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Evaluating AI adoption among university students in Indonesia: A case study at the Department of Office Administration Education at the Universitas Sebelas Maret

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Abstract

The integration of artificial intelligence (AI) in education has gained global attention, yet significant gaps exist in the understanding of how AI adoption varies across academic disciplines and geographical regions. In Indonesia, particularly in office administration education, limited empirical evidence exists regarding the intersection of AI adoption patterns, user preferences, and educational outcomes. This study examines AI tool adoption among office administration students at Universitas Sebelas Maret (UNS), Indonesia, via an integrated framework that combines the technology acceptance model (TAM) and the information system (IS) success model. Structural equation modeling (SEM) analysis of data from 61 undergraduate students revealed that ChatGPT was the predominant AI tool among students. The analysis identified key relationships between information quality, system quality, and user acceptance factors. The findings support experiential learning theory principles and demonstrate that successful AI integration in education depends on user-friendly interfaces, quality content delivery, and robust support systems. These insights enhance our understanding of AI tool adoption in Indonesian higher education and provide practical strategies for effective AI integration in academic curricula.

Keywords: Artificial intelligence, Technology acceptance model, IS success model, Higher education, Educational technology

Introduction

The integration of artificial intelligence (AI) has fundamentally transformed various sectors of society, revolutionizing operational paradigms across industries and institutions (Krishna, 2024). This technological evolution, characterized by advanced machine learning algorithms and natural language processing systems, represents a pivotal shift in the Fourth Industrial Revolution (Ally & Perris, 2022). The impact of AI spans multiple domains, demonstrating significant potential in enhancing operational efficiency and decision-making processes through data analytics and task automation (Haleem et al., 2022). Recent developments have shown AI's ability to optimize customer experiences, enable predictive maintenance, and strengthen security measures across industries (Alowais et al., 2023; Josyula, 2023).

However, the proliferation of AI technologies presents notable challenges, particularly with respect to security and ethical considerations. Research has highlighted increasing concerns about the potential misuse of AI in fraudulent activities, including sophisticated deepfake technology and automated cyberattacks (Odeyemi et al., 2024). The evolution of AI-driven systems has introduced complex challenges in cybersecurity, as malicious actors have developed increasingly sophisticated methods to exploit technological vulnerabilities (Naitali et al., 2023; Schmitt & Flechais, 2024). These concerns extend to issues of algorithmic bias and discrimination, necessitating careful consideration of the societal impact of AI (Borgesius, 2018).

In educational contexts, AI offers transformative potential for enhancing teaching and learning processes while optimizing administrative functions. Current research has demonstrated AI's capacity to facilitate personalized learning pathways and streamline educational administration (Kamalov & Gurrib, 2023). This technology enables data-driven decision-making in education, supporting precise interventions and improved learning outcomes (Owan et al., 2023). However, this integration raises significant concerns regarding privacy, data security, and educational equity (Božić, 2023; Creely, 2023; Korir et al., 2023).

The Indonesian educational landscape presents a unique context for examining AI integration. Recent studies in various Indonesian cities have revealed diverse approaches to AI adoption in education, with contrasting perspectives among educators and students (Abdullah et al., 2023; Dangin et al., 2023). Research in Gorontalo and Yogyakarta indicates varying levels of AI implementation and acceptance, highlighting the need for comprehensive investigations into the educational applications of AI within Indonesia's specific context (Alatas, 2022).

This study addresses a significant research gap regarding AI utilization in Indonesian higher education, with a specific focus on office administration students at Universitas Sebelas Maret (UNS) Surakarta. By employing the Technology Acceptance Model (TAM) integrated with IS success factors, this research examines patterns of AI adoption, usage preferences, and impacts on learning experiences. This investigation aims to provide empirical evidence to inform curriculum development and policy formation in office administration education while contributing to a broader understanding of AI integration in Indonesian higher education.

Methodology

This study employs a quantitative research approach to examine AI tool adoption patterns among office administration students. The selection of a quantitative methodology allows for the statistical analysis of relationships between variables and hypothesis testing through structural equation modeling (SEM). This design choice aligns with similar studies in technology acceptance research (Legramante et al., 2023; Mohammadi, 2015) and enables objective measurement of adoption factors.

Research design

The integrated framework combines essential constructs from both the technology acceptance model (TAM) and the information system (IS) success model to provide a comprehensive understanding of AI adoption. The TAM components include five key elements: perceived ease of use (PEOU), perceived usefulness (PU), attitude toward use (ATU), behavioral intention to use (BIU), and actual usage (AU). These components are complemented by three fundamental IS success factors: information quality (IQ), system quality (SYQ), and service quality (SQ), as illustrated in Figure 1. This integration enables a more thorough examination of both the technological and behavioral aspects influencing AI adoption in educational settings.

On the basis of this integrated framework, fourteen hypotheses were developed to examine the relationships between these constructs (Table 1). The model adaptation follows Rahayu’s (2023) framework for examining ChatGPT acceptance among Indonesian students, with modifications to address broader AI based applications (Rahayu, 2023).

Hypothesis development

The research hypotheses were developed on the basis of an extensive literature review and theoretical foundations:

1) Information Quality and Perceived Usefulness (H1): Previous studies by El Koshiry et al. (2023) and Baroni et al. (2022) demonstrated that information quality significantly influences users’ perceptions of technology usefulness (Baroni et al., 2022; El Koshiry et al., 2023).

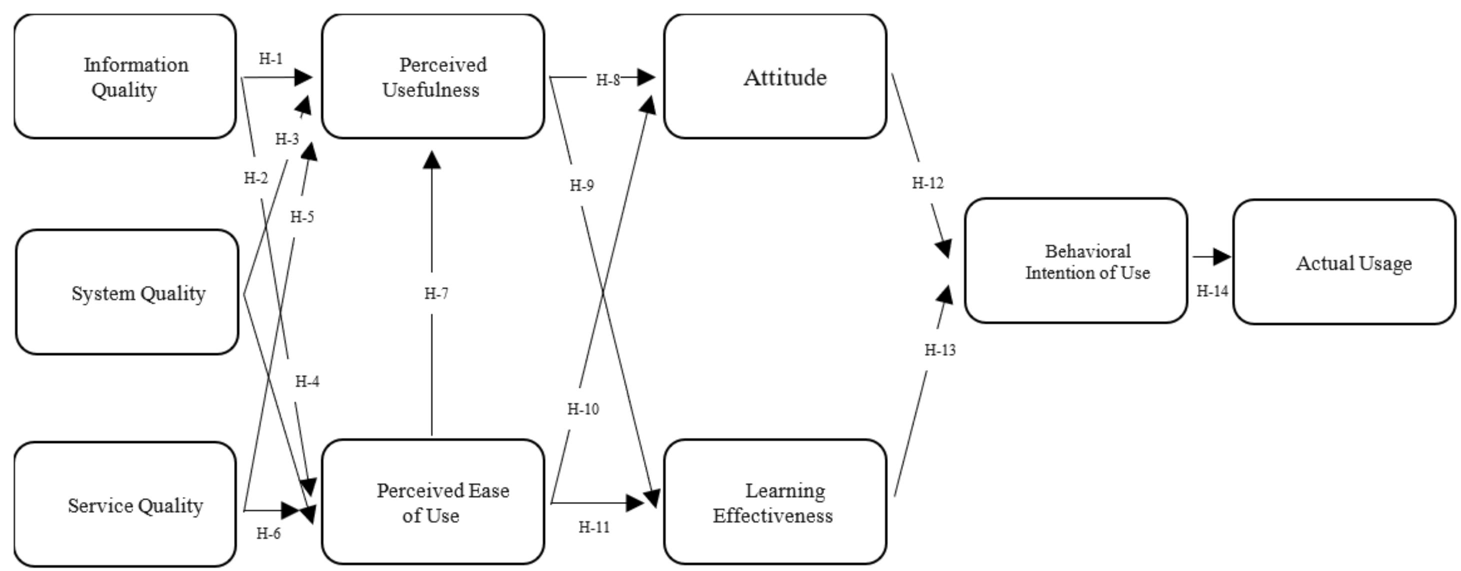

Fig. 1 Research design

Table 1 Research hypotheses

Number of Hypothesis	Hypothesis
Hypothesis 1 (H1)	Information quality (IQ) using the AI based application has a significant influence on perceived usefulness (PU)
Hypothesis 2 (H2)	Information quality (IQ) using the AI based application has a significant influence on perceived ease of use (PEOU)
Hypothesis 3 (H3)	System quality (SYQ) using the AI based application has a significant influence on perceived usefulness (PU)
Hypothesis 4 (H4)	System quality (SYQ) using the AI based application has a significant influence on perceived ease of use (PEOU)
Hypothesis 5 (H5)	Service quality (SQ) using the AI based application has a significant influence on perceived usefulness (PU)
Hypothesis 6 (H6)	Service quality (SQ) using the AI based application has a significant influence on perceived ease of use (PEOU)
Hypothesis 7 (H7)	Perceived ease of use (PEOU) using the AI based application has a significant influence on perceived usefulness (PU)
Hypothesis 8 (H8)	Perceived usefulness (PU) using the AI based application has a significant influence on attitude (ATU)
Hypothesis 9 (H9)	Perceived usefulness (PU) using the AI based application has a significant influence on learning effectiveness (LE)
Hypothesis 10 (H10)	Perceived ease of use (PEOU) using the AI based application has a significant influence on attitude (ATU)
Hypothesis 11 (H11)	Perceived ease of use (PEOU) using the AI based application has a significant influence on learning effectiveness (LE)
Hypothesis 12 (H12)	Attitude (ATU) using the AI based application has a significant influence on behavioral intention of use (BIU)
Hypothesis 13 (H13)	Learning effectiveness (LE) using the AI based application has a significant influence on behavioral intention of use (BIU)
Hypothesis 14 (H14)	Behavioral intention of use (BIU) using the AI based application has a significant influence on actual usage (AU)

2) Information Quality and Perceived Ease of Use (H2): Research by Davis and Davis (1989) and recent work by Legramante et al. (2023) establish that high-quality information enhances users' perception of system usability (Davis & Davis, 1989; Legramante et al., 2023).
3) System Quality and Perceived Usefulness (H3): Studies by Mohammadi (2015) indicate that system quality directly affects users' perceptions of technology usefulness in educational contexts (Mohammadi, 2015).
4) System Quality and Perceived Ease of Use (H4): Previous research by Delone & McLean (2003) shows that system quality significantly influences how easily users can interact with technology (Delone & McLean, 2003).
5) Service Quality and Perceived Usefulness (H5): Korir et al. (2023) demonstrated that quality support services enhance users' perceptions of technology utility (Korir et al., 2023).

6) Service Quality and Perceived Ease of Use (H6): Research by Božić (2023) indicates that effective support services significantly improve users' ability to navigate new technologies (Božić, 2023).
7) Perceived Ease of Use and Perceived Usefulness (H7): The original TAM framework by Davis and Davis (1989) establishes this fundamental relationship, which is supported by numerous subsequent studies (Davis & Davis, 1989).
8) Perceived Usefulness and Attitude (H8): Research by El Koshiry et al. (2023) confirms that users' perceptions of utility significantly shape their attitudes toward technology (El Koshiry et al., 2023).
9) Perceived Usefulness and Learning Effectiveness (H9): Owan et al. (2023) reported that perceived usefulness directly impacts learning outcomes in educational technology contexts (Owan et al., 2023).
10) Perceived Ease of Use and Attitude (H10): The TAM model and recent studies by Legramante et al. (2023) validate this relationship in educational settings (Legramante et al., 2023).
11) Perceived Ease of Use and Learning Effectiveness (H11): Research by Kamalov and Gurrib (2023) demonstrates that ease of use significantly affects learning outcomes (Kamalov & Gurrib, 2023).
12) Attitude and Behavioral Intention to Use (H12): Studies by Abdullah et al. (2023) confirm that positive attitudes toward technology lead to stronger usage intentions (Abdullah et al., 2023).
13) Learning Effectiveness and Behavioral Intention to Use (H13): Research by Dangin et al. (2023) shows that perceived learning benefits influence future usage intentions (Dangin et al., 2023).
14) Behavioral Intention to Use and Actual Usage (H14): The original TAM framework and recent studies by Garaika et al. (2020) validate this final relationship in the technology adoption process (Garaika, 2020).

Each hypothesis is grounded in established theoretical frameworks and supported by recent empirical studies on educational technology adoption, particularly in the context of AI tools in higher education.

Population and sampling

Target population

The study population comprises undergraduate office administration students at Universitas Sebelas Maret (UNS), Surakarta, Indonesia (N = 72).

Sampling criteria

The study implemented specific inclusion and exclusion criteria to ensure data quality and research validity. The participants were required to be currently enrolled students in the Office Administration program with active participation in courses utilizing AI tools. To ensure adequate experience with AI applications, only students with a minimum of one semester of experience using AI tools were included, with participants falling within the age range of 18 to 23 years. The study excluded students on academic leave, exchange students, temporary enrollees, and those in nonregular programs. Additionally, students who had not incorporated AI tools in their coursework were not eligible to participate. These criteria were established to maintain sample homogeneity and ensure that participants had sufficient experience with AI applications in their academic work.

Sample size and selection

The study employed a systematic approach to determine the appropriate sample size via Yamane's formula, where n represents the sample size, N represents the total population size of 72 students, and represents the margin of error set at 0.05. This calculation yielded a required sample size of 61 participants, ensuring statistical significance while maintaining practical feasibility. The sampling process considers both the mathematical requirements for statistical validity and the practical constraints of data collection within the academic environment. This approach aligns with established research practices in educational technology studies and provides a representative sample of the target population.

Data collection instrument

Data collection was conducted via a structured questionnaire distributed through Google Forms. The research instrument utilized a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) to measure various constructs derived from the integrated TAM-IS success model. The questionnaire was designed to assess three main categories of constructs. The first category focuses on information system quality measures, which include information quality (IQ), system quality (SYQ), and service quality (SQ). The second category addressed Technology Acceptance Measures, comprising Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (ATU), Behavioral Intention to Use (BIU), and Actual Usage (AU). The third category examined learning effectiveness (LE). This comprehensive structure enabled the measurement of both the technical and behavioral aspects of AI technology adoption among students. The indicators and questionnaires used are presented in Table 2.

Table 2 Questionnaire Items

Variable	Code	Indicator	Questionnaire item	Reference from the previous research
Perceived Ease of Use (PEOU)	PEOU1	Easy to learn	It was easy for me to learn the AI based application to support my academics.	(Ali & Widiati, 2023; Widaningsih & Mustikasari, 2022)
	PEOU2	Easy to reach the goal	By using the AI based application to enhance my studies, I can easily locate what I'm looking for.	
	PEOU3	Easy to understand	My connection with the AI-powered software is straightforward and comprehensible.	
	PEOU4	Flexible	I would use an AI based application for my everyday needs since it is incredibly flexible and can be used at any time and from any location.	
	PEOU5	Free from difficulties	I was able to easily learn and use the AI based program.	
	PEOU6	Easy to use		
Perceived Usefulness (PU)	PU1	Increase productivity	Overall, I believe that the AI based program is quite straightforward to use for my academic needs.	(Baroni et al., 2022; Park & Kim, 2023)
	PU2	Increasing effectivity	I believe AI based applications can boost my productivity.	
	PU3	Increasing working output	I believe AI based applications can boost my work efficiency.	
	PU4	The work can be done faster	I believe AI based applications can increase my work output.	
	PU5	Make the work much easier	I believe that AI based applications allow me to work faster.	
	PU6	Usable	I believe that the AI based application enables me to work easier.	
Attitude (ATU)	ATU1	Comfort of interaction	I believe that the AI based application is quite handy for my daily use.	(Mahendra, 2016; Wicaksono, 2022)
	ATU2	Happy to use the product	I feel comfortable when I need to use AI based applications.	
	ATU3	Not boring to use	I feel happy every time I utilize an AI based application.	
	ATU4	Good privacy policy	I believe that the user experience when using the AI based application is enjoyable.	
Behavioral Intention to Use (BIU)	BIU1	Desire	I feel my personal data is completely protected when I utilize the AI based application.	(Aditia et al., 2018; Ali & Widiati, 2023; Baroni et al., 2022)
	BIU2	Capability	I always wish to use AI based applications for educational objectives.	
	BIU3	Continuity	I feel that I am highly capable of using AI based applications.	

Actual Usage (AU)	AU1	Customer satisfaction	I will continue to utilize the AI based application for long-term objectives, including those not related to schooling.	(Aditia et al., 2018; Baroni et al., 2022; Mahendra, 2016)
	AU2	Duration of use	I'm quite satisfied with using the AI based program for my educational purposes.	
	AU3	Intensity	I utilize the AI based application for more than two hours a day.	
Information Quality (IQ)	IQ1	Information accuracy	I open the AI based application more than five times every day.	(Aditia et al., 2018; Legramante et al., 2023; Mohammadi, 2015)
	IQ2	Relevance	The AI based application provides an accurate information.	
	IQ3	Completeness	The AI based application provides a relevance information.	
	IQ4	Ontime	The AI based application provides a complete information.	
	IQ5	Clarity	The AI based application provides a real time information.	
System Quality (SYQ)	SYQ1	User friendly	The AI based application provides a clear information.	(Aditia et al., 2018; Legramante et al., 2023; Mohammadi, 2015)
	SYQ2	Safety	The AI based application graphical interface is very user friendly.	
	SYQ3	Fast response time	The AI based application has a good privacy security feature.	
	SYQ4	Reliable	The AI based application provides a fast-loading time.	
	SYQ5	Interesting feature	The AI based application is very reliable for everyday use.	
	SYQ6	Accessibility	The AI based application has very interesting features.	
Service Quality (SQ)	SQ1	Responsiveness	The AI based application very easy to be accessed anytime and anywhere.	(Aditia et al., 2018; Delone & Mclean, 2003; Legramante et al., 2023; Mohammadi, 2015)
	SQ2	Empathy	The AI based application is very responsive, that I can access easily across devices.	
	SQ3	Guidelines	The AI based application is always updated based on the previous user experience.	
Learning Effectiveness (LE)	LE1	Study results	The AI based application provides a very helpful guidelines that make new user can easily learn about it.	(Aditia et al., 2018; Legramante et al., 2023; Mohammadi, 2015)
	LE2	Study material	The AI based application has a positive result on my study report last semester.	
	LE3	Evaluation of study	I can find a good study material by using the AI based application.	

Data analysis

Data analysis in this study was conducted via structural equation modeling (SEM) through SmartPLS software to examine the relationships between variables. The analytical process included four main components. First, the measurement model assessment evaluated reliability and validity to ensure the robustness of the constructs. Second, structural model evaluation was performed for hypothesis testing to determine the significance of the proposed relationships. Third, descriptive statistics were employed to analyze the demographic data, providing insights into the sample characteristics. Finally, path analysis was conducted to examine both direct and indirect effects between variables, offering a comprehensive understanding of the relationships within the integrated TAM-IS success model.

Results

Descriptive analysis

A survey of 61 office administration undergraduate students at Universitas Sebelas Maret Surakarta revealed distinct patterns in AI tool adoption. ChatGPT emerged as the dominant generative AI platform, with 44% of the students identifying it as their primary tool. This preference indicates the platform's perceived utility for academic tasks such as writing assignments and language learning. Digital platforms, particularly search engines, served as the primary source of AI-related knowledge for 66% of participants, whereas 31% engaged with online learning communities for AI-related information exchange (see Table 3).

Table 3 Demographic results

Demographic Information	Frequency	Percentage
Name of AI Based Application		
Chat GPT	27	44
Perplexity AI	8	13
Google Gemini	13	21
Poe AI	8	13
Microsoft Co-Pilot	5	8
N =	61	100
Student Grades		
Semester 2	33	54
Semester 4	28	46
N =	61	100
AI Information Source		
Internet (e.g., Search Engine)	40	66
Learning Community	19	31
Friend	2	3
N =	61	100

Measurement model assessment

The measurement model was evaluated through factor loadings, internal consistency reliability tests, and validity tests. All factor loadings exceeded the 0.7 threshold recommended by Hair et al. (2021), indicating robust indicator reliability. Most of the constructs had Cronbach's alpha values above 0.7, meeting Tavakol and Dennick's (2011) criterion for internal consistency reliability. The average variance extracted (AVE) values surpassed 0.5 for all scales, confirming satisfactory convergent validity (Hair et al., 2017) (see Table 4).

Cross-loading analysis was used to assess discriminant validity, following Sarstedt et al.'s (2014) criterion that cross-loadings should not exceed 0.4 to avoid construct overlap. The analysis revealed distinct construct measurements, with cross-loadings remaining below primary construct loadings (Sarstedt et al., 2014) (see Table 5).

The Heterotrait–Monotrait (HTMT) ratio analysis further confirmed discriminant validity, with all values falling below the 0.90 threshold (Hair & Alamer, 2022; Henseler et al., 2015) (see Table 6). This indicates a clear distinction between the constructs and validates the measurement model's structure.

Structural model analysis

Structural equation modeling (SEM) analysis revealed significant relationships between key variables (see Table 7). The strongest effect was observed between perceived usefulness and attitudes toward the use of AI tools (H2: $\beta = 0.706$, $t = 9.103$, $p < 0.001$). Information quality had a substantial influence on perceived usefulness (H6: $\beta = 0.571$, $t = 5.135$, $p < 0.001$), whereas system quality significantly affected both perceived usefulness (H8: $\beta = 0.508$, $t = 3.709$, $p < 0.001$) and perceived ease of use (H10: $\beta = 0.536$, $t = 3.022$, $p = 0.003$). However, several hypothesized relationships were not supported by the data, including the relationship between perceived ease of use and attitudes toward use (H3: $\beta = -0.085$, $t = 0.567$, $p = 0.571$) and the influence of service quality on perceived usefulness (H7: $\beta = 0.092$, $t = 0.509$, $p = 0.611$).

Table 4 Factor loadings, Cronbach Alpha, and AVE values

Indicators	Cronbach Alpha	Composite Reliability (Rho_a)	Composite Reliability (Rho_c)	Average Variance Extracted (AVE)
ATU	0.835	0.858	0.835	0.566
BIU	0.854	0.854	0.853	0.66
IQ	0.918	0.928	0.917	0.691
LE	0.862	0.879	0.861	0.677
PEOU	0.917	0.924	0.917	0.65
PU	0.898	0.903	0.898	0.559
SQ	0.8	0.809	0.804	0.579
SYQ	0.874	0.879	0.874	0.538

Table 5 Cross-loading results

	ATU	AU	BIU	IQ	LE	PEOU	PU	SQ	SYQ
ATU1	0.884	0.629	0.634	0.6	0.541	0.79	0.741	0.658	0.653
ATU2	0.701	0.419	0.56	0.615	0.555	0.585	0.582	0.676	0.565
ATU3	0.831	0.496	0.67	0.537	0.499	0.711	0.665	0.656	0.702
ATU4	0.548	0.345	0.441	0.428	0.278	0.5	0.404	0.355	0.391
AU1	0.641	1	0.765	0.554	0.584	0.56	0.68	0.609	0.617
BIU1	0.681	0.625	0.815	0.552	0.505	0.578	0.596	0.51	0.69
BIU2	0.608	0.607	0.824	0.466	0.631	0.439	0.505	0.438	0.594
BIU3	0.597	0.632	0.798	0.52	0.547	0.538	0.554	0.591	0.629
IQ1	0.524	0.492	0.483	0.887	0.612	0.408	0.76	0.642	0.675
IQ2	0.696	0.496	0.615	0.941	0.698	0.541	0.723	0.752	0.79
IQ3	0.401	0.41	0.408	0.666	0.571	0.353	0.535	0.687	0.661
IQ4	0.642	0.492	0.575	0.829	0.476	0.486	0.63	0.708	0.572
IQ5	0.706	0.422	0.524	0.922	0.588	0.584	0.667	0.732	0.722
LE1	0.583	0.56	0.616	0.637	0.91	0.522	0.639	0.646	0.77
LE2	0.591	0.469	0.572	0.626	0.875	0.539	0.602	0.611	0.742
LE3	0.363	0.402	0.519	0.467	0.662	0.347	0.427	0.558	0.666
PEOU2	0.657	0.34	0.396	0.498	0.508	0.743	0.597	0.591	0.528
PEOU3	0.777	0.509	0.574	0.494	0.341	0.761	0.647	0.587	0.548
PEOU4	0.607	0.377	0.472	0.453	0.508	0.859	0.777	0.761	0.755
PEOU5	0.738	0.565	0.625	0.408	0.49	0.827	0.787	0.598	0.659
PEOU6	0.809	0.565	0.566	0.606	0.56	0.938	0.813	0.697	0.736
PU1	0.558	0.478	0.442	0.454	0.497	0.551	0.629	0.514	0.503
PU2	0.53	0.542	0.612	0.489	0.51	0.642	0.698	0.66	0.569
PU3	0.578	0.578	0.423	0.581	0.476	0.629	0.696	0.594	0.532
PU4	0.656	0.467	0.532	0.533	0.506	0.735	0.796	0.744	0.691
PU5	0.674	0.451	0.489	0.563	0.524	0.842	0.856	0.791	0.747
PU6	0.714	0.577	0.578	0.495	0.462	0.765	0.774	0.663	0.649
SQ1	0.433	0.322	0.475	0.522	0.521	0.554	0.599	0.693	0.749
SQ2	0.719	0.568	0.473	0.722	0.62	0.603	0.766	0.826	0.737
SQ3	0.638	0.482	0.496	0.672	0.53	0.612	0.649	0.757	0.695
SYQ1	0.554	0.469	0.443	0.573	0.512	0.59	0.562	0.67	0.702
SYQ2	0.655	0.465	0.538	0.711	0.674	0.45	0.54	0.581	0.605
SYQ3	0.567	0.611	0.772	0.649	0.755	0.622	0.667	0.646	0.787
SYQ4	0.521	0.325	0.553	0.489	0.585	0.62	0.593	0.676	0.74
SYQ5	0.646	0.429	0.623	0.676	0.753	0.541	0.63	0.809	0.715
SYQ6	0.539	0.424	0.524	0.56	0.616	0.667	0.695	0.802	0.831
PEOU1	0.63	0.327	0.441	0.313	0.373	0.682	0.605	0.489	0.614

Table 6 Heterotrait–Monotrait (HTMT) ratio results

	ATU	AU	BIU	IQ	LE	PEOU	PU	SQ	SYQ
ATU									
AU	0.632								
BIU	0.771	0.765							
IQ	0.717	0.556	0.627						
LE	0.616	0.58	0.691	0.703					
PEOU	0.865	0.555	0.636	0.565	0.567				
PU	0.799	0.686	0.681	0.762	0.679	0.869			
SQ	0.779	0.605	0.637	0.846	0.738	0.775	0.882		
SYQ	0.784	0.62	0.786	0.833	0.888	0.791	0.834	0.961	

Table 7 Hypothesis test calculation results

Hypothesis	Original Results	t-statistics	p-value	Results
H1	0.478	3.792	0	Accept
H2	0.706	9.103	0	Accept
H3	-0.085	0.567	0.571	Reject
H4	0.257	2.017	0.044	Accept
H5	0.335	2.669	0.008	Accept
H6	0.571	5.135	0	Accept
H7	0.092	0.509	0.611	Reject
H8	0.508	3.709	0	Accept
H9	0.255	2.122	0.034	Accept
H10	0.536	3.022	0.003	Accept
H11	0.292	2.011	0.044	Accept
H12	0.21	1.763	0.078	Reject
H13	0.548	2.936	0.003	Accept
H14	0.024	0.16	0.873	Reject

This study employed structural equation modeling (SEM) to examine the factors influencing AI technology adoption among office administration students at Universitas Sebelas Maret (UNS) Surakarta (see Figure 2). SEM analysis revealed several significant relationships between the variables studied. The strongest influence was found in H2 ($\beta = 0.706$, $t = 9.103$, $p < 0.001$), indicating a robust relationship between perceived usefulness and attitudes toward the use of AI tools. Another substantial effect was demonstrated in H6 ($\beta = 0.571$, $t = 5.135$, $p < 0.001$), indicating the significant impact of information quality on perceived usefulness. System quality also had a considerable influence on perceived usefulness (H8: $\beta = 0.508$, $t = 3.709$, $p < 0.001$) and perceived ease of use (H10: $\beta = 0.536$, $t = 3.022$, $p = 0.003$).

Interestingly, some hypothesized relationships were not supported by the data. For instance, the relationships between perceived ease of use and attitudes toward use (H3: $\beta = -0.085$, $t = 0.567$, $p = 0.571$) and between service quality and perceived usefulness (H7: $\beta = 0.092$, $t = 0.509$, $p = 0.611$) were not statistically significant. These findings align with contemporary educational technology research while providing new insights into the specific factors that drive AI adoption in academic settings (Dempere et al., 2023).

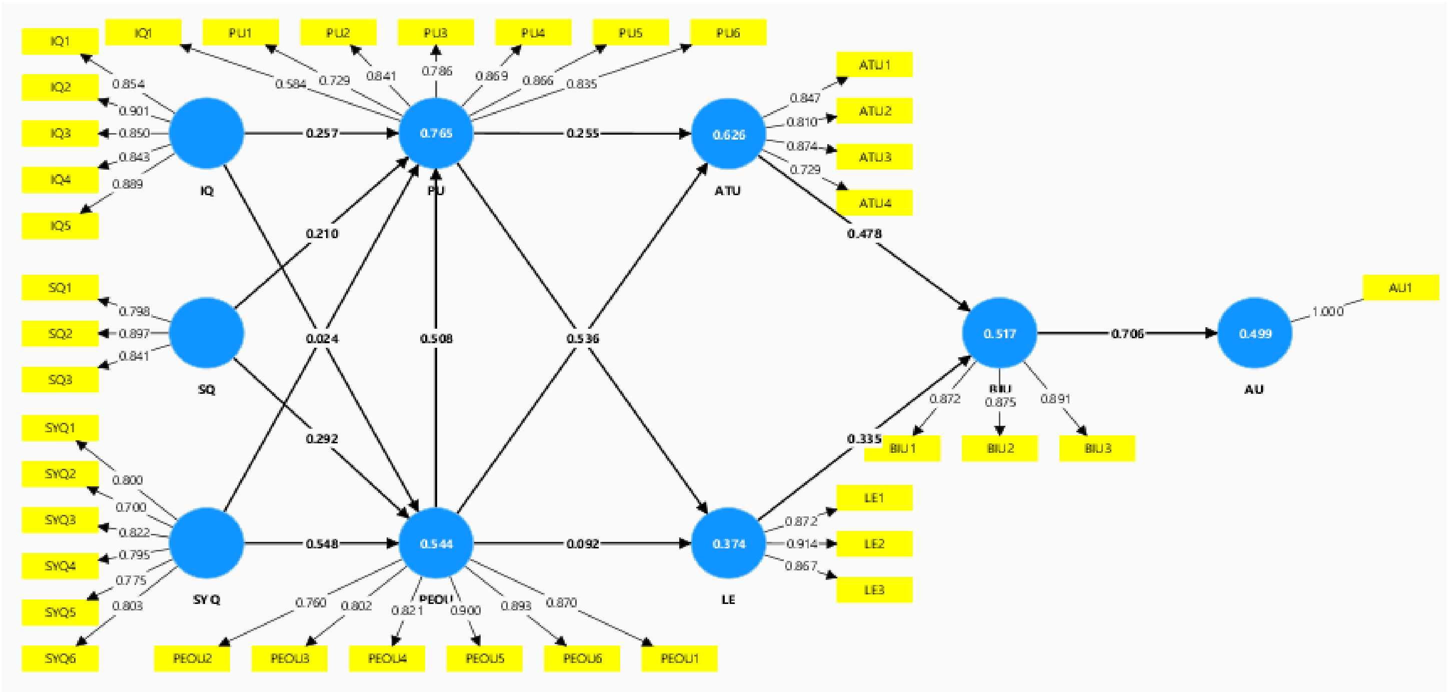

Fig. 2 Structural equation modeling (SEM) results

Discussion

Patterns of AI tool adoption

The predominance of ChatGPT (44%) as the preferred AI tool among office administration students indicates a clear preference for accessible and versatile generative AI platforms. This finding aligns with contemporary studies on AI adoption in educational settings, where ease of use and perceived utility significantly influence tool selection (El Koshiry et al., 2023). The distribution of preferences across other tools—Google Gemini (21%), Perplexity AI and Poe AI (13% each), and Microsoft CoPilot (8%)—suggests that students actively explore various AI platforms to support their academic activities.

Factors influencing AI adoption

Perceived usefulness and ease of use

The strong relationship between perceived usefulness and technology adoption (H1, H8, H9, H10, H11, H13; $p < 0.05$) reinforces the fundamental principles of the technology acceptance model (Baroni et al., 2022). Students demonstrate higher adoption rates when they perceive AI tools as valuable assets for enhancing their educational experience. Similarly, the significant correlation between perceived ease of use and adoption (H2: $t = 9.103$, $p < 0.001$) underscores the importance of user-friendly interfaces in promoting technology acceptance (Davis & Davis, 1989).

Quality dimensions

Information quality (H4: $t = 2.017$, $p = 0.044$) and service quality (H5: $t = 2.669$, $p = 0.008$) emerged as significant determinants of AI adoption. These findings align with Mohammadi’s (2015) assertion that quality factors significantly influence technology acceptance in educational contexts (Mohammadi, 2015). The strong impact of information quality on perceived usefulness (H6: $t = 5.135$, $p < 0.001$) suggests that students value accurate and reliable AI-generated content for their academic work (Legramante et al., 2023).

Nonsignificant relationships

The absence of significant relationships in system quality (H3), specific behavioral aspects (H7, H12), and certain correlations (H14) suggests that some traditional technology adoption factors may not apply uniformly in the context of AI tools in education. This finding indicates the need for context-specific models when studying AI adoption in academic settings.

Theoretical implications

The findings support experiential learning theory (ELT) principles in technology adoption (Bentley & Pang, 2012). The significant relationship between AI engagement and learning participation (H6) demonstrates how hands-on technology experience enhances educational engagement (de Rosa et al., 2022). This aligns with ELT's emphasis on concrete experiences and active experimentation in learning processes.

Practical implications

The findings of this research highlight several significant practical implications for educational institutions seeking to integrate AI technology effectively. Educational institutions should prioritize the development of user-friendly AI interfaces specifically designed to meet academic requirements, ensuring that these tools align with students' learning needs and objectives. Additionally, institutions must implement robust quality assurance measures to maintain the integrity and reliability of AI-generated information, establishing clear guidelines and standards for its use in academic contexts. The integration of experiential learning approaches in AI tool training is crucial, allowing students to gain hands-on experience while developing practical skills in AI applications. Furthermore, as supported by Senok et al. (2021), institutions should focus on creating supportive environments that facilitate AI technology adoption, including adequate technical infrastructure, training resources, and ongoing support systems for both students and faculty members (Senok et al., 2021).

Conclusion

This study provides empirical evidence of AI adoption patterns among office administration students at Universitas Sebelas Maret Surakarta. Through the integration of the technology acceptance model and the IS success model, several key findings have emerged. First, ChatGPT's dominance (44% adoption rate) among AI tools indicates students' preference for accessible and versatile generative AI platforms. Second, perceived usefulness and ease of use significantly influence AI adoption decisions, as evidenced by strong statistical relationships (H2: $\beta = 0.706$, $p < 0.001$). Third, information quality has a substantial effect on perceived usefulness (H6: $\beta = 0.571$, $p < 0.001$), highlighting the importance of reliable AI-generated content in academic contexts.

The findings contribute to both theoretical understanding and practical applications. Theoretically, the study validates the integration of the TAM and the IS success model in examining AI adoption in educational settings while supporting experiential learning theory principles in technology acceptance. Practically, the results suggest that educational institutions should focus on ensuring AI tool accessibility, maintaining information quality, and providing adequate support systems to enhance student adoption.

However, this study has several limitations. The sample size (61 students) and single-institution focus may limit generalizability. Additionally, the cross-sectional nature of the study prevents examination of adoption patterns over time. Future research should consider longitudinal studies across multiple institutions, investigate the role of cultural factors in AI adoption, and examine the long-term impact of AI tool usage on academic performance.

These findings have important implications for educational policy and practice. Institutions should develop comprehensive AI integration strategies that emphasize user-friendly interfaces, quality content, and robust support systems. Moreover, curriculum designers should consider incorporating AI literacy and practical training to prepare students for increasingly AI-enhanced workplace environments.

Abbreviations

AI: Artificial Intelligence; ATU: Attitude Toward Use; AU: Actual Usage; AVE: Average Variance Extracted; BIU: Behavioral Intention to Use; ELT: Experiential Learning Theory; ELT: Exponential Learning Theory; IQ: Information Quality; IS: Information System; LE: Learning Effectiveness; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; SEM: Structural Equation Modeling; SQ: Service Quality; SYQ: System Quality; TAM: Technology Acceptance Model; UNS: Universitas Sebelas Maret.

Authors' contributions

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Availability of data and materials
The datasets used and/or analyzed during the current study may not be shared due to data privacy and protection policies. Some processed datasets/results other than those already included in the manuscript may be made available by the corresponding author on reasonable request. All summary outputs of the data are shared within the article. Requests for more detailed information should be directed to the first author.

Declarations

Competing interests
The authors declare that they have no competing interests.

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