*Proceedings of the 7th International Conference on Economics and Social Sciences (2024), ISSN 2704-6524, pp. 326-335*

**The 7th International Conference on Economics and Social Sciences**
**Exploring Global Perspectives:**
**The Future of Economics and Social Sciences**
**June 13-14, 2024**
**Bucharest University of Economic Studies, Romania**

# Professors versus Students: An Introductive Bibliometric Review of AI Acceptance in Higher Education's Specialisations of Tertiary Sector

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DOI: 10.24818/ICESS/2024/033

## Abstract

*The increasing development of artificial intelligence (AI) technology has raised considerable interest in its application within educational environments, particularly in higher education. This study examines the dynamics of AI technology acceptance among service sector academia with the intent of delineating the critical determinants that influence its adoption and utilisation. Emphasising a comparative analysis, this investigation juxtaposes the perceptions of both students and professors. A systematic keyword search was implemented to evaluate pertinent studies encompassing these determinants, in conjunction with relevant theoretical constructs and academic fields. Although the existing literature offers substantial information on AI adoption factors within the service sector, a lacuna persists in understanding the variables and conceptual frameworks that characterise the acceptance of AI technology in higher education in the service sector. Identifying these drivers of adoption could be of great benefit to students, professors, but mostly to policy-makers who are poised to devise and execute strategic initiatives advocating for the seamless integration of AI into pedagogy, scholarly inquiry, and the broader academic field.*

**Keywords:** artificial intelligence, technology acceptance models, higher education, professors, students.

**JEL Classification:** I23, O33, O14.

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# 1. Introduction

The tertiary sector of higher education has developed rapidly in recent decades, driven by technological advances, changing demographics, and needs. The emergence of artificial intelligence (AI) technologies has had a significant impact not only on individuals, but also on organisations and societies in various fields. The context of higher education is no exception, with AI teaching assistants or bots (e.g., Bilquise et al., 2023; Pillai et al., 2024) and especially ChatGPT (e.g., Duong et al., 2023; Romero-Rodríguez et al., 2023) playing an essential role for all stakeholders in the tertiary sector. Although technology adoption is one of the most studied topics related to AI in various fields, and some studies since 2020 (Kim et al., 2020) have started to engage in the empirical investigation of factors influencing the usage behaviour of students or professors, there is still little consensus on the main determinants of AI adoption or usage in the case of tertiary sector actors from higher education. Moreover, some of the existing work is limited to theoretical acceptance models and their standard constructs that do not fit the specificities of AI technology (Polyportis and Pahos, 2024). This study thus contributes to previous research on the adoption of AI technologies in higher education, in the service sector, by providing an introductory bibliometric analysis of the main variables used to analyse AI acceptance by both students and professors. In addition, a third subject category was found to be relevant, relating to professors who hold leadership positions in these institutions.

# 2. Problem Statement

As AI technology continues to advance, its integration into higher education requires a comprehensive understanding of the factors that influence its acceptance by both professors and students. In order to assess the degree of acceptance of such innovative technologies, a brief overview of the most important acceptance models with their defining variables was considered relevant. The Technology Acceptance Model (TAM) was developed by Davis (1989) as one of the most important models to evaluate technology acceptance following the creation of theories such as Ajzen's (1991) Theory of Planned Behaviour (TPB), which focusses on human behaviour. In the TAM, there are two main variables that determine the behavioural intention (BI) to use a technology: perceived usefulness (PU), which refers to the impact of the technology on improving performance, and perceived ease of use (PEOU), which focusses on the technical use or the ease and pleasure of using a particular technology. Venkatesh and Davis (2000) extended the TAM theory to the Technology Acceptance Model 2 (TAM2), in which constructs such as the subjective norm or output quality were included, and adapted it more closely to the Internet and online technologies. In addition, the Technology Acceptance Model 3 (TAM3) has emerged with new factors such as self-efficacy (SE), perceived enjoyment (PE), or anxiety (Venkatesh and Bala, 2008), which have also been adapted to the characteristics of AI technology (Zhang et al., 2023). The Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2012) has been implemented in previous research on user acceptance and use of AI, AI assistants, and even ChatGPT. The new predictors of technology use added to the initial TAM are performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating condition (FC), BI, and user behaviour (UB). Moreover, the UTAUT2 model has included hedonic motivation (HM), price value (PV), and habit (H) as relevant variables. Both UTAUT and UTAUT2 consider in the analysis sociodemographic factors as age and gender (Venkatesh et al., 2012). Despite the recognised importance of attitude in the early stages of technology adoption, its role in educational research has been largely undervalued, with studies favouring the use of TAM or UTAUT models. In addition to the traditional variables, there are many factors, such as those included in the Meta-UTAUT model (Dwivedi et al. 2019), that have been shown to be successful and useful in areas such as AI-integrated customer relationships, mobile banking, tourism, or education and are briefly explained in the current research.

## 3. Aims of the Research

The study consolidates and compares existing research to identify key determinants and theoretical frameworks that influence the adoption of AI in higher education. The article attempts to fill a literature gap by providing an introductory bibliometric analysis of the adoption behaviour of key educational stakeholders in education and highlighting the importance of adapting new acceptance variables to traditional models. The aim is to make a small contribution to the future development of strategies that facilitate the effective integration of AI into educational practice and institutional structures in the tertiary sector.

## 4. Research Methods

A systematic keyword-based review of the AI acceptance literature in higher education in the tertiary sector, using the Web of Science, was conducted to analyse the uptake of AI technologies among stakeholders: students (undergraduate and/or postgraduate) and professors and/or academics. Initally, the keywords and conditions were defined: “artificial intelligence in higher education” OR “AI in higher education”, as topics, with the condition AND “technology acceptance model” OR “technology acceptance” OR “technology acceptance” “technology acceptance”. The search was conducted from 2000 to the present and resulted in a set of 14809 published articles. Further restrictions were made in terms of research area (services), participants (students, professors/academics and staff), and language. After analysing the abstracts of 248 articles, the selection was narrowed down to 49 publications, of which 21 were finally selected because they were in line with the objectives of the study and provided an introductory basis for future research on AI implementation in tertiary education.

## 5. Findings

The 21 studies identified were published between 2020 and 2024 in 6 main research areas: 57% in Education and Educational Research (12), 19,05% in Computer Science and Engineering (4), Information Science and Library Science

(1), Business and Economics; Education and Educational Research (1), Science and Technology - Other Topics (1) and Psychology (1). Twenty of the 21 studies encompass a range of service sector areas from multispecialisation universities, apart from a single study that surveyed medical students (Li and Qin, 2023). As shown in Tables 1-3, regardless of the research subjects (students, professors, or in some cases academic staff), TAM (Davis, 1989) and TAM extensions are the predominant models used in the studies. Polyportis (2024) opted for the implementation of PBC (Ajzen, 1991) focussing on trust, emotional creepiness, perceived behavioural control. Among the groups of constructs used (Table 1-3), PU and other functional beliefs (e.g., perceived risk, trust, perceived value), are the most widely accepted technology-related beliefs (Kim et al., 2020; Duong et al., 2023; Wang et al., 2021). Constructs pertaining to personal traits such as technological pedagogical content knowledge (Jain and Raghuram, 2024), work engagement, job relevance, anxiety (Abdaljaleel et al., 2024; Zhang et al., 2023), behavioural control beliefs as PEU, SE and FC (Rahiman and Kodikal, 2024; Romero-Rodríguez et al., 2023) or affective/hedonic responses such as interactivity (Pillai et al., 2024), anthropomorphism (Bilquise et al., 2023), attitude (Xu et al., 2024) hedonic motivation (Romero-Rodríguez et al., 2023) were also found to be relevant. One study was conducted using a mixed method (Pillai et al., 2024), in which both a survey (students) and the interview (academics) were used. Xu et al. (2024) opted for a qualitative research method (peer-to-peer interview), and 19 studies conducted surveys (Likert scale items) in accordance with the constructs used. Other variables such as gender, age, major, experience, or grade were also taken into account (Polyportis, 2024; Romero-Rodríguez et al., 2023).

## *5.1 Students*

To assess AI teacher bots or assitance (Table 1), various authors (e.g. Kim et al., 2020, Ayanwale and Molefi, 2024) have used the TAM framework (Davis, 1989) in combination with other variables such as interactivity, anthropomorphism, or personalisation. To investigate the acceptability of AI-enhanced academic support and its impact on students' performance, Dahri et al. (2024) chose the UTAUT framework (Venkatesh et al., 2003) in combination with other variables (e.g., information accuracy, pedagogical fit). Ka et al. (2023) opted for an adapted version of the EVT framework (Wigfield, 1994), considering knowledge, perceived value, perceived cost, and intention to use. Authors like Li and Qin (2023) focused only on medicine students, using the UTATUT2 (Venkatesh et al.,2012) and found that students' willingness to use medical AI is influenced by how useful they think it is, how much they enjoy using it, their habits, and how much they trust it. Students' intention to adopt AI-based (T-bots) or assistants was found to be influenced by factors such as perceived ease of communication (Kiet et al., 2020), PEU, PU, personalisation, interactivity, perceived trust, anthropomorphism, and perceived intelligence (Pillai et al., 2024). While PU, autonomy, and trust showed no significant influence on the acceptance of chatbots, Bilquise et al. (2023) emphasised the importance of these functional elements in shaping students' attitudes toward AI-driven academic advising tools. In addition, students' willingness to engage with chatbots for educational purposes is higher if they believe that these tools increase their learning efficiency (Ka et al., 2023; Dahri et al., 2024) and correspond to their learning habits (Ayanwale and Molefi, 2024).

**Table 1. Research subjects: students**

| Authors | Themes | Methods & instruments | Framework | Variables |
|---|---|---|---|---|
| (Kim et al., 2020) | Explores students' perceptions of *AI teaching assistants* in higher education. | Quantitative (survey) | TAM | Perceived Usefulness, Perceived Ease of Communication, Attitudes Toward New Technologies, Intention to adopt AITA |
| (Pillai et al., 2024) | Examines students' adoption of *AI-based teacher-bots* in higher education. | Mixed methods (survey & interview. | TAM + other variables | Perceived Ease of Use, Perceived Usefulness, Personalization, Interactivity, Perceived Trust, Anthropomorphism, Perceived Intelligence |
| (Duong et al., 2023) | Explores *ChatGPT* impact on higher education students' learning adoption and knowledge sharing. | Quantitative (survey) | TAM - education | Effort Expectancy, Performance Expectancy, Behavioural Intention to use, Actual Use, Knowledge Sharing |
| (Romero-Rodríguez et al., 2023) | Explores *ChatGPT*'s acceptance by university students. | Quantitative (survey) | UTAUT2 | Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Behavioural Intention, Use Behaviour |
| (Bilquise et al., 2023) | Examines the factors influencing university students' acceptance of *academic advising chatbots*. | Quantitative (survey) | TAM<br>UTAUT<br>sRAM<br>SDT | Perceived Ease of Use, Perceived Usefulness, Social Influence, Perceived Trust, Perceived Autonomy, Anthropomorphism, Behavioural Intention |
| (Li and Qin, 2023) | Explores the factors that influence the acceptance and use of *AI in medicicine* education | Quantitative (survey) | UTAUT 2 | Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Price Value, Habit, Facilitating Conditions, Technology Fear, Trust, Behavioural Intention, User Behaviour |
| (Abdaljaleel et al., 2024) | Factors influencing *ChatGPT usage* and attitudes in university students from domains like: medical, healthcare, education, mathematics. | Quantitative (TAME-ChatGPT survey) | TAME-ChatGPT | Perceived Usefulness, Behavioural/cognitive factors, Perceived risk of use, Perceived ease of use, General perceived risks, Anxiety, Technology social influence, Attitude to technology/social influence |
| (Polyportis, 2024) | Examines *AI adoption* and *ChatGPT usage* in higher education. | Quantitative (longitudinal survey) | PBC | Trust, Emotional Creepiness, Perceived Behavioural Control, Usage Behaviour |
| (Ayanwale and Molefi, 2024) | Analyses the factors influencing students' adoption of *AI chatbots* for educational purposes. | Quantitative (survey) | TAM<br>IDT | Relative Advantages, Compatibility, Trialability, Perceived Trust, Perceived Usefulness, Perceived Ease of Use, Behavioural Intention |
| (Dahri et al., 2024) | Investigates *AI-based academic support* acceptance and impact on students' performance. | Quantitative (survey) | UTAUT + other variables | Performance Expectancy, Facilitating Conditions, Students' Engagement, Assessment Effectiveness, Student's Interaction, Information Accuracy, Personal Innovations, Pedagogical Fit, AI Tools Use, Behavioural Intentions, Students Satisfaction |
| (Xu et al., 2024) | Explores students' perceptions and experiences with *ChatGPT*. | Qualitative (peer-to-peer interview) | TAM | Perceived Usefulness, Perceived Ease of Use, Attitude towards use, Behavioural Intention |
| (Polyportis and Pahos, 2024) | Examines factors driving students' use behaviour of *ChatGPT* in higher education. | Quantitative (survey) | meta-UTAUT + other variables | Performance Expectancy, Effort expectancy<br>Social influence, Facilitating conditions, Perceived anthropomorphism, Trust<br>Design novelty, Institutional policy, Attitude, Behavioural intention, Use behaviour |
| (Tian et al., 2024) | Investigates *AI Chatbot acceptance* among Chinese graduate students | Quantitative (survey) | UTAUT<br>ECM +<br>Personal Innovativeness | Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Confirmation, Satisfaction, Personal, Innovativeness, Behavioural Intention, Use Behaviour. |
| (Alshammari and Alshammari, 2024) | Factors influencing students' use of *ChatGPT* in higher education. | Quantitative (survey) | UTAUT | Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behaviour Intention |
| (Ka et. al, 2023) | Explores student perceptions of *GenAI* in higher education | Quantitative (survey) | EVT | Knowledge, Perceived Value, Perceived Cost, Intention to Use |

*Notes: TAM=Technology Acceptance Model; UTAUT=The Unified Theory of Acceptance and Use of Technology; sRAM= The Service Robot Acceptance Model; SDT= The intrinsic motivation Self Determination Theory (SDT) model; TAME-ChatGPT= TAM edited to asses ChatGPT acceptance; PBC= Perceived Behavioural Control; IDT= Innovation Diffusion Theory, EVT= Expectancy-Value Theory; ECM=Expectation-Confirmation Model*

*Source:* developed by authors (2024).

The second common theme analysed in the students' category refers to students' adoption and use of ChatGPT in the learning process with the following theoretical models implemented: PBC (Polyportis, 2024), TAM (Xu et al., 2024; Duong et al., 2023), TAME ChatGPT (Abdaljaleel et al., 2024), UTAUT (Alshammari and Alshammari, 2024), UTAUT and ECM (Tian et al., 2024), metaUTAUT (Polyportis and Pahos, 2024), UTAUT 2 (Romero-Rodríguez et al., 2023). The predominant theoretical model for AI learning technologies is TAM, often with variations, whereas UTAUT and its iterations are frequently chosen by researchers studying ChatGPT. EE directly impacted students' actual use of ChatGPT (Duong et al., 2023) meaning that students are more likely to use ChatGPT if they perceive it to be easy to use and require minimal effort. The positive attitude and use of ChatGPT is influenced by the ease of use, positive attitude toward technology, SI, PU, behavioural/cognitive factors, low perceived risk, and low anxiety (Abdaljaleel et al., 2024). They are more inclined to use ChatGPT if they believe it will improve their academic performance (Alshammari and Alshammari, 2024), if they have experience using it (Romero-Rodríguez et al., 2023), if they feel supported by their social environment, and if they have the necessary resources (Polyportis and Pahos, 2024), indicating the importance of PU and community support in the adoption of new technologies. Students' positive attitudes toward ChatGPT are significantly influenced by anthropomorphism, trust, and novelty of design, suggesting that the more likeable and trustworthy a technology is, the more likely it is to be accepted (Duong et al., 2023; Polyportis and Pahos, 2024). Personal innovativeness was found to be a significant determinant of behavioural intentions, suggesting that greater openness to new technologies leads to higher adoption rates (Tian et al., 2024). User satisfaction was a central factor in the decision to continue using AI chatbots, emphasising the importance of meeting users' expectations to keep them engaged with the technology (Tian et al., 2024). Furthermore, a decrease in emotional creepiness was observed from the initial phase to follow-up, suggesting that the students became comfortable with ChatGPT over time (Polyportis, 2024).

## *5.2 Professors*

Research on the acceptance of AI technologies by professors in higher education in the tertiary sector has so far proven to be scarce. Three studies were found relevant using the TAM model (Wang et al., 2021; Rahiman and Kodikal, 2024) as well as TAM3 (Zhang et al., 2023) and UTAUT (Rahiman and Kodikal, 2024). All papers were quantitative with the survey as a main instrument. While two articles focused on professors who have graduated and are using AI in their activity, Zhang et al. (2023) focused on future professors enroled in education programs. PEU was found to have a significant positive direct effect on PU, suggesting that professors who perceive AI applications as easy to use also perceive them as useful (Wang et al., 2021). SE (Wang et al., 2021), the institution’s conditions, and their awareness of new technologies (Rahiman and Kodikal, 2024) are also factors that positively influence the attitude towards AI, emphasising professors’ belief in their ability to use AI technologies effectively. Anxiety does not have a significant impact on BI

(Rahiman and Kodi kal, 2024), suggesting that professors' level of anxiety does not play a significant role in their decision to use AI technologies in the classroom.

**Table 2. Research subjects: professors/academics**

| Authors | Themes | Methods & instruments | Framework | Variables |
|---|---|---|---|---|
| (Wang et al., 2021) | Explored factors influencing teachers' *adoption of AI* in higher education (AIEd). | Quantitative (survey) | TAM + Self efficacy + Anxiety | Perceived Usefulness, Perceived Ease of Use, Attitude towards use, Behavioural Intention, Anxiety, Self-efficacy |
| (Zhang et al., 2023) | Explores pre-service teachers' *acceptance of AI* in education. | Quantitative (survey) | TAM3 | AI Self-Efficacy, Perceived Enjoyment, AI Anxiety, Perceived Ease of Use, Perceived Usefulness, Job Relevance, Subjective Norm, Behavioural Intention. |
| (Rahiman and Kodikal, 2024) | Explores *AI's impact* on higher education, focusing on faculty engagement. | Quantitative (survey) | TAM UTAUT | Facilitating Conditions, Awareness, Perceived Risk, Performance Expectancy, Effort Expectancy, Adoption, Attitude, Behavioural Intention, Work Engagement, Artificial intelligence in Higher Education. |

*Notes: TAM=Technology Acceptance Model; UTAUT=The Unified Theory of Acceptance and Use of Technology.*

*Source:* developed by authors (2024).

Professors' perceptions of ease of use, SE, and attitude towards AI are key factors influencing their intention to use AI-based applications in higher education (Wang et al., 2021; Rahiman and Kodikal, 2024). The UTAUT model emphasises that PE, EE, SI, and FC significantly influence the acceptance and use of technology, including AI, in education (Rahiman and Kodikal, 2024). PEU and PU were also found to be significant factors in pre-service teachers' intentions to use AI-based educational applications (Zhang et al., 2023). Gender differences in AI anxiety and perceived enjoyment were observed among pre-service teachers (Zhang et al., 2023).

## *5.3 Students, professors, and Academic (Management) Staff*

Although the main purpose of the research was to analyse the most common variables in AI acceptance by two main stakeholders in higher education, the research led to the creation of a third category, professors holding management positions (e.g., dean, director) at universities.

**Table 3. Research subjects: students, academics and staff**

| Authors | Themes | Methods & instruments | Framework | Variables |
|---|---|---|---|---|
| (Chatterjee and Bhattacharjee, 2020) | Explores *AI adoption* in higher education in India. | Quantitative (survey) | UTAUT | Perceived Risk, Performance Expectancy, Effort Expectancy, Facilitating Condition, Attitude, Behavioural Intention. |
| (Jain and Raghuram, 2024) | Explores factors influencing *Gen-AI* adoption in Higher Education. | Quantitative (survey) | TAM + UTAUT + other variables | Perceived Risk, Perceived Ease of Use, Perceived Usefulness, technological pedagogical content knowledge, Perceived Trust, Intention to Use |
| (Sharma et al., 2024) | Investigates *AI adoption* (e.g. applications, dimensions) in Indian higher education institutions. | Quantitative (survey) | UTAUT SCT HCI | Perceived Organisational Support, Perceived Ease of Use, AI Self Efficacy, Perceived Effectiveness, Perceived Risk, Behavioural Intention, Adoption of AI. |

*Notes: TAM=Technology Acceptance Model; UTAUT=The Unified Theory of Acceptance and Use of Technology; SCT= Social Cognitive Theory (SCT); HCI=Human–Computer Interaction.*

*Source:* developed by authors (2024).

In these studies, while EE and FC are consistent positive predictors of AI adoption (Chatterjee and Bhattacharjee, 2020; Jain and Raghuram, 2024; Sharma et al., 2024), the influence of PU varies. SE, trust, and demographic considerations also play significant roles, as vital elements in a broader understanding of AI acceptance in the educational sphere.

## 6. Conclusions

This paper contributes to the existing literature by identifying the most common determinants of AI acceptance in higher education and providing a clearer analysis of the level of adoption among students and professors. Overall, the studies indicate that AI acceptance in higher education in the tertiary sector is multifaceted, with factors belonging to traditional acceptance models having a significant impact on the current research landscape. In addition, a number of new variables adapted to higher education and AI technology have emerged. Most articles focus on the factors that influence students' AI acceptance, while comparatively little attention is paid to professors. Future research on AI adoption in higher education may also examine cross-disciplinary adoption patterns to understand how different academic areas of the higher education sector respond to AI integration, allowing the development of customised AI applications that meet discipline-specific needs. The development of AI-based predictive modelling is another innovative approach that could help institutions anticipate trends in AI adoption and prepare targeted responses. Such research efforts will be critical to creating adaptive, inclusive learning environments and facilitating the strategic adoption of AI across the educational spectrum, shaping the future of teaching and learning in an era of AI integration. While this analysis is comprehensive, its limitations lie in elements such as the use of a single database, limited areas of research, or language.

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