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Factors Influencing Higher Education Educators' Behavioral Intention to Use AI Educational Tools: A Technology Acceptance Model Perspective

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Abstract: Artificial intelligence (AI) educational tools are increasingly used in higher education, but adoption depends on educators' willingness to use them. Guided by the Technology Acceptance Model, this study examined how perceived ease of use (PEOU) and perceived usefulness (PU) predict higher education educators' behavioral intention (BI). A cross-sectional online questionnaire yielded 256 eligible responses from educators who had used or tried AI tools for teaching in the previous 12 months. The PEOU, PU, and BI scales showed strong internal consistency (α = .912, .920, and .890). Pearson correlations were positive and significant. Multiple regression showed that both PEOU (β = .329, $p < .001$) and PU (β = .423, $p < .001$) significantly predicted BI, explaining 45.2% of its variance. PU was the stronger predictor. The findings support the applicability of TAM to AI-supported teaching and suggest that institutions and developers should prioritize practical teaching value, usability, training, and technical support to encourage sustained adoption.

Keywords: Artificial intelligence; AI educational tools; Technology acceptance model; Behavioral intention; Higher education educators.

1. Introduction

1.1. Research Background

With rapid advances in artificial intelligence (AI), AI-based educational tools are increasingly used in higher education for lesson preparation, content creation, assessment, student feedback, and teaching decisions [1]. Compared with conventional digital tools, AI technologies offer capabilities such as content generation, data analysis, and personalized feedback that may improve teaching efficiency. However, availability does not guarantee educators' adoption or continued use. Educators may differ in how easy they find AI tools to use and how useful they consider them for improving teaching processes and outcomes [2]. The Technology Acceptance Model (TAM) identifies perceived ease of use (PEOU) and perceived usefulness (PU) as key determinants of technology acceptance and behavioral intention [3]. Guided by TAM, this study examines how PEOU and PU influence higher education educators' behavioral intention to use AI educational tools and offers theoretical and practical implications for higher education and educator development.

1.2. Research Objectives

The study has three research objectives:

To assess higher education educators' perceived ease of use of AI educational tools.

To assess higher education educators' perceived usefulness of AI educational tools.

To determine how perceived ease of use and perceived usefulness predict higher education educators' behavioral intention to use AI educational tools.

1.3. Research Questions

As AI educational tools become more common in higher education, educators' perceptions of their usability and practical value may shape future adoption. This study therefore addresses the following research questions:

RQ1: To what extent do higher education educators perceive AI educational tools to be easy to use?

RQ2: To what extent do higher education educators perceive AI educational tools to be useful?

RQ3: To what extent do perceived ease of use and perceived usefulness predict higher education educators' behavioral intention to use AI educational tools?

RQ1 and RQ2 describe educators' evaluations of AI educational tools, while RQ3 tests whether those evaluations explain the study's dependent variable, behavioral intention.

1.4. Research Gap and Contributions

Despite growing research on AI in higher education, limited evidence focuses specifically on educators' behavioral intention to use AI educational tools in routine teaching. Educators differ from student users because their adoption decisions are tied to lesson preparation, content creation, assessment, feedback, and other professional tasks. Moreover, AI educational tools offer generative and analytical capabilities that differ from those of conventional digital tools, making both usability and practical teaching value especially salient. Guided by TAM, this study focuses on PEOU, PU, and BI. It contributes by testing this simplified model with questionnaire data from higher education educators, extending evidence on TAM in AI-supported teaching, and identifying practical priorities for institutions and tool developers.

2. Literature Review

2.1. The Concept and Research Status of AI Educational Tools

2.1.1. Definition and Development of AI Educational Tools

AI educational tools are AI-based digital tools or systems

that support teaching, learning, assessment, feedback, and educational decision-making [4]. Compared with conventional digital tools, they use technologies such as machine learning, natural language processing, and data analytics to generate content, analyze information, provide personalized support, and assist decision-making. With the development of AI, particularly generative artificial intelligence, these tools have expanded from adaptive learning and automated assessment to content generation, instructional feedback, and teaching support [5]. They can assist educators with lesson preparation, material creation, assessment, and feedback. In this study, AI educational tools refer to AI-based tools used by higher education educators to support teaching activities and improve teaching efficiency; the focus is on educators' perceptions and acceptance rather than the technical performance of any specific application.

2.2. Educators' Perceptions and Behavioral Intention Toward AI Educational Tools

2.2.1. Perceived Ease of Use and Behavioral Intention

Perceived ease of use (PEOU) is a core TAM construct referring to the degree to which individuals believe that using a technology requires minimal effort. In this study, PEOU refers to higher education educators' perceptions of how easy AI educational tools are to learn and use in teaching. When the tools are easy to understand, operate, and integrate into existing practices, educators may experience lower learning costs and fewer operational barriers [6]. Tools perceived as complex may reduce behavioral intention. Therefore, higher PEOU is expected to be associated with stronger behavioral intention to use AI educational tools.

2.2.2. Perceived Usefulness and Behavioral Intention

Perceived usefulness (PU) is a core TAM construct referring to the degree to which individuals believe that using a technology can improve their work performance. In this study, PU refers to higher education educators' perceptions of whether AI educational tools can improve teaching efficiency and quality and support teaching tasks [7]. When educators believe that the tools reduce repetitive work, assist lesson preparation, support content creation and assessment, and provide useful feedback, they are more likely to recognize their practical value. Therefore, higher PU is expected to be associated with stronger behavioral intention to use AI educational tools.

2.3. Theoretical Basis: Technology Acceptance Model (TAM)

2.3.1. Development and Core Constructs of TAM

The Technology Acceptance Model (TAM), proposed by Davis [8], is widely used to explain individuals' acceptance and use of information technology. TAM emphasizes that acceptance is influenced by users' subjective perceptions of a technology, particularly perceived ease of use (PEOU) and perceived usefulness (PU). PEOU refers to the degree to which users believe a technology is easy to use, while PU refers to the degree to which they believe it can improve performance. These perceptions influence attitudes, behavioral intention, and actual use. Consistent with the research objectives, this study focuses on PEOU, PU, and behavioral intention to explain higher education educators' acceptance of AI educational tools.

2.3.2. Application of TAM in Educational Technology Research

TAM has been widely applied in educational technology research to explain educators' and students' acceptance of digital technologies. Technology adoption depends not only on access but also on users' perceptions and behavioral intentions. In educational contexts, PEOU reflects how easily users can learn and operate a technology, while PU reflects whether the technology can improve teaching or learning outcomes [9]. These factors are especially important for educators, who must consider both usability and practical teaching value. TAM therefore provides a suitable framework for examining higher education educators' behavioral intention to use AI educational tools.

2.3.3. Application of TAM to AI Educational Tools

The Technology Acceptance Model (TAM) can be applied to explain educators' acceptance of AI educational tools. When deciding whether to adopt these tools, educators may consider both their ease of use and their practical value in teaching.

Perceived ease of use reflects whether AI tools are easy to learn, operate, and integrate into existing teaching activities, while perceived usefulness reflects whether they can improve teaching efficiency, quality, assessment, and feedback. Positive perceptions of these factors may increase educators' willingness to use AI educational tools.

Therefore, this study adopts a simplified TAM framework, using perceived ease of use and perceived usefulness as key factors influencing higher education educators' behavioral intention to use AI educational tools.

2.4. Conceptual Framework and Hypotheses

2.4.1. Conceptual Framework

Based on TAM and the reviewed literature, this study specifies a simplified acceptance model in which perceived ease of use (PEOU) and perceived usefulness (PU) are the independent variables and behavioral intention (BI) is the dependent variable. As shown in Figure 1, the model tests whether educators' judgments of usability and practical teaching value influence their intention to use AI educational tools.

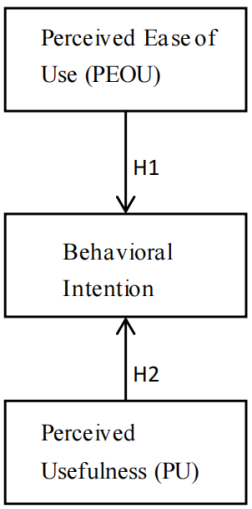


Figure 1. Conceptual Framework. Source: Developed by the author based on Davis [8].

The framework proposes that educators who perceive AI educational tools as easier to use will report stronger behavioral intention. It also proposes that educators who

believe the tools improve teaching efficiency, quality, and task support will report stronger behavioral intention. Examining PEOU and PU together makes it possible to compare the effects of these two core perceptions on educators' intention to use AI educational tools.

2.4.2. Research Hypotheses

Based on the fundamental theoretical logic of TAM and the aforementioned literature analysis, this study argues that perceived ease of use can reduce the perceived technical complexity and learning costs for educators when using AI educational tools. When educators perceive AI educational tools as easy to learn, understand, and operate, their barriers to applying these tools in teaching activities are likely to decrease, thereby enhancing their willingness to use such tools in the future. Therefore, this study proposes its first research hypothesis:

H1: Perceived ease of use has a significant positive effect on higher education educators' behavioral intention to use AI educational tools.

On the other hand, perceived usefulness reflects educators' evaluation of the actual teaching value of AI educational tools. When educators believe that AI educational tools can improve teaching efficiency, enhance teaching quality, and effectively assist teaching tasks, they are more likely to believe that using AI tools will bring actual benefits to their teaching work, thus forming a stronger willingness to use them. Therefore, this study proposes its second research hypothesis:

H2: Perceived usefulness has a significant positive effect on higher education educators' behavioral intention to use AI educational tools.

3. Methodology

3.1. Research Design

This study adopted a quantitative, cross-sectional questionnaire design to examine higher education educators' perceived ease of use (PEOU), perceived usefulness (PU), and behavioral intention (BI) toward AI educational tools. PEOU and PU were treated as independent variables, while BI was the dependent variable. A structured questionnaire measured the 11 core items on a five-point Likert scale [10]. The final analytic sample comprised 256 eligible questionnaire responses (N = 256). Descriptive statistics, reliability analysis, Pearson correlation analysis, and multiple linear regression analysis were used.

3.2. Population and Sampling

The target population consisted of higher education educators who had used or tried at least one AI educational tool for teaching-related work during the previous 12 months. Because the population was geographically dispersed and recruitment was conducted online, convenience sampling was used. The Chinese-language questionnaire link was distributed through WeChat and education-related networks, reaching educators primarily based in China.

Eligibility was confirmed through three screening questions covering voluntary consent, current work in higher education teaching or teaching-related roles, and recent experience with AI educational tools. All 256 submitted responses met these criteria and contained complete data for the 11 core measurement items; consequently, all were retained for the main analysis.

3.3. Research Instrument

A structured questionnaire served as the research instrument. The first part contained eligibility questions and collected gender, age, higher education teaching experience, academic rank, discipline, institution type, region, AI-use frequency, and teaching-related AI-use activities. The second part measured perceived ease of use, perceived usefulness, and behavioral intention.

PEOU and PU were each measured with four items, while BI was measured with three items, resulting in 11 core items. All items used a five-point Likert scale, where 1 represented "Strongly Disagree," 2 "Disagree," 3 "Neutral," 4 "Agree," and 5 "Strongly Agree." Construct scores were calculated as the mean of the relevant items.

3.4. Measurement of Variables

Table 1. Measurement of Research Variables. Source: Developed by the author for this study.

Variable	Code	Measurement Item
Perceived Ease of Use (PEOU)	PEOU1	Learning to use AI educational tools is easy for me.
	PEOU2	My interaction with AI educational tools is clear and understandable.
	PEOU3	It is easy for me to become skillful at using AI educational tools.
	PEOU4	Overall, I find AI educational tools easy to use.
Perceived Usefulness (PU)	PU1	Using AI educational tools improves my teaching efficiency.
	PU2	Using AI educational tools improves the quality of my teaching-related work.
	PU3	Using AI educational tools improves my effectiveness in completing teaching-related tasks.
	PU4	Overall, AI educational tools are useful for my teaching-related work.
Behavioral Intention (BI)	BI1	I intend to continue using AI educational tools in teaching-related work over the next six months.
	BI2	I plan to use AI educational tools frequently in my teaching-related work.
	BI3	I expect to increase my use of AI educational tools in the future.

3.5. Data Collection

Data were collected through the formal online questionnaire from September 10 to September 11, 2026. The first page explained the study purpose, participation procedures, voluntary nature of participation, and intended use of the data. No names or contact details were requested. The questionnaire link was distributed through WeChat and educator-related networks. After collection, the responses were screened, de-identified for analysis, organized, and coded. The final dataset contained 256 eligible respondents and 11 core measurement items.

3.6. Data Analysis

3.6.1. Data Screening, Descriptive Statistics, and Reliability Analysis

Responses were screened for eligibility, missing core data, duplicate answer profiles, repeated IP addresses, completion time, invariant responding, and demographic consistency. All 256 respondents met the eligibility criteria and completed every core item. No identical full-response profiles or repeated IP addresses were found, and completion times ranged from 232 to 370 seconds (Mdn = 307). Eight records were flagged for sensitivity analysis: six invariant core-item patterns, one missing response to the multi-select activity question, and one age–teaching-experience inconsistency. They were retained in the main analysis because no prespecified exclusion rule or corroborating indicator justified removal. Frequencies and percentages summarized respondent characteristics; means and standard deviations summarized PEOU, PU, and BI. Cronbach's alpha assessed internal consistency, with $\alpha \geq .70$ treated as acceptable.

3.6.2. Pearson Correlation and Multiple Regression Analysis

Pearson correlation analysis examined the relationships among PEOU, PU, and BI. Multiple linear regression then tested the simultaneous predictive effects of PEOU and PU on BI. The analysis reported unstandardized coefficients (B), standard errors (SE), standardized coefficients (β), t-values, p-values, R^2, adjusted R^2, and the model F-statistic. A positive coefficient with $p < .05$ was interpreted as statistical support for the corresponding hypothesis. A sensitivity analysis repeated the standardized regression after excluding the eight flagged records.

The main and sensitivity analyses were compared to determine whether the conclusions for H1 and H2 were robust to the quality flags.

4. Results and Discussions

4.1. Results Overview

This section presents the results for the 256 eligible questionnaire responses. The analyses cover respondent characteristics, AI-use activities, descriptive statistics, reliability, Pearson correlations, multiple regression, sensitivity analysis, and hypothesis testing.

The sample included 146 women (57.0%), 98 men (38.3%), seven respondents identifying with another gender (2.7%), and five who preferred not to say (2.0%). The largest age group was 30–39 years (37.5%), followed by 40–49 years (31.3%). Respondents represented different teaching-experience levels, academic ranks, disciplines, institution types, and regions; 68.4% worked at public institutions and 40.6% were based in Eastern China. AI tools were used several times per week by 40.2% and daily or almost daily by 21.1%. Among the 255 respondents with a recorded activity selection, the most common uses were teaching-material development (84.3%), lesson preparation (74.1%), and academic writing or research (68.6%).

Table 2. Characteristics of Respondents (N = 256). Source: Author's analysis of formal survey data.

Characteristic	Category	Frequency	Percentage
Gender	Male	98	38.3%
	Female	146	57.0%
	Another gender identity	7	2.7%
	Prefer not to say	5	2.0%
Age	Under 30	30	11.7%
	30–39	96	37.5%
	40–49	80	31.3%
	50–59	39	15.2%
	60 or above	11	4.3%
Teaching Experience	Less than 5 years	54	21.1%
	5–10 years	65	25.4%
	11–15 years	58	22.7%
	16–20 years	49	19.1%
	More than 20 years	30	11.7%
Academic Rank	Teaching assistant	15	5.9%
	Lecturer	76	29.7%
	Associate professor	76	29.7%
	Professor	50	19.5%
	No academic title	29	11.3%
	Other	10	3.9%
Discipline	Humanities	16	6.3%
	Social sciences	22	8.6%
	Business, economics, or management	27	10.5%
	Science, engineering, or information technology	52	20.3%
	Medicine or health sciences	31	12.1%
	Education	39	15.2%
	Agriculture or forestry	23	9.0%
	Interdisciplinary	25	9.8%
	Other	21	8.2%
Institution Type	Public institution	175	68.4%
	Private institution	45	17.6%
	Sino-foreign cooperative institution	22	8.6%
	Other	14	5.5%
Region	Eastern China	104	40.6%
	Central China	54	21.1%
	Western China	55	21.5%
	Northeast China	28	10.9%
	Hong Kong, Macao, or Taiwan	6	2.3%
	Outside China	9	3.5%
AI-use Frequency	Less than once per month	22	8.6%
	Several times per month	77	30.1%
	Several times per week	103	40.2%
	Daily or almost daily	54	21.1%

4.2. Descriptive Statistics

Descriptive statistics were calculated for PEOU, PU, and BI. As shown in Table 3, the mean scores of all three variables were above the five-point scale midpoint of 3.00.

PU had the highest mean score (M = 3.75, SD = 0.94), followed by BI (M = 3.63, SD = 0.94) and PEOU (M = 3.59, SD = 0.91). These results indicate that respondents generally viewed AI educational tools as useful and moderately easy to use and reported a moderately positive intention to continue or increase their use.

Table 3. Descriptive Statistics of Research Variables. Source: Author's analysis of formal survey data.

Variable	N	Mean	SD
Perceived Ease of Use (PEOU)	256	3.59	0.91
Perceived Usefulness (PU)	256	3.75	0.94
Behavioral Intention (BI)	256	3.63	0.94

4.3. Reliability Analysis

Cronbach's alpha was used to examine the internal consistency of the three measurement scales. As shown in Table 4, α was .912 for PEOU, .920 for PU, and .890 for BI. All values exceeded .70, indicating strong internal

consistency and supporting the use of mean composite scores in the subsequent analyses.

Table 4. Reliability Analysis. Source: Author's analysis of formal survey data.

Variable	Number of Items	Cronbach's Alpha
Perceived Ease of Use (PEOU)	4	.912
Perceived Usefulness (PU)	4	.920
Behavioral Intention (BI)	3	.890

4.4. Pearson Correlation Analysis

Pearson correlation analysis examined the relationships among PEOU, PU, and BI. As shown in Table 5, all three variables were positively and significantly correlated.

PEOU was positively correlated with BI ($r = .580$, $p < .001$), while PU was positively correlated with BI ($r = .618$, $p < .001$). PEOU was also positively correlated with PU ($r = .593$, $p < .001$). The PU–BI correlation was the strongest of the three relationships.

Table 5. Pearson Correlation Analysis. Source: Author's analysis of formal survey data.

Relationship	Pearson Correlation (r)	p-value	Result
PEOU–PU	.593	< .001	Significant
PEOU–BI	.580	< .001	Significant
PU–BI	.618	< .001	Significant

The positive bivariate relationships provided preliminary support for H1 and H2 and justified testing the simultaneous contribution of PEOU and PU in the regression model.

4.5. Multiple Regression Analysis

Multiple linear regression was used to test whether PEOU and PU jointly predicted BI. The overall model was statistically significant, $F(2, 253) = 104.38$, $p < .001$. The model yielded $R = .672$, $R^2 = .452$, and adjusted $R^2 = .448$, indicating that PEOU and PU jointly explained 45.2% of the variance in behavioral intention.

Table 6. Multiple Regression Model Summary. Source: Author's analysis of formal survey data.

R	R^2	Adjusted R^2	F	df	p-value
.672	.452	.448	104.38	2, 253	< .001

PEOU was a significant positive predictor of BI ($B = .340$, $SE = .060$, $\beta = .329$, $t = 5.69$, $p < .001$). Thus, respondents who perceived AI educational tools as easier to use tended to report stronger behavioral intention.

PU was also a significant positive predictor of BI ($B = .425$, $SE = .058$, $\beta = .423$, $t = 7.32$, $p < .001$). Its standardized coefficient was larger than that of PEOU, making PU the stronger predictor in the model.

Table 7. Multiple Regression Coefficients. Source: Author's analysis of formal survey data.

Predictor	B	SE	Standardized β	t	p-value
PEOU	.340	.060	.329	5.69	< .001
PU	.425	.058	.423	7.32	< .001

Note. Dependent variable: Behavioral Intention (BI). B = unstandardized coefficient; SE = standard error; β = standardized coefficient.

4.6. Hypothesis Testing

The regression results supported both research hypotheses. The results were also robust in the sensitivity analysis.

H1 proposed that perceived ease of use has a significant positive effect on higher education educators' behavioral intention to use AI educational tools. The standardized effect was positive and significant ($\beta = .329$, $p < .001$), supporting H1. H2 proposed that perceived usefulness has a significant positive effect on behavioral intention. This effect was also positive and significant ($\beta = .423$, $p < .001$), supporting H2.

Table 8. Summary of Hypothesis Testing. Source: Author's analysis of formal survey data.

Hypothesis	Relationship	β	p-value	Result
H1	PEOU → BI	.329	< .001	Supported
H2	PU → BI	.423	< .001	Supported

A sensitivity analysis excluding all eight flagged records produced the same substantive conclusion ($n = 248$): PEOU ($\beta = .318$, $p < .001$) and PU ($\beta = .415$, $p < .001$) remained positive and significant, and the model explained 42.5% of BI variance ($R^2 = .425$). The findings are therefore not dependent on retaining the flagged records.

4.7. Discussion of Findings

This study examined the effects of PEOU and PU on higher education educators' BI to use AI educational tools. Both predictors were positive and significant, supporting H1 and H2. The PEOU result ($\beta = .329$, $p < .001$) indicates that educators are more willing to use AI educational tools when the tools are easy to learn, understand, and operate. Lower effort and clearer interaction may reduce technical barriers to integration into teaching practice. The PU result ($\beta = .423$, $p < .001$) indicates that educators' intentions are stronger when they believe the tools improve teaching efficiency, work quality, and task effectiveness. PU was the stronger predictor, suggesting that practical teaching value matters more than ease of use alone.

Together, PEOU and PU explained 45.2% of the variance in BI ($R^2 = .452$). This explanatory power, along with the unchanged sensitivity-analysis conclusions, supports the basic logic of the Technology Acceptance Model in the context of AI-supported higher education teaching.

4.8. Theoretical Contributions

This study provides further support for the application of the Technology Acceptance Model in the context of AI educational tools. The significant effects of PEOU and PU on BI indicate that the core cognitive factors of TAM remain relevant for explaining educators' acceptance of emerging AI technologies. In addition, this study simplifies the traditional TAM framework by focusing on three core variables: PEOU, PU, and BI. This provides a more focused approach to understanding how educators' perceptions of AI educational tools are related to their future usage intentions. The findings also provide additional empirical evidence for the application of TAM in the context of higher education and AI-supported teaching.

5. Conclusion

This study investigated higher education educators' behavioral intention to use AI educational tools through the Technology Acceptance Model. Analysis of 256 eligible questionnaire responses showed that both perceived ease of use and perceived usefulness significantly and positively predicted behavioral intention, supporting H1 and H2. Perceived usefulness was the stronger predictor, while the two variables jointly explained 45.2% of the variance in behavioral intention.

The findings indicate that educators' adoption intentions depend on both manageable interaction and demonstrable teaching value. They also provide empirical support for applying TAM to AI educational tools and offer practical implications for universities and educational technology developers.

5.1. Research Limitations and Future Research

This study has several limitations. First, convenience sampling and online recruitment limit the generalizability of the findings. The sample was recruited mainly through China-based networks, was concentrated in public institutions and Eastern China, and included a small proportion of respondents outside China. Future studies should use probability-based or stratified sampling and recruit larger samples across institutions and regions.

Second, the short, cross-sectional data-collection period captures perceptions at one point in time and does not establish causality. Longitudinal studies could examine whether acceptance changes with experience. Third, the model included only PEOU, PU, and BI. Although the predictors explained 45.2% of BI variance, future research could add AI literacy, trust, AI anxiety, institutional support, and actual-use measures. Finally, the questionnaire used self-reported data; future studies could combine survey responses with interviews or behavioral usage records.

6. Recommendations

Higher education institutions should provide practical training, clear operating guidance, and accessible technical support so that educators can use AI educational tools effectively. Because PU was the stronger predictor of BI, implementation should demonstrate how the tools improve lesson preparation, content development, assessment, feedback, and research-related work rather than present AI only as a new technology.

Developers should prioritize clear interaction, low learning effort, and reliable support for authentic teaching tasks. Institutions should also evaluate adoption over time, establish appropriate guidance for responsible use, and address differences in AI literacy, trust, anxiety, and local technical support when planning wider implementation.

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Qiaoyu Zhai is affiliated with the Rattanakosin International College of Creative Entrepreneurship at Rajamangala University of Technology Rattanakosin. The author's academic interests include higher education, educational technology, artificial intelligence in teaching, and technology acceptance. This research examines how perceived ease of use and perceived usefulness shape higher education educators' behavioral intention to adopt AI educational tools.

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