HE has started as computer technologies, and transferred into web-based online education services, and the newest transformation is into humanoid robots and chatbots that serve as educators independently of the instructors. The use of AI could make it easier to perform different administrative tasks, such as assessment and grading of student work, curriculum customization and review of other teaching materials (Chen *et al.*, 2020) and improve assessments to better prepare students for careers (Slimi & Carballido, 2023). Therefore, it is necessary to reshape the HE system because otherwise, people will no longer see it as a means of employment or career development (Siau, 2017). Moreover, AI can improve the studying experience through the customization of international student support. By 2025 the number of international students will increase to 8 million, and this trend brings challenges such as language barriers, cultural differences, or specificities of the local education system. AI can play an important role in solving these issues (Wang *et al.*, 2023; Marcus *et al.*, 2023). Academic counselling is another possibility, but it is still in the testing phase (Khare *et al.*, 2018).

The implementation of AICBs in HE presents many challenges and concerns (Westman *et al*., 2024). These include concerns about data privacy, over-reliance on AI and erosion of critical thinking skills (Duran, 2024), reduced human interactions (Duran, 2024), potential algorithmic bias and plagiarism risk (Williams, 2024), transparency, reliability, and access equity (Al-Zahrani, 2024). Maeda and Quan-Haase (2024) emphasise the negative consequences of anthropomorphised chatbots that play social roles and often just want to earn the trust of their human users, while this trust can potentially be misused and opens a series of ethical questions like sensitive information leaks etc. These negative aspects of AICB implementation in HE resulted in mistrust and prejudice that represent a critical barrier to the full realization of the technology's potential (Hutson & Plate, 2024). Therefore, there is a need for balanced regulation of AICBs application in HE to ensure thoughtful and responsible integration of AICBs within HEIs (Dempere *et al*., 2023).

To summarise, the influence of AI on the HE system is complex and multifaceted. The number of research papers that use concrete indicators is very limited since AI is developing rapidly. There is a need for additional research on AI effects on HE systems using a comprehensive approach that integrates different research areas (Cox, 2021). The future development of HE will certainly include different AI-based tools. Therefore, it is important to explore students' expectations and perceptions of widely available AI tools, and based on that, monitor the service quality performance.

The primary focus of this article is the direct students' attitude and experience with publicly available AI-based tools, highlighting the AICB. We centred the research on AICB because they are adopted by users at a rapid pace including many university students, who found them very useful for everyday study purposes (Dempere *et al.*, 2023; Rudolph *et al.*, 2023; Crawford *et al.,* 2023; Neumann *et al.*, 2023). Furthermore, HEIs will eventually need to offer their versions of AICB at different levels resulting from the changing customer needs (Hien *et al.*, 2018; Heryandi, 2020). However, it seems that the rapid adoption of commercialised AICB like ChatGPT has shifted the focus from developing customised AICB to investigating what is the best way of using the ones that are already available to students in the context of HE (Rudolph *et al*., 2023).

Measuring AI Service Quality Dimensions

The measurement process and dimensions of service quality differs between sectors. According to the literature, when focusing on technology, service quality should include perceived quality dimensions and dimensions related to technology dissemination. As Dou *et al.* (2024) presented, the incorporation of AI into various processes could strategically influence the performance and the value created, therefore, its service quality evaluation is very important. Yan *et al.* (2023) highlighted that user service and information security are some of the main factors related to AI service quality measurement. There are various scales for measuring AICB service quality, based on different dimensions (Alwagdani, 2024; Grassini, 2023; Jabborow *et al*., 2023; Lazar *et al*., 2020; Lupo & Buscarino, 2021; Kim-Soon *et al*., 2014; Noor *et al*., 2022; Prentice, 2023; Qian *et al.,* 2022; Scharowski *et al*., 2024; Westman *et al*., 2021). Most of the scales are derived from the E-S-QUAL scale for assessing electronic service quality with the following variables: efficiency, system availability, fulfilment, and privacy (Parasuraman *et al*., 2005). Prentice (2023) developed a scale specific to AI application as a service with the following dimensions: reliability, assurance, tangibility, empathy, and responsiveness. A study by Noor *et al.* (2022) focused on AICB service quality and used a scale with seven second-order and eighteen first-order constructs. The authors found a positive influence on customer satisfaction, perceived value, and intention of continuous use of AICBs. Moreover, Qian *et al.* (2022) proposed a multidimensional scale to evaluate service quality across AI service agents with dimensions such as efficiency, security, availability, enjoyment, contact, and anthropomorphism. Although each article focused on different special areas, part of their conclusions were the same: more and deeper research is needed to discover and validly measure the service quality of AI in general.

Scholars usually conduct studies with AI in HE focus concerning web-based online education service quality. These studies are based on the technology acceptance model (TAM) developed by Davis (1989). The model suggests that perceived ease of use is an antecedent of perceived usefulness which directly influences IT system usage. Lupo and Buscarino (2021) developed an effective measurement tool considering the students' perspectives and revealed the three-factor structure, including usability, security, and fundamental content. Kim-Soon *et al.* (2014) extracted the following dimensions: availability, convenience, organised interface, ease of use, meeting needs, and schedule flexibility. Meanwhile, Al-Mughairi and Bhaskar (2024) did not exactly deal with the service quality aspect of AI in HE, however, their findings give input to the determination of these dimensions. They presented that the main motivating factors of using AI in teaching (by the teachers) are the exploration of innovative education technologies, the personalization of teaching and learning, time-saving and the support in professional development. The inhibiting factors included the reliability and accuracy concerns, the reduced human interaction, the privacy and data security problems, the lack of institutional support and the possible overreliance on them. Pereira *et al.* (2023), Hamam (2021) and Huddar *et al.* (2020) studied the HE AICBs demonstrating that they play a significant role in the digital transformation of education, offering support for university education and providing individualised experiences for students. They pinpointed that they improve teaching and learning, increase student engagement, and provide 24/7 availability for answering queries. Since AI-based services are largely incorporated into HE processes, there is a need to develop a comprehensive and reliable instrument for measuring its quality from the perspective of students.

Another stream of literature (Chadha, 2024; Maeda & Quan-Haase, 2024; Lazar *et al*., 2020) focuses more on variables closer to customer experience with AI. Chadha (2024) analysed AI-driven personalised learning systems through case studies, showing how they improve student engagement and tailor educational experiences, while also addressing concerns about fairness and accessibility.

As we may see from previous research they are mostly oriented on developing scales for measuring AI quality or they analyse customer experiences. In this article, we focus on connecting these two areas of research. One may assess AICB service quality as any other service, more precisely, user perceptions and experiences can serve to define key dimensions of AICB service quality, considering both the quality of the technology and its dissemination.

RESEARCH METHODOLOGY

Our study aimed to determine core elements that could represent the variables of AI quality related to chatbots and put these variables into the broader context of customer experience. The research contained the following steps (Figure 1). Based on the literature review, we determined the main service quality elements related to the HE student perspectives of AI. Then, we conducted 48 mini-focus groups to understand these elements more deeply and complete the list of AI service quality factors. As a result of the literature review and focus group interviews, we developed an online questionnaire and shared it with the students of the Faculty of Economics and Business. Based on the collected data exploratory factor analysis (EFA), and confirmatory factor analysis (CFA), we performed scale reliability analysis and correlation analysis.

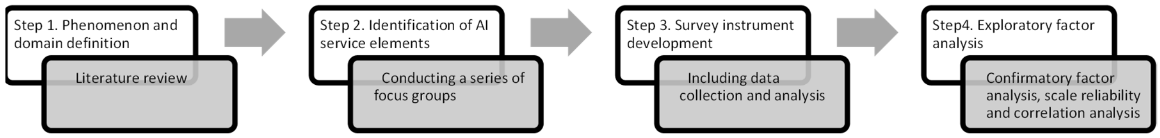

Figure 1. Outline of research methodology
Source: own elaboration.

Identification of AI Service Elements

We conducted the focus group interviews in September and delved into the perceptions and perspectives of 222 HE students regarding the incorporation of AI within the realm of academia. Employing a structured approach through 48 mini-focus groups, consisting of 4-6 participants each, we sought to elucidate three critical dimensions of AI's role in HE.

Defining Quality in AI Operations

We prompted students to articulate their understanding of quality in AI operations, resulting in the identification and delineation of a comprehensive array of 192 distinct quality dimensions. Participants highlighted speed and accuracy as top priorities regarding the quality of AI. Many students pinpointed the reliability and validity of the information provided by the AI. Therefore, the incorporation of AI in the operation of various frameworks should handle these two dimensions on a high level, since their absence would fundamentally deteriorate the effectiveness of the implementation, the users' experience and commitment as well.

Artificial Intelligence's Role in Institutional Operations

The study sought to extract insights into the perceived utility and applicability of AI within the operational framework of HEIs. Participants delineated 116 potential use cases, outlining a diverse spectrum of applications spanning administrative, pedagogical, and operational facets (most of which the literature pinpointed as well). Students saw the support provided by AI in many institutional areas. According to the responses, it could help in optimal timetable planning (from both students' and lecturers' points of view), task design, case study and exams, as well as, in the correction of them. Students pointed to the help of administrative activities and frequently asked questions operation. They also saw its relevance in the improvement of presentation slideshows and the support of research work.

Artificial Intelligence's Support in HE Studies

We encouraged participants to envision scenarios where AI could serve as a facilitative tool in augmenting their HE pursuits. This elicited 125 scenarios, highlighting the students' perspectives on the potential integration of AI as a supportive mechanism in academic endeavours, including personalised learning aids and advanced research assistance. Mainly, students would use AI to improve their thesis works, and their essays and to help their preparation for the exams. Moreover, they would implement it in an AICB to aid the student life on the university campus.

As highlighted, the students participating in these focus groups worked mainly alone on the received three topics, the primary work of the moderators was to start or continue the discussion along the results of the literature analysis, whether it stops or gets stuck, and to gain a deeper understanding of the highlighted aspects and dimensions to prepare the questionnaire.

Survey Instrument Development

We created the survey in view of the performed focus groups and literature review. The questionnaire included five phases with 37 questions each measured on a Likert scale from 1 to 7 (for the questions see Appendix).

The first phase focused on the student experience of quality dimensions pinpointed by previous research: accuracy, reliability, efficiency, scalability/objectivity, interoperability, adaptability, design and context, min. error or biases (eight questions). For deriving these questions, we used the work of Jabborow *et al*. (2023) which delves into quality assessment metrics for AI-based systems. Noor *et al*. (2022) also performed a study on the service quality scale for AI service agents and we used those results to define our questions. The second phase included AICB mistrust (six questions). To develop these questions, we used the work of Scharowski *et al*. (2024) whose study highlights the need to differentiate between the measures of AI trust and AI mistrust. We primarily derived the usability of AICB (nine questions) from Westman *et al*. (2021) although their primary focus was developing AI for career guidance. The fourth phase concentrated on AICB engagement (ten questions). For deriving the questions about engagement, we used the work of several authors (Maeda & Quan-Haase, 2024; Grassini, 2023; Westman *et al*., 2021). The last phase focused on AICB adoption (four questions). The standpoint from which scholars addressed AI adoption differed from author to author: attitude towards AI (Grassini, 2023), using the technology acceptance model (TAM) as a starting point (Lazar *et al*., 2020), and using AI as a career guiding tool (Westman *et al*., 2021). When defining questions, a distinction between usability and engagement needs to be made. Under usability, we primarily focused on the reasons why the students are using AICB while under engagement more focus is on how they use them. Usability resolves around how well AICB does certain tasks (Weichbroth, 2020) while engagement covers more fundamental changes based on preferences and behaviours (Prentice *et al*., 2020).

Data Collection

We researched a sample of students from the Faculty of Economics and Business, University of Zagreb. We created the questionnaire using an online platform and distributed it to students who actively attended classes during the winter semester of the academic year 2023/2024. The sample included students from undergraduate and graduate programs. We distributed the questionnaire to 1000 students, and after sending two reminders, we received 308 properly completed questionnaires. One of the questions eliminated those students who did not have proper experience with AI tools, and for that reason, we performed further analyses with 235 answers. The survey responses allowed us to conduct EFA with the statistical package for social sciences (SPSS 25) software.

RESULTS AND DISCUSSION

Primarily, this article aimed to identify the key aspects that define service quality for AI chatbots in higher education. Additionally, it is possible to put AI quality into the broader context of other key variables associated with student experience of AICB, such as AICB adoption, AICB usability, AICB engagement, and AICB mistrust. Table 1 presents descriptive statistics for the analysed variables.

Exploratory Factor Analysis

Exploratory factor analysis (EFA) allows researchers to explore the underlying structure of service quality by identifying patterns in data. It can reveal latent factors that represent key components (Bartholomew *et al*., 2011; Yong & Pearce, 2013) of service quality for AI. The results of the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity are key indicators used to evaluate the suitability of data for factor analysis. In this case, the data was very suitable for factor analysis, as evidenced by the high KMO value (0.852) and the significant Bartlett's test of sphericity ($p < 0.001$).

Table 6 (in Appendix 1) lists the eigenvalues associated with each factor before extraction, after extraction, and after rotation. SPSS extracts all factors with eigenvalues greater than one which leaves us with nine factors.

Table 1. Descriptive statistics for statements used

Aspect	Mean	Std. deviation	Aspect	Mean	Std. deviation
QUALD1	5.02	1.21	ENG6	5.14	1.68
QUALD2	4.74	1.25	ENG7	4.50	1.49
QUALD3	5.50	1.14	ENG8	3.83	1.84
QUALD4	4.97	1.24	ENG9	4.24	1.78
QUALD5	5.15	1.23	ENG10	3.38	1.42
QUALD6	5.17	1.32	USE1	5.44	1.44
QUALD7	5.35	1.31	USE2	4.95	1.57
QUALD8	4.68	1.39	USE3	4.78	1.61
MIST1	3.09	1.28	USE4	4.72	1.57
MIST2	3.21	1.34	USE5	4.20	1.64
MIST3	3.85	1.58	USE6	3.88	1.70
MIST4	4.07	1.61	USE7	5.15	1.34
MIST5	3.83	1.65	USE8	5.37	1.54
MIST6	4.14	1.67	USE9	5.00	1.65
ENG1	3.56	1.84	ADOP1	3.37	1.98
ENG2	5.35	1.41	ADOP2	4.07	1.92
ENG3	4.77	1.53	ADOP3	4.86	1.63
ENG4	4.68	1.59	ADOP4	4.73	1.68
ENG5	3.28	1.94	–	–	–

Source: own study in SPSS.

Another important aspect to consider is the rotated component matrix. The factors that we defined in the first part of the research process were: AICB quality, AICB mistrust, AICB engagement, AICB usability, and AICB adoption. After the rotation, there were four factors and suppressing of loadings less than 0.4 made interpretation considerably easier. The four factors retained for further analysis were: AICB quality, AICB mistrust, AICB usability and AICB adoption.

Table 2. Rotated component matrix (principal component analysis, varimax rotation with Kaiser normalization)

Variable	1	2	3	4	5	6	7	8	9
QUAL5	0.748								
QUAL4	0.738								
QUAL1	0.698								
QUAL3	0.692								
QUAL2	0.669								
QUAL6	0.607								
QUAL7	0.598								
QUAL8	0.566								
USE5		0.826							
USE6		0.746							
USE3		0.736							
USE9		0.639							
USE2		0.638							
USE4		0.634							
USE7		0.570					0.405		
USE8		0.461							
MIST4			0.778						
MIST3			0.775						
MIST1			0.690						
MIST2			0.606						

Variable	1	2	3	4	5	6	7	8	9
MIST6			0.569						
MIST5			0.529						
ADOP2				0.694					
ADOP3				0.676	0.478				
ADOP4				0.659	0.541				
ENG5				0.594			0.442		
ENG7				0.591					
ADOP1(R)					-0.680				
USE1					0.661				
ENG3						0.679			
ENG2					0.436	0.631			
ENG1						0.562			
ENG4						0.557			
ENG6							0.640		
ENG10								0.812	
ENG9									0.807
ENG8									0.503

Source: own study in SPSS.

We conducted a principal component analysis (PCA) on the 37 items with orthogonal rotation (varimax). The KMO measure verified the sampling adequacy for the analysis, KMO= 0.852, and all KMO values for individual items were above 0.6 which was above the cut-off level. Bartlett's test of sphericity = 3673.971, $p \leq 0.001$, indicated that correlations between items were sufficiently large for PCA. We ran an initial analysis to obtain eigenvalues for each component in the data. Nine components had eigenvalues over Kaisers criterion of 1 and in combination explained 63.91% of the variance. We chose four factors instead of nine to balance statistical rigour with interpretability and practical significance. While the Kaiser criterion suggests retaining nine factors, the first four explained a sufficient cumulative variance of 46.467%, and the scree plot showed a clear break after the fourth factor, indicating diminishing contributions from additional factors. This approach ensures a more parsimonious and meaningful model aligned with the article's theoretical framework. Table 2 shows the factor loadings after rotation. The items that cluster on the same component suggest that component 1 represents AICB quality, component 2 AICB usability, component 3 AICB mistrust, and component 4 AICB adoption.

Confirmatory Factor Analysis

Ideally, researchers should perform confirmatory factor analysis (CFA) on an independent sample to validate the model further (Byrne, 2016). However, due to practical constraints, we conducted the analysis on the same dataset used for initial development. We will acknowledge this limitation, and future research will aim to replicate the findings on a separate sample to enhance the model's generalizability and robustness. We decided to follow through with this step because it significantly adds to our conclusions about AICB quality and its context. We conducted the confirmatory factor analysis of 15 items and four variables to verify the model. We used a sample of 235 student users of AICB to conduct this analysis. Before presenting the analysis results, we needed to remove several items (Qual5, Qual6, Use9 and Adop2) because of low factor loadings or high residual variances as suggested by the first CFA output. After removing these items, the quality of our model increased above key threshold levels. Using indices recommended by Bagozzi and Yi (1988), initial CFA results indicated a significant chi-square value ($\chi^2 = 234.147$, $p < 0.001$).

Moreover, CFA results indicated that the proposed model demonstrated an acceptable fit to the data, supporting its use in subsequent analyses. Incremental fit indices, such as the comparative fit index (CFI = 0.906) and incremental fit index (IFI = 0.908), exceed the commonly recommended threshold of 0.90, indicating a good level of fit (Hu & Bentler, 1999). Absolute fit measures, including the root mean square error of approximation (RMSEA = 0.090, 90% CI [0.076, 0.103]), fell within the acceptable range (< 0.10), though slightly above the ideal threshold of 0.06 (Browne & Cudeck, 1993). Furthermore, the standardized root mean square residual (SRMR = 0.067) was below the recommended cutoff of 0.08 (Hu & Bentler, 1999). All factor loadings are statistically significant ($p < 0.001$) and substantively meaningful, providing further evidence for the construct validity of the factors. We will address minor areas for improvement, such as reducing residual variances for certain items, in future research. We will also elaborate on the theoretical justification for the model in the discussion, linking the constructs and their interrelations to the broader literature.

Scale Reliability Analysis

When using factor analysis to validate a questionnaire, one should examine the scale's reliability. Cronbach's alpha is the most common measure of scale reliability. The usual cut-off point for scale reliability is 0.8 or 0.7 (Heyes, 2009). Regarding the reliability analysis for the scale measuring AI quality, we used the previously determined four factors as subscales: AI Service quality, AI use for studying, AI mistrust and AI interactions. As Table 4 demonstrates, in all subscales, the reliability result is acceptable.

Table 3. Scale reliability analysis for AICB

Subscale	Cronbach alpha	Mean	No of items
AI quality	0.851	5.037	4
AI usability	0.865	4.518	5
AI mistrust	0.781	3.589	4
AI adoption	0.882	4.805	2

Source: own study in SPSS.

Factor Correlation Analysis

As we may see from correlation analysis AI was positively correlated to AI usability and AI mistrust, but negatively correlated to AI mistrust. This means that raising the quality of AICB positively impacts its usability and adoption. On the other hand, the lower quality of AICB increases mistrust in AI. All correlations were significant except for the one describing the connection between AI usability and AI mistrust.

Table 4. Correlation analysis

Correlations		AI quality	AI usability	AI mistrust	AI adoption
AI quality	Pearson Correlation	1	0.378**	-0.486**	0.257**
	Sig. (2-tailed)		0.000	0.000	0.000
	N	235	230	234	225
AI usability	Pearson Correlation	0.378**	1	-0.182**	0.377**
	Sig. (2-tailed)	0.000		0.006	0.000
	N	230	231	230	223
AI mistrust	Pearson Correlation	-0.486**	-0.182**	1	−0.108
	Sig. (2-tailed)	000	0.006		0.108
	N	234	230	234	225
AI adoption	Pearson Correlation	0.257**	0.377**	−0.108	1
	Sig. (2-tailed)	0.000	0.000	0.108	
	N	225	223	225	226

Note. **Correlation is significant at the 0.01 level (2-tailed).
Source: own study in SPSS.

Discussion

Both EFA and CFA confirmed four primary variables contributing to AICB implementation among the student population in higher education: 1) AICB quality, 2) AICB usability, 3) AICB mistrust, and 3) AICB adoption. The AICB quality dimension is the factor that includes accuracy, reliability, efficiency, and scalability/objectivity. The list of quality items excluded from research includes interoperability, adaptability, design and context, and min. error and biases. These resemble previous findings from Noor *et al*. (2022) who found six dimensions of quality in AI service agents (overlap in efficiency). Jabborov *et* *al*. (2023) also investigated the quality of AI systems through a list of quality attributes and our results overlap in the attributes of reliability, scalability, and efficiency.

The second factor was AICB usability which addresses different ways AI helps in the learning process. The items that were significant in the research cover topics as: language learning, social conversations, team assembly, and career help. Westman *et al*. (2022) focused on career guidance and found a positive contribution from AI. In a similar vein, Lupo and Buscarino (2021) recognised usability as a dimension of online education service quality. The work of Weichbroth (2020) focuses on the usability of mobile applications but it reveals the lack of definitions that make different aspects of new technology use hard to investigate.

The factor of AICB mistrust is related to results that are incorrect and confusing, or that require previous knowledge and clarifications. The literature mentions that AI algorithms work on the principle of 'customer satisfaction' which means their primary goal is delivering answers and the correctness of those answers is secondary (Mollick, 2024). Previous studies also emphasise the lack of accuracy and confidence in the AI results (Al-Mughairi & Bhaskar, 2024; Cox, 2021). Other studies also highlight the importance of trust in AI as a central element for improving performance and engagement and the need for treating trust and mistrust as two separate concepts (Scharowski *et al*., 2024, Marimon *et al*., 2024). Moreover, Alwagdani (2024) emphasised the role of mistrust in his research on the use of AI tools by the teacher population and proposed an approach based on targeted, collaborative, and ethical implementation.

The fourth factor, namely AI adoption, basically describes the preferences of students when it comes to including AI as a topic in courses and curriculum. The analysis left out two. The first one that related to teacher's bias and was reverse coded and the second one connected to including AI in student jobs and career opportunities.

We included the variable AI engagement in our theoretical framework as previous research emphasised the need to investigate how people engage chatbots in every aspect of human life including studying. Maeda and Quan-Haase (2024) emphasise the capability of AI tools to play human roles sometimes with bad and unethical considerations. The attitude that chatbots can roleplay as humans and therefore easily engage students is present in literature (Georgescu, 2018; Yang & Evans, 2019). Our scale emphasised the questions on how students engage with AICB but we excluded them from the final analysis due to the poor fit with the model. As suggested by Prentice *et al*. (2020), engagement covers more fundamental changes based on the preferences and behaviours of customers and we can conclude that although the adoption of AI technologies has been rapid, changing human behaviour will probably take some more time.

The scale also allows for recommending some of AICBs to students for faculty and work purposes. This will also become increasingly important since more HEIs will need to include AI services in various activities at the level of institution, program, and individual courses and all of these services require monitoring according to objective criteria. The article provides chatbot developers with feedback because they can track both the quality and experience certain groups like HE students get from using their services. Moreover, the study suggests there is still a high level of mistrust in AI services that both service providers and users need to address.

However, we noted several limitations. The study did not account for students' expectations regarding AICB quality, and the research sample was limited to students from a single faculty. Future research should validate this scale across different AI services and investigate causal relationships between AICB quality and influencing factors, as well as the impact of AICB quality on other implementation issues. Moreover, conducting a CFA on another sample would further validate the results. When it comes to the questions used our general impression is that we used questions that were too broad and not easy to understand by the student population.

We recommend several directions for future research, such as validating the AICB quality scale for other AI services and exploring the causal factors influencing AI service quality. Moreover, investigating variables such as student experience, which may be affected by AI service quality, will provide further insights into the broader implications of AI in HE. We also think research should address the link between AICB implementation and student performance in terms of their grades and overall satisfaction. Moreover, scholars may also investigate moderating factors related to services, the student and the student performance to uncover the boundary conditions under which the AICB service quality scale is likely to influence service outcomes. Researchers may also conduct longitudinal studies to assess how ongoing use of AICB can change HE outcomes. It would also be interesting to perform a similar survey on the population of teachers to check whether there are some big discrepancies in the treatment of AI from student and teacher perspectives.

CONCLUSIONS

The widespread adoption of AI tools and services is anticipated to permeate all key stakeholders in HE. As lead users, students have already recognised the advantages of these tools (Chen *et al.*, 2020). Conversely, HEIs, as formal entities, must address the implementation of AI services in a structured manner, raising questions related to regulation, ethics, and service quality (Cox, 2021; Marcus *et al.*, 2023; Yan *et al.*, 2023). To facilitate the mass adoption of AI services, it is crucial to evaluate their quality systematically (Dou *et al.*, 2024). This study proposes using an AICB scale for assessing the quality of commercially available AICBs and recommends their application for educational purposes. Moreover, the study highlights other key aspects of AICB experience in HE and their connection to AICB quality.

This study aimed to develop a robust scale for measuring the quality of AICBs, such as ChatGPT. Noteworthy, students already widely use AICBs in HE (Dempere *et al.*, 2023; Rudolph *et al.*, 2023; Crawford *et al.*, 2023; Neuman *et al.*, 2023). The research commenced with an extensive literature review to identify key variables associated with customer experience in AI services, particularly from the students' perspective. We conducted qualitative research, including focus groups with the student population, to refine these variables. The resulting core elements for assessing AICB quality in HE included: 1) AICB quality, 2) AICB usability, 3) AICB mistrust, 4) AICB adoption, and 5) AICB engagement. Compared to previous research (Hamam, 2021; Huddar *et al.*, 2020; Noor *et al.*, 2022; Prentice, 2023; Qian *et al.*, 2022), we further advanced the concept of AICB quality by investigating the relationship between AICB quality and other variables associated with AICB experience. The combination of EFA and CFA confirmed four primary variables contributing to AICB student experience: 1) AICB quality, 2) AICB usability, 3) AICB mistrust, and 4) AICB adoption.

The developed AICB quality factor provides a theoretical framework for linking AICB service quality with various aspects of the AICB experience. As a practical implementation direction, HEIs can utilise this scale to assess and enhance the implementation of accessible AICB services. Moreover, this study contributes to the service quality literature by presenting a scale with sound psychometric properties for measuring AICB quality.

Four key dimensions shape the implementation of AICB in higher education: quality, usability, mistrust, and adoption. The AICB scale quality is defined by attributes such as accuracy, reliability, efficiency, and scalability, which aligns with previous studies (e.g., Noor *et al*., 2022; Jabborov *et al*., 2023). However, the scale excludes aspects like adaptability and design. Moreover, AICB usability highlights the practical benefits of AI in areas like language learning and career guidance, supported by findings from Westman *et al*. (2022) and Lupo and Buscarino (2021). Noteworthy, AICB mistrust emerges as a critical factor, rooted in inaccuracies and ethical concerns, consistent with literature emphasising trust as pivotal for engagement and performance (Mollick, 2024; Scharowski *et al*., 2024). Finally, AICB adoption underscores the importance of integrating AI into curricula, reflecting student preferences, although broader engagement dynamics remain underexplored. These findings reinforce the need for targeted, ethical, and collaborative approaches to AI integration in academic contexts.

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Appendix:

Table 5. Questions used in the survey

S.No.	Abbreviation of the element	Question	Adapted according to
1	**QUALD1**	How would you rate your experience with AI tools in terms of accuracy?	Jaborov *et al*., 2023; Noor *et al*., 2022; Parasuraman *et al*., 2005
2	**QUALD2**	How would you rate your experience with AI tools in terms of reliability?	Jaborov *et al*. 2023; Noor *et al*., 2022; Parasuraman *et al*., 2005
3	**QUALD3**	How would you rate your experience with AI tools in terms of efficiency?	Jaborov *et al*., 2023; Noor *et al*., 2022; Parasuraman *et al*., 2005
4	**QUALD4**	How would you rate your experience with AI tools in terms of scalability/objectivity?	Jaborov *et al*., 2023; Noor *et al*., 2022; Parasuraman *et al*., 2005
5	**QUALD5**	How would you rate your experience with AI tools in terms of interoperability?	Jaborov *et al*., 2023; Noor *et al*., 2022; Parasuraman *et al*., 2005
6	**QUALD6**	How would you rate your experience with AI tools in terms of adaptability?	Jaborov *et al*., 2023; Noor *et al*., 2022; Parasuraman *et al*., 2005
7	QUALD7	How would you rate your experience with AI tools in terms of design and context?	Jaborov *et al*., 2023; Noor *et al*., 2022; Parasuraman *et al*., 2005
8	QUALD8	How would you rate your experience with AI tools in terms of min. error or biases?	Jaborov *et al*., 2023; Noor *et al*., 2022; Parasuraman *et al*., 2005
9	**MIST1**	The results provided by AI tools are incorrect.	Scharowski *et al*., 2024; Marimon *et al*., 2024
10	**MIST2**	The results provided by AI tools are confusing.	Scharowski *et al*., 2024; Marimon *et al*., 2024
11	**MIST3**	The results provided by AI tools typically require some basic knowledge of the field.	Scharowski, *et al*., 2024; Marimon *et al*., 2024
12	**MIST4**	The results provided by AI tools typically require further clarification.	Scharowski *et al*., 2024; Marimon *et al*., 2024
13	MIST5	The typical use of AI tools offers too many bullets/enumerations.	Scharowski *et al*., 2024; Marimon *et al*., 2024
14	MIST6	I have noted examples of incorrect statements in AI output.	Scharowski *et al*., 2024; Marimon *et al*., 2024
15	ENG1	I use AI tools for studying needs on a regular basis.	Maeda and Quan-Haase, 2024; Grassini, 2023; Westman *et al*., 2021
16	ENG2	The AI tools interface is user-friendly.	Maeda and Quan-Haase, 2024; Grassini, 2023; Westman *et al*., 2021
17	ENG3	The typical use of AI tools for me would be/is in the process of gathering new ideas.	Maeda and Quan-Haase, 2024; Grassini, 2023; Westman *et al*., 2021
18	ENG4	The typical use of AI tools for me would be/is in search of clear definitions.	Maeda and Quan-Haase, 2024; Grassini, 2023; Westman *et al*., 2021
19	ENG5	I would be/am ready to pay for some additional AI features.	Maeda and Quan-Haase, 2024; Grassini, 2023; Westman *et al*., 2021
20	ENG6	I usually/would double-check the results provided by AI tools.	Maeda and Quan-Haase, 2024; Grassini, 2023; Westman *et al*., 2021
21	ENG7	When I see the result from AI I typically (would) want to know more.	Maeda and Quan-Haase, 2024; Grassini, 2023; Westman *et al*., 2021
22	ENG8	When using AI tools, I (would) often get the feeling that I am communicating with a person.	Maeda and Quan-Haase, 2024; Grassini, 2023; Westman *et al*., 2021
23	ENG9	I have some concerns about the ethical implications of AI tools, such as biases in algorithms and job displacements.	Maeda and Quan-Haase 2024; Grassini, 2023; Westman *et al*., 2021
24	ENG10	A lot of teachers use some form of AI in their teachings.	Maeda and Quan-Haase, 2024; Grassini, 2023; Westman *et al*., 2021

S.No.	Abbreviation of the element	Question	Adapted according to
25	**USE1**	AI can help with F.A.Q.	Westman *et al*., 2021; Davis, 1989
26	**USE2**	AI can help with language learning.	Westman *et al*., 2021; Davis, 1989
27	**USE3**	AI can help with having a social conversation.	Westman *et al*., 2021; Davis, 1989
28	**USE4**	AI is useful in everything.	Westman *et al*., 2021; Davis, 1989
29	**USE5**	AI can help in team assembly.	Westman *et al*., 2021; Davis, 1989
30	**USE6**	AI can help choose the right career path.	Westman *et al*., 2021; Davis 1989
31	USE7	AI can provide additional and supplementary materials.	Westman *et al*., 2021; Davis, 1989
32	USE8	AI can provide immediate answers.	Westman *et al*., 2021; Davis, 1989
33	USE9	AI can help the exam preparation with examples and tasks.	Westman *et al*., 2021; Davis, 1989
34	ADOP1 (R)	I noticed teachers have a negative bias toward using AI for studying.	Lazar *et al*., 2020; Grassini, 2023; Westman *et al*., 2021
35	ADOP2	I am interested in working in AI-related fields or incorporating AI into my future career.	Lazar *et al*., 2020; Grassini 2023; Westman *et al*., 2021
36	**ADOP3**	I believe universities should incorporate more AI-related courses or education into their curriculum.	Lazar *et al*., 2020; Grassini, 2023; Westman *et al*., 2021
37	**ADOP4**	I believe universities should incorporate more AI-related tasks and examples into their courses.	Lazar *et al*., 2020; Grassini, 2023; Westman *et al*., 2021

Note. Each of the proposed statements was rated on a Likert scale from 1-7; Bolded items are questions with a load of 0.6 or higher; R stands for reverse coded.
Source: own study.

Table 6. Total variance explained (Principal Component analysis)

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.151	24.733	24.733	9.151	24.733	24.733	4.400	11.893	11.893
2	3.805	10.283	35.016	3.805	10.283	35.016	4.336	11.720	23.613
3	2.426	6.557	41.573	2.426	6.557	41.573	3.413	9.224	32.836
4	1.811	4.895	46.467	1.811	4.895	46.467	2.765	7.474	40.310
5	1.709	4.619	51.086	1.709	4.619	51.086	2.249	6.077	46.387
6	1.361	3.677	54.764	1.361	3.677	54.764	2.211	5.976	52.363
7	1.268	3.426	58.190	1.268	3.426	58.190	1.602	4.331	56.694
8	1.102	2.980	61.170	1.102	2.980	61.170	1.403	3.792	60.487
9	1.015	2.744	63.914	1.015	2.744	63.914	1.268	3.427	63.914
10	0.917	2.479	66.393						
11	0.883	2.387	68.780						
12	0.866	2.341	71.121						
13	0.795	2.149	73.270						
14	0.753	2.035	75.304						
15	0.730	1.974	77.278						
16	0.707	1.910	79.189						
17	0.627	1.695	80.884						
18	0.603	1.629	82.513						
19	0.559	1.511	84.023						
20	0.540	1.460	85.483						
21	0.510	1.379	86.862						
22	0.465	1.257	88.118						
23	0.458	1.237	89.356						
24	0.426	1.150	90.506						
25	0.416	1.124	91.629						
26	0.390	1.053	92.683						
27	0.355	0.960	93.643						
28	0.327	0.884	94.526						
29	0.310	0.838	95.364						
30	0.271	0.731	96.095						
31	0.252	0.681	96.777						
32	0.247	0.668	97.444						
33	0.235	0.635	98.079						
34	0.217	0.587	98.666						
35	0.199	0.538	99.204						
36	0.157	0.424	99.628						
37	0.138	0.372	100.000						

Source: own elaboration in SPSS.

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The contribution share of authors is equal and amounted to 33% for each of them. VS – conceptualisation, literature writing, TB and ID – methodology, calculations, discussion.

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Acknowledgements and Financial Disclosure

The research was part of an EKÖP-24-4-II University Research Fellowship supported by the National Research, Development and Innovation Fund of the Ministry of Culture and Innovation, Hungary.

Use of Artificial Intelligence

GAI tools (ChatGPT) were used soley for language editing and proofreading. The authors take full responsibility for the content and conclusions of this work.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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