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# Understanding teachers' intentions and use of AI tools for research

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**Abstract**

The rapid advancement of artificial intelligence (AI) has led to the development of a wide array of tools which are transforming the education industry. The study investigates the adoption and use of AI tools by teachers within higher education institutions (HEIs), using the context of India. By employing an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model, the study empirically examines the influence of two technological attributes (i.e. performance expectancy and effort expectancy), two contextual factors (i.e. social influence and facilitating conditions) and two personal characteristics (i.e. personal innovativeness and computer self-efficacy) on teachers' behavioral intention to use AI tools for research work. The primary data were collected from 331 teachers working with HEIs in the Delhi-National Capital Region (NCR) of India. PLS-SEM technique was used to analyze the data. The causal model included performance expectancy, effort expectancy, social influence, facilitating conditions, personal innovativeness, and computer self-efficacy as exogeneous variables; and behavioral intention to adopt AI tools and actual use of AI tools as endogenous variables. The findings indicate that teachers' intention to adopt AI tools for research work is positively influenced by performance expectancy, effort expectancy, social influence, computer self-efficacy and personal innovativeness. Further, their actual use of AI tools is influenced by their behavioral intention and facilitating conditions. The model explained 70.2% variation in behavioral intention and 39.2% variation in actual use of AI tools. The study provides further verification of the effectiveness of the UTAUT framework in the context of using emerging technologies in the education sector. Findings from this study provide beneficial insights for HEIs and developers of AI tools.

**KEYWORDS:** Artificial Intelligence, Academic Research, UTAUT, Teachers, Higher Education Institutions.

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## 1. Introduction

Academic research is a fundamental component of higher education, which plays a pivotal role in advancing knowledge and fostering innovation. The quality and productivity of academic research are paramount goals for higher education institutions (HEIs). Thus, writing and publishing research papers are key research-related activities for teachers in HEIs. However, today's academic environment faces various challenges such as increasing competition and limited resources (Edvardsen et al., 2017). Technology and digital tools have the potential to significantly enhance research quality and productivity as they can help overcome the difficulties encountered while publishing scientific papers, such as data collection, data analysis, citation management, academic writing and copyediting (Brunetti et al., 2022).

The rapid advancement of artificial intelligence (AI) has led to the development of a wide array of tools which are transforming the education industry (Marsh, 2023; Greco & Cinganotto, 2023). AI is not only enhancing traditional teaching methods but also revolutionizing the way research is conducted in HEIs (Al-Mughairi & Bhaskar, 2023). AI tools have become increasingly prevalent, offering innovative solutions to streamline and enhance the research process. For example, ChatGPT can be used as an advanced language model to generate ideas and research questions which can help teachers determine the direction of the research study (Sok & Heng, 2023). Grammarly can help improve the quality of academic writing by providing suggestions for grammar, spelling

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and clarity (Aljuaid, 2024). By offering paraphrasing capabilities, HumanizeAI can help researchers to avoid plagiarism and improve the readability of their research papers. AI tools (such as Semantic Scholar) can quickly identify relevant papers, significantly speeding up the literature review process (Atkinson, 2023).

Despite the numerous benefits of AI tools in academic research, there is a paucity of empirical studies investigating the factors influencing teachers' adoption of these tools. Though there is an extensive body of literature examining teachers' acceptance and use of various technologies within teaching and learning contexts, there remains a notable gap in empirical studies that are specifically focused on the adoption of AI tools for research purposes. Previous studies have largely explored teachers' use of technologies in contexts such as online distance learning (Atiqah et al., 2024); e-learning (Sánchez-Prieto et al., 2019), mobile learning (Hu et al., 2020), learning management systems (LMS) (Alharbi et al., 2022), learning analytics (El Alfy & Kehal, 2024), and technology-enhanced teaching through virtual reality applications (Gupta and Bhaskar, 2023), Google classrooms (Oguguo et al., 2023), and cloud services (Wang et al., 2017).

Though some recent studies (e.g. Guillén-Gámez et al., 2023) have examined the factors influencing the integration of technological tools in research work, the specific context of using AI tools for academic research remains underexplored in the literature. The absence of empirical research in this area represents a critical gap in the literature, that needs to be addressed. Understanding the unique challenges and motivators associated with the adoption of AI tools for research work of teachers is essential as it can help design institutional policies and create conducive environments that support the integration of AI technologies in research activities. By addressing these factors, universities can enhance their research output, thereby maintaining a competitive edge in the academic landscape. Understanding how AI tools are adopted by teachers can help leverage their full potential, ultimately improving the quality and efficiency of academic research.

Thus, the present study explores the factors that influence teachers' acceptance and use of AI tools for their research work, by employing the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical lens. Premised in the context of Indian HEIs, the study attempts to answer the following research questions:

- RQ1: How do technological characteristics of AI tools (i.e. performance expectancy and effort expectancy) influence teachers' behavior towards using these tools for research?
- RQ2: How do contextual factors (i.e. social influence and facilitating conditions) influence teachers' behavior towards using AI tools for research?
- RQ3: How do teachers' individual characteristics (i.e. personal innovativeness and computer self-efficacy) influence their behavior towards using AI tools for research?

The remaining paper is structured as follows: section 2 describes the theoretical framework and section 3 discusses the methodology used in the study. The results are presented and discussed in sections 4 and 5 respectively. Finally, the study is concluded in section 6.

## 2. Theoretical framework

A few studies have explored the applications and implications of using AI tools for academic research. For example, Shtykalo and Yamnenko (2024) discussed the capabilities of various freely available AI tools that can perform tasks related to academic activities, including research and analysis. Perkins and Roe (2024) examined the impact of generative AI tools on academic research by focusing on their implications for qualitative and quantitative data analysis. Casal and Kessler (2023) examined the issues pertaining to research ethics, human judgements and accuracy, within the context of using AI chatbots (such as ChatGPT) in academic research.

The conceptual framework of the present study is grounded in the UTAUT model (Venkatesh et al., 2003). The UTAUT framework includes four constructs (namely, performance expectancy, effort expectancy, social influence and facilitating conditions) that determine users' behavior towards the acceptance and use of a technology. Performance expectancy (PE) and effort expectancy (EE) constitute the technological attributes, whereas social influence (SI) and facilitating conditions (FC) represent the contextual or environmental factors. The users' behavioral outcomes within the UTAUT are conceptualized by two constructs i.e. behavioural intention (BI) and actual use (AU). BI refers to the degree to which an individual has formulated conscious plans to adopt a technology, whereas AU (or usage behavior), refers to the extent to which an individual utilizes the technology in his/her activities (Venkatesh et al., 2003). Several studies in the recent past have used the UTAUT framework to understand the adoption of AI-based technologies in various educational contexts (Chatterjee & Bhattacharjee, 2020; Lin et al., 2022). For example, Wu et al. (2022) examined students' willingness to accept AI-assisted learning environments by using an integrated framework of UTAUT and perceived risk theory. Tian et al. (2024) utilized the UTAUT model to investigate the acceptance of AI Chatbot technology among students.

Clifford (2024) employed the UTAUT framework to investigate the HEI teachers' intention towards adopting AI from a pedagogical perspective.

In order to gain a comprehensive understanding of teachers' behavior towards using AI tools, we extend the UTAUT framework by two variables namely, computer self-efficacy (CSE) and personal innovativeness (PI), that represent teachers' personal characteristics. The proposed model is depicted in Figure 1 and the hypotheses are discussed below.

PE and BI

PE refers to the degree to which an individual believes that using a technology can assist in achieving task-oriented goals (Venkatesh et al., 2003). Prior studies indicate that PE plays a key role in shaping teachers' behavior towards using technologies. Buabeng-Andoh and Baah (2020) found that PE has a significant influence on teachers' attitude towards using learning management system. El Alfy and Kehal (2024) demonstrated that PE has a positive influence on educators' attitude and behavioural intention to use learning analytics. For teachers, the expectation that AI tools will improve their research productivity, can be a strong motivator for adopting such tools. AI tools such as Semantic Scholar, Google Scholar, and Grammarly can significantly enhance research productivity of teachers, by expediting literature searches and improving writing quality. These performance enhancements can motivate teachers to use AI tools for their research work. Hence, we posit that:

H1: PE has a significant positive influence on teachers' BI to adopt AI tools for research work

EE and BI

EE is defined as the degree of ease associated with the use of a technology (Venkatesh et al., 2003). Extant studies have demonstrated that EE is a key predictor of BI to adopt technologies in various educational contexts such as mobile learning (Hu et al., 2020; Raza et al., 2022) and Google classrooms (Jakkaew & Hemrungrote, 2017). Prior research on e-learning and using digital tools in educational contexts highlights that ease of use significantly influences teachers' decisions to adopt technologies (Teo 2011; Sánchez-Prieto et al., 2019; Atiqah et al., 2024). EE addresses the cognitive and physical effort required to use a technology. The intuitive and user-friendly interfaces of AI tools can minimize these efforts and provide more accessibility to teachers who may not have advanced technical skills. When teachers will perceive that AI tools are easy to learn and use, they will be more likely to incorporate them into their research workflows. Hence, we postulate that:

H2: EE has a significant positive influence on teachers' BI to adopt AI tools for research work

SI and BI

SI refers to the degree to which an individual perceives that relevant persons who are important for him/her expect that he/she should use a particular technology (Venkatesh et al., 2003). Studies in the educational sector have highlighted the importance of social influence in the adoption of new technologies such as AI-enabled warning systems in higher education (Raffaghelli et al., 2022), and AI-enabled language online e-learning products (Lin et al., 2022). Teachers are often influenced by their colleagues' attitudes and behaviors regarding technology use (El Alfy & Kehal, 2024; Buabeng-Andoh & Baah, 2020). If their peers, seniors and members in broader research community advocate for the use of AI tools, they are more likely to adopt those tools for their own research work. Hence, we propose that:

H3: SI has a significant positive influence on teachers' BI to adopt AI tools for research work

FC, BI and AU

FC refers to the degree to which an individual believes that necessary resources exist to support the use of a technology (Venkatesh et al., 2003). Prior studies on educational technology adoption consistently shows that FC including technical support, access to resources, and training programs significantly impact teachers' intention to use technology as well as their actual usage behavior (Teo, 2011; Strzelecki, 2023). Kocaleva et al. (2015) observed that FC had the strongest effect on e-learning acceptance and use by teaching staff in HEIs. Hu et al. (2020) demonstrated that the FC significantly influences teachers' behavioural intention and use behaviour regarding mobile technologies in higher education. Access to reliable technical infrastructure (e.g., high-speed internet, computers), and supportive institutional policies that encourage the use of AI tools, is crucial for motivating teachers to use these tools. When teachers perceive that these resources and institutional support are readily available, they will be more likely to adopt and use AI tools for their research work. Hence, we posit that:

H4: FC has a significant positive influence on teachers' BI to adopt AI tools for research work

H5: FC has a significant positive influence on teachers' AU of AI tools for research work

CSE and BI

CSE refers to an individual's belief in his/her capability to successfully perform tasks using a computer (Compeau & Higgins, 1995). It encompasses confidence in using various computer applications and information technologies such as AI tools. Research in educational settings has found that CSE is a significant predictor of teachers' intention to use technology (Joo et al., 2018; Alharbi & Drew, 2018). For example, Zhao and Zhao (2021) found that teachers' CSE influences the ease of using a technology, which in turn helps in shaping a positive attitude towards the technology. Gupta and Bhaskar (2023) concluded that teachers' CSE positively influences teachers' intention to use virtual reality applications for teaching purposes. Effective use of AI tools often involves integrating them into existing research workflows, which requires certain technical skills. Teachers with high CSE are more likely to explore and effectively leverage the AI tools to meet their specific research needs. Hence, we propose that:

H6: CSE has a significant positive influence on teachers' BI to adopt AI tools for research work

PI and BI

Within the context of technology adoption, PI refers to the willingness of an individual to try out innovative technologies on his/her own (Agarwal & Prasad, 1998). It is a trait that reflects openness to new experiences and a proactive approach to adopting emerging technologies. Prior studies suggest that innovative teachers are more likely to integrate digital tools into their academic activities (Mazman Akar, 2019; Lopez-Perez, 2019; Gupta & Bhaskar, 2023). Loogma et al. (2012) demonstrated that PI significantly influenced teachers' adoption of e-learning platforms. Gökçearslan et al. (2022) concluded that individual innovativeness is a significant predictor of teachers' acceptance of Internet of Things (IoT) technologies in educational contexts. Teachers who are innovative are driven by their inherent tendency to experiment with new solutions, such as AI tools. Therefore, they are more likely to see the potential benefits of AI tools and incorporate them into their research processes. Hence, we postulate that:

H7: PI has a significant positive influence on teachers' BI to adopt AI tools for research work

BI and AU

Prior research demonstrates a strong correlation between intention to adopt a technology and its actual use (Nikolopoulou et al., 2020; Budhathoki et al., 2024). The relationship between BI and AU has also been demonstrated in the context of technology adoption by teachers. Teo (2011) found that teachers' intention to use technology significantly predicted their actual use in the classroom. Siyam (2019) demonstrated the positive relationship between teachers' acceptance and actual use of technology. Teachers who recognize the benefits and have a positive intention towards AI tools are more likely to use them effectively. Hence, we propose that:

H8: Teachers' BI has a significant influence on their AU of AI tools.

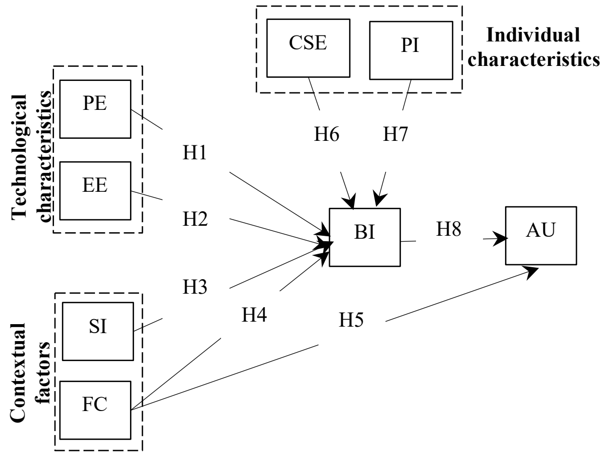


**Figure 1** - Proposed Model.

## 3. Methodology

3.1 Measures

The items for measuring the constructs in the proposed model were adopted from prior studies (see Annexure 1). The items for PE, EE, SI and BI were adapted Strzelecki (2023). The items for PI and CSE were adapted from Sun and Jeyraj (2013) and Zhao et al. (2020) respectively. The items for FC and AU were adapted from Budhathoki et al. (2024). A five-point Likert response ranging from 1 (strongly disagree) to five (strongly agree) was used to measure all the items.

3.2 Sample and Data Collection

We conducted a survey in 24 HEIs in the National Capital Region (NCR) of Delhi, India. The teachers teaching in various undergraduate and graduate programs served as our target respondents. The convenience sampling technique (Saunders, 2012) was used to select the HEIs as well as the teachers. Convenience sampling is a relatively fast and easy approach to achieve the required sample size (Lopez and Whitehead, 2013). Though, convenience sampling sometimes suffers from the limitation of under-representing or over-representing particular groups within the target population, it is commonly used by researchers as it offers an effective approach of data collection in terms of time and cost (Bornstein et al., 2013). Hence, we employed convenience sampling technique in the present study.

A self-administered structured questionnaire was used as the survey instrument to collect primary data from the target respondents. The questionnaire comprised questions on the demographic characteristics of the teachers, as well as the items for measuring various research constructs. The initial draft of the questionnaire was checked for face validity through pilot testing with ten academicians and researchers.

 

For the final survey, 400 teachers were contacted out of which 353 responded for filling the questionnaire. After removing unviable responses, 331 usable questionnaires were obtained. Hence the final sample size of our study was 331. The sample consisted of 65.9% females and 34.1% males. The mean age of female respondents was 41±1.22 years, and the mean age of male respondents was 48.4±1.12 years.

## 4. Results

We employed Structural Equation Modelling (SEM) to analyze the data and test the proposed hypotheses. There are two widely used SEM techniques i.e. co-variance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). The choice of appropriate SEM technique depends upon the sample size, normality characteristics, and purpose (Hair et al., 2016). Since the major focus of our study is testing relationships among various constructs in the proposed model, we employed the PLS-SEM technique. SmartPLS 4 software was used to employ the PLS-SEM technique.

### 4.1 Measurement Model

Firstly, the measurement model was assessed through confirmatory factor analysis (CFA) to evaluate the reliability and validity of the model constructs. Table 1 indicates the results of reliability and convergent validity of the constructs. As can be observed from Table 1, all items had significant loadings ($p<0.001$) with their respective constructs. Moreover, the standardized loadings of all items were greater than 0.5, indicating adequate convergent validity (Hair et al., 2016). Additionally, the average variance extracted (AVE) of all the latent constructs was greater than 0.5, further confirming the validity of the constructs (Fornell & Larcker, 1981). Further, the Cronbach's alpha (CA) and composite reliability (CR) of all constructs were greater than 0.70, ensuring the reliability and internal consistency of the constructs (Hair et al., 2016).

To assess the discriminant validity of the constructs, we employed two approaches, namely Fornell and Larcker criterion (see Table 2) and heterotrait–monotrait (HTMT) criterion (see Table 3). As can be observed from Table 2, the square roots of AVE values of all constructs were greater than the inter-construct correlations; which confirmed the discriminant validity of the constructs (Fornell & Larcker, 1981). Moreover, the HTMT ratios were less than 0.85 (see Table 3), further confirming the discriminant validity (Henseler et al., 2015).

### 4.2 Structural Model

After confirming the reliability and validity of the constructs, the proposed hypotheses were tested through the structural model. The significance and strength of the relationships between the underlying factors of our proposed model was assessed by answering the following questions: (1) How much variation is explained by the exogenous variables in the endogenous variables? and (2) What is the contribution of each exogenous variable in predicting the variance of the endogenous variables?

The coefficient of determination ($R^2$) was used to answer the first question, while the second question was answered by analyzing the path coefficients, levels of significance and effect sizes.

Figure 2 indicates that 70.2% variance in behavioural intention is explained by the factors – performance expectancy, effort expectancy, social influence, facilitating conditions, computer self-efficacy and personal innovativeness. Further, 39.2% variance in actual use of AI tools is explained by behavioural intention and facilitating conditions.

Table 4 indicates the path coefficients of the hypothesized relationships (β), along with the corresponding levels of significance (p-values) and effect sizes ($f^2$). The hypothesis 1 (H1) tests whether performance expectancy significantly affects the behavioral intention of teachers regarding the use of AI tools for research. The results ($t = 4.281$, $\beta = 0.216$, p-value $< 0.001$) confirm the significance of this relationship, thereby providing support for H1. The hypotheses H2 and H3 respectively focus on the significance of the influence of effort expectancy and social influence on teachers' behavioral intention of using AI tools for research. The results confirm both hypotheses: H2 ($t = 4.176$, $\beta = 0.210$, p-value $< 0.001$), H3 ($t = 1.890$, $\beta = 0.163$, p-value $< 0.01$).

The hypotheses H4 and H5 test the significance of the influence of facilitating conditions on teachers' behavioral intention to use AI tools, and their actual use of AI tools for research. The results provide support for the two hypotheses: H4 ($t = 4.208$, $\beta = 0.223$, p-value $< 0.001$), H5 ($t = 5.474$, $\beta = 0.298$, p-value $< 0.001$). The hypotheses H6 and H7 regarding the significant influences of computer self-efficacy and personal innovativeness on teachers' behavioral intention to use AI tools are also accepted: H6 ($t = 3.381$, $\beta = 0.175$, p-value $< 0.001$), H7 ($t = 2.552$, $\beta = 0.157$, p-value $< 0.01$).

Finally, the hypothesis concerning the significant influence of teachers' behavioral intention to use AI tools on the actual use of AI tools for research is also accepted ($t = 7.482$, $\beta = 0.388$, p-value $< 0.01$). The strengths of the proposed relationships were assessed

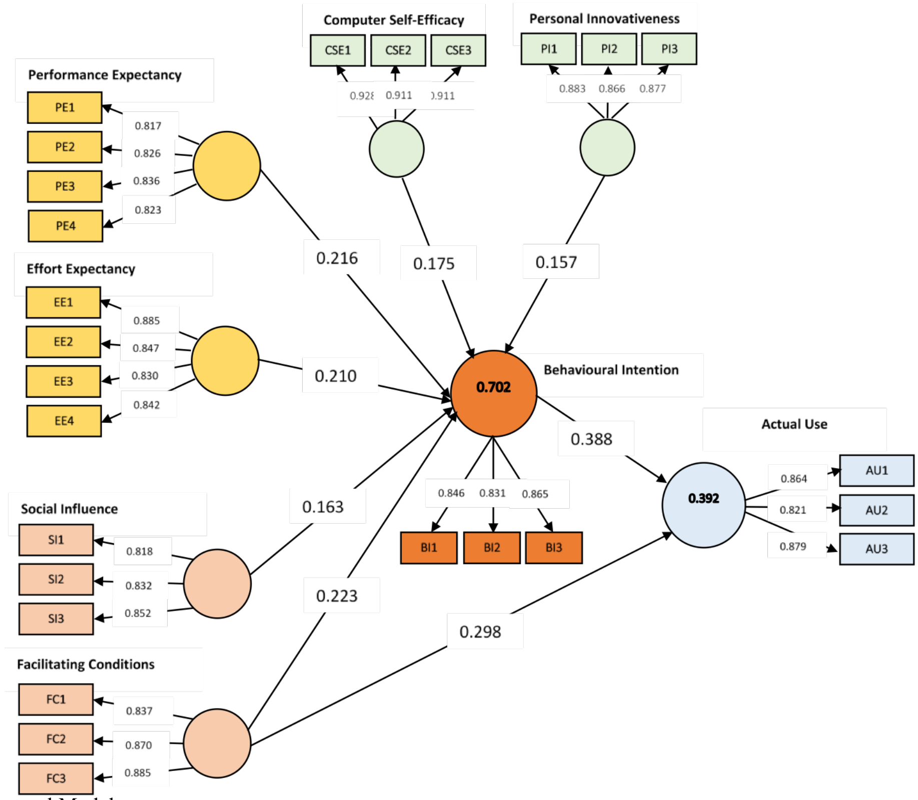

**Figure 2** - Structural Model.

through their effect size ($f^2$) coefficients (Cohen, 1988). As suggested by Cohen (1988), $f^2 \geq 0.02$ indicates a small effect, $f^2 \geq 0.15$ signifies a medium effect and $f^2 \geq 0.35$ indicates a large effect. In the present study, the values of $f^2$ range between 0.01 to 0.13 (see Table 4), indicating small effects in the relationships of performance expectancy, social influence, computer self-efficacy and personal innovativeness with behavioral intention, and medium effects in the relationships between effort expectancy and behavioral intention; facilitating conditions and behavioral intention; facilitating conditions and actual use; and behavioral intention and actual use.

## 5. Discussion

The objective of the present study was to explore the factors influencing teachers' acceptance and use of AI tools for their research work, through the theoretical lens of UTAUT. Specifically, the study examined the influence of technological characteristics of AI tools, contextual factors, and teachers' individual characteristics on their behavior towards using these tools for research. The findings of the study are discussed below:

RQ1: How do technological characteristics of AI tools (i.e., performance expectancy and effort expectancy) influence teachers' behavior towards using these tools for research?

The study found that the technological characteristics of AI tools are the most critical predictors of teachers' intention to use AI tools for their research work. This aligns with the core tenets of the UTAUT framework, where performance expectancy and effort expectancy are crucial determinants of technology acceptance (Venkatesh et al., 2003).

Our findings suggest that the AI tools that offer utilitarian benefits to teachers by enhancing their research quality are more likely to be adopted. AI tools (such as Grammarly, Semantic scholar, ChatGPT) can significantly reduce the time required for various research-related tasks such as generating ideas, conducting literature reviews, and improving the clarity of academic writing (Sok & Heng, 2023; Aljuaid, 2024). If teachers believe that AI tools can improve their efficiency by faster completion of tasks, they are more inclined to adopt those tools for their research work. Our findings are in line with those of who Hu et al. (2020) found similar relationships in the context of teachers' acceptance of emerging technologies in higher education for classroom purposes.

Our findings further suggest that the ease of accessing and utilizing the AI tools (effort expectancy) also encourages their adoption.

| Construct | Item | Item loading | CA | CR | AVE |
|---|---|---|---|---|---|
| **PE** | **PE1** | 0.817*** | 0.844 | 0.846 | 0.681 |
| | **PE2** | 0.826*** | | | |
| | **PE3** | 0.836*** | | | |
| | **PE4** | 0.823*** | | | |
| **EE** | **EE1** | 0.885*** | 0.873 | 0.874 | 0.724 |
| | **EE2** | 0.847*** | | | |
| | **EE3** | 0.830*** | | | |
| | **EE4** | 0.842*** | | | |
| **SI** | **SI1** | 0.818*** | 0.785 | 0.804 | 0.696 |
| | **SI2** | 0.832*** | | | |
| | **SI3** | 0.852*** | | | |
| **FC** | **FC1** | 0.836*** | 0.830 | 0.833 | 0.747 |
| | **FC2** | 0.870*** | | | |
| | **FC3** | 0.885*** | | | |
| **PI** | **PI1** | 0.883*** | 0.847 | 0.849 | 0.766 |
| | **PI2** | 0.866*** | | | |
| | **PI3** | 0.877*** | | | |
| **CSE** | **CSE1** | 0.928*** | 0.905 | 0.914 | 0.840 |
| | **CSE2** | 0.911*** | | | |
| | **CSE3** | 0.911*** | | | |
| **BI** | **BI1** | 0.846*** | 0.804 | 0.804 | 0.718 |
| | **BI2** | 0.831*** | | | |
| | **BI3** | 0.865*** | | | |
| **AU** | **AU1** | 0.864*** | 0.815 | 0.817 | 0.731 |
| | **AU2** | 0.821*** | | | |
| | **AU3** | 0.879*** | | | |

**Table 1** - Reliability and Convergent Validity.

**Notes**: *** p<0.001, CA=Cronbach's alpha, CR=Composite reliability, AVE=Average variance extracted

| | AU | BI | CSE | EE | FC | PE | PI | SI |
|---|---|---|---|---|---|---|---|---|
| **AU** | 0.855 | | | | | | | |
| **BI** | 0.586 | 0.847 | | | | | | |
| **CSE** | 0.498 | 0.502 | 0.917 | | | | | |
| **EE** | 0.428 | 0.675 | 0.313 | 0.851 | | | | |
| **FC** | 0.555 | 0.663 | 0.428 | 0.525 | 0.864 | | | |
| **PE** | 0.375 | 0.631 | 0.233 | 0.609 | 0.473 | 0.825 | | |
| **PI** | 0.439 | 0.608 | 0.417 | 0.515 | 0.517 | 0.452 | 0.875 | |
| **SI** | 0.407 | 0.567 | 0.304 | 0.493 | 0.441 | 0.433 | 0.351 | 0.834 |

**Table 2** - Discriminant Validity (Fornell and Larcker criterion).

**Note**: Diagonal values indicate the square roots of averange variance extracted

| | AU | BI | CSE | EE | FC | PE | PI |
|---|---|---|---|---|---|---|---|
| **AU** | | | | | | | |
| **BI** | 0.723 | | | | | | |
| **CSE** | 0.576 | 0.584 | | | | | |
| **EE** | 0.508 | 0.805 | 0.350 | | | | |
| **FC** | 0.674 | 0.810 | 0.490 | 0.617 | | | |
| **PE** | 0.450 | 0.763 | 0.261 | 0.708 | 0.561 | | |
| **PI** | 0.528 | 0.734 | 0.474 | 0.596 | 0.612 | 0.532 | |
| **SI** | 0.501 | 0.699 | 0.351 | 0.593 | 0.541 | 0.529 | 0.419 |

**Table 3** - Discriminant Validity (HTMT criterion).

| Hypothesis | Path | β | t-value | p-value | $f^2$ |
|---|---|---|---|---|---|
| H1 | PE→BI | 0.216 | 4.281 | 0.000*** | 0.146 |
| H2 | EE→BI | 0.210 | 4.176 | 0.000*** | 0.154 |
| H3 | SI→BI | 0.163 | 1.890 | 0.001** | 0.057 |
| H4 | FC→BI | 0.223 | 4.208 | 0.000*** | 0.154 |
| H5 | FC→AU | 0.298 | 5.474 | 0.000*** | 0.163 |
| H6 | CSE→BI | 0.175 | 3.381 | 0.000*** | 0.105 |
| H7 | PI→BI | 0.157 | 2.552 | 0.007** | 0.085 |
| H8 | BI→AU | 0.388 | 7.482 | 0.000*** | 0.230 |

**Table 4** – Summary of Hypotheses Testing.

**Notes**: **$p<0.01$, ***$p<0.001$, β=standardized beta coefficient, $f^2$=effect size

This implies that AI tools that have user-friendly interfaces and put less cognitive load on teachers are more likely to be adopted by them. The ease of using the AI tools is particularly important for teachers who may not be very tech-savvy. However, our findings are in contrast with the prior studies (e.g., Sánchez-Prieto et al., 2019; Hu et al., 2020) which indicate that effort expectancy has no significant influence on teachers' adoption of mobile technologies for teaching purposes. One possible explanation of this contradictory finding could be that teaching involves repetitive and structured tasks, which require less effort to use technologies. In contrast, research is more dynamic and exploratory, where the effort expectancy of AI tools becomes more crucial.

Hence when teachers perceive AI tools as both beneficial and easy to use, they are more likely to incorporate them into their research workflows.

RQ2: How do contextual factors (i.e., social influence and facilitating conditions) influence teachers' behavior towards using AI tools for research?

Regarding contextual factors, our findings demonstrate that social influence significantly affects teachers' intention to use AI tools for their research work. This indicates that teachers are highly influenced by the opinions and behaviors of their colleagues in the academic community. When influential peers or academic leaders endorse the use of AI tools, other teachers are also encouraged to use them. This highlights the importance of social influence in academic environments where collaboration and peer review are integral to the research process. Our findings are in line with prior studies that indicate a positive influence of social influence on teachers' acceptance of technologies (El Alfy & Kehal, 2024; Buabeng-Andoh & Baah, 2020; Rodríguez-Gil, 2024).

Further, we observed significant influence of facilitating conditions on behavioral intention as well as actual use of AI tools. This suggests that the availability of resources and support not only shape teachers' intention to use AI tools, they are also essential for actual utilization. The institutional support and an enabling environment including access to high-speed internet, necessary technical infrastructure, and technical support makes it feasible for teachers to make sustained use AI tools in their research processes. This finding is in consistence with those prior studies (Teo, 2011; Strzelecki, 2023).

RQ3: How do teachers' individual characteristics (i.e., personal innovativeness and computer self-efficacy) influence their behavior towards using AI tools for research?

The results of our study indicate that teachers' individual characteristics i.e. personal innovativeness and computer self-efficacy also determine their behavioral intention to adopt AI tools for research. Teachers who are more innovative and confident in their technical skills are more likely to adopt AI tools. Personal innovativeness drives teachers to explore and experiment with AI tools to enhance their research productivity. Teachers with high innovativeness are proactive in not only adopting the AI tools but also in exploring their advanced functionalities to make their best possible utilization. Such teachers actively seek to understand the advanced capabilities of AI tools. This contributes to their intention to adopt AI tools for research work. Our finding is in line with prior studies that indicate significant influence of personal innovativeness on teachers' acceptance of e-learning (Loogma et al., 2012) and IoT technologies (Gökçearslan et al., 2022).

Similarly, computer self-efficacy instills confidence in teachers to effectively use these tools, overcoming potential barriers and technical challenges. Teachers who believe in their capability to use AI tools are more likely to integrate them into their research processes, thereby improving research outcomes. Teachers who are confident in their technological skills are more open to adopting and experimenting with new technologies (Teo, 2009). They are more likely to engage in exploratory behaviors such as seeking out training resources, and overcoming initial usage difficulties (Zhao & Zhao, 2021). Such behavior supports their adoption of AI tools for research work. Our finding is in line with that of Gupta and Bhaskar (2023), which indicates a strong influence of computer self-efficacy on teachers' intention to adopt virtual reality applications for teaching purposes.

## 5. Conclusion

This study empirically examined the factors influencing teachers' adoption of AI tools for research by using an extended UTAUT model. The findings of the study highlighted the importance of technological, contextual, and teachers' personal attributes in shaping their intentions and actual usage of AI tools in research work. The technological attributes included the performance expectancy and effort expectancy of AI tools; contextual factors included social influence and facilitating conditions; teachers' personal characteristics included personal innovativeness and computer self-efficacy.

The quantitative findings of the study provide various implications for the developers of AI tools as well as the HEIs. Firstly, the developers should focus on creating AI tools that are compatible with the existing systems used by teachers. This could reduce the effort required to switch between different platforms and enhance the overall usability of AI tools. Integration of AI tools such as Grammarly with commonly used word processors (e.g., Microsoft Word) can streamline the editing process, making it more convenient for teachers to use these tools. Moreover, the AI tools should have intuitive and user-friendly interfaces. Simplified navigation and clear instructions are particularly important for teachers with varying levels of technical expertise. Developers should offer step-by-step instructions and tutorials to teachers who may struggle with new technologies and require more assistance. Second, to encourage the use of AI tools, HEIs should ensure that necessary facilitating conditions are readily available to all teachers. HEIs should conduct training programs and provide technical assistance to their teachers so that they can become proficient in using AI tools. HEIs should also focus on enhancing the technical self-efficacy of their teachers, so that they can make effective utilization of the AI tools. Various learning opportunities can be provided to the teachers through online courses on platforms such as Coursera or edX that focus on specific AI tools for research, such as data analysis software or text editors.

The study has several limitations that must be addressed in future studies. First, the study is based on a convenience sample which may not fully represent the broader population of teachers in diverse educational contexts. This can limit the ability to make generalizations of our findings to a wider population of teachers. Hence, the results of the present study should be interpreted with caution in the context of other teachers with similar characteristics. Future research should include more diversified samples to enhance the generalizability of our findings. Second, the present study was based on a cross-sectional research design. Future studies should use longitudinal designs to understand the dynamic nature of teachers' adoption of AI tools over time. Further research could also employ other research methods, such as interviews and case studies to make the findings more convincing and gain deeper insights. Finally, future studies can investigate the perceptions of other stakeholders such as policymakers, and institutional leaders. Understanding their views can help identify systemic barriers and facilitators that influence the broader adoption and effective utilization of AI tools in academic research.

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**Annexure 1** - Measurement Items.

**Performance Expectancy**
PE1: I believe that AI tools are useful in my research work
PE2: Using AI tools increases my chances of achieving important things in my research work
PE3: Using AI tools helps me get tasks done faster in my research work
PE4: Using AI tools increases my productivity in research work

**Effort Expectancy**
EE1: Learning how to use AI tools is easy for me
EE2: My interaction with AI tools is clear and understandable
EE3: I find AI tools easy to use
EE4: It is easy for me to become skillful at using AI tools

**Social Influence**
SI1: People who are important to me think I should use AI tools
SI2: People who influence my behavior believe that I should use AI tools
SI3: People whose opinions I value prefer me to use AI tools

**Facilitating conditions**
FC1: I have the resources necessary to use AI tools
FC2: I have the knowledge necessary to use AI tools
FC3: Using AI tools fits into my work style

**Computer Self Efficacy**
CSE1: I know how to use computers, Internet and AI tools
CSE2: I am confident about using AI tools and related technologies for my research work
CSE3: I feel I am in control when I use AI tools for my research work

**Personal Innovativeness**
PI1: If I heard about a new information technology, I would look for ways to experiment with it.
PI2: Among my peers, I am usually the first to try out new information technologies.
PI3: In general, I like to experiment with new information technologies.

**Behavioural Intention**
BI1: I intend to continue using AI tools in the future
BI2: I will always try to use AI tools in my research work
BI3: I plan to continue to use AI tools frequently

**Actual Use**
AU1: I use the free version of AI tools
AU2: I use AI tools as AI powered writing assistant
AU3: I use AI tools to generate assessed work