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Institutional and Individual Drivers of AI Adoption in Higher Education: An Integrative TAM–TOE Model

Baiq Sri Mardiani[1], Ema Utami[2]

[1,2]Master's Program in Distance Learning Informatics, Graduate School, Universitas Amikom Yogyakarta, Yogyakarta, Indonesia

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Corresponding Author:
Author Name*:
Baiq Sri Mardiani
Email*:
baiqsrimardiani@students.amikom.ac.id

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Abstract. The rapid diffusion of artificial intelligence (AI) in higher education necessitates a deeper understanding of both institutional and individual factors influencing its adoption, particularly in developing-country contexts. This study examines the drivers of AI adoption in Indonesian higher education institutions by integrating the Technology Acceptance Model (TAM) and the Technology, Organization, Environment (TOE) framework. Addressing a gap in prior research that often separates individual acceptance from institutional readiness, this study adopts a quantitative survey approach involving 366 academic stakeholders, including lecturers, students, and administrative staff. Data collected between October and December 2025 were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate that perceived ease of use strongly influences attitude toward AI, which in turn significantly affects behavioral intention. Perceived usefulness also has a positive, albeit weaker, effect on behavioral intention. At the institutional level, environmental context is found to significantly influence AI readiness, while other contextual factors exhibit limited explanatory power. Several hypothesized relationships, including the effects of AI readiness on perceived usefulness and the moderating roles of digital literacy and top management support, are not supported. These results suggest that AI adoption in higher education is primarily shaped by user-centered factors, while institutional readiness may depend on additional determinants not fully captured in the model. This study provides empirical insights into the role of AI readiness as an intermediate construct within an integrated TAM–TOE framework in higher education.

Keywords: AI Adoption; AI Readiness; Technology Acceptance Model; TOE Framework; Higher Education Institutions; PLS-SEM

1. INTRODUCTION

The rapid advancement of artificial intelligence (AI) has significantly reshaped higher education by enabling automated cognitive processes, strengthening analytical capabilities, and supporting more adaptive learning and academic decision-making practices. AI technologies are increasingly integrated into educational activities through applications such as intelligent tutoring systems, learning analytics, and generative AI tools. These technologies offer the potential to enhance personalized learning experiences, support metacognitive development, and facilitate more efficient academic workflows. However, despite the growing prominence of AI in higher education, its implementation remains uneven and often fragmented across institutions. Differences in institutional infrastructure, governance structures, and the preparedness of academic stakeholders frequently influence the extent to which AI technologies can be effectively integrated into academic environments. Consequently, the adoption of AI in higher education involves not only technical considerations but also organizational and behavioral challenges that require systematic investigation [1], [2], [3].

On the one hand, AI is widely perceived as a transformative technology capable of enhancing educational outcomes through adaptive feedback mechanisms, automated knowledge generation, and advanced data-driven decision support. Tools such as generative AI agents, including ChatGPT, have demonstrated the potential to assist students and faculty members in various academic tasks, ranging from content generation and information retrieval to collaborative learning support. On the other hand, the rapid diffusion of AI has also raised concerns related to the reliability of AI-generated outputs, ethical implications, data governance, and the potential disruption of established academic practices. Faculty members and institutional administrators often face uncertainties regarding how AI technologies should be regulated, integrated into teaching processes, and aligned with academic integrity standards. These contrasting perspectives suggest that AI adoption occurs within a complex socio-technical context shaped by the interaction between technological capabilities, institutional governance, and user trust [4], [5], [6].

Within the broader literature on technology adoption, the Technology Acceptance Model (TAM) has long been recognized as one of the most widely used frameworks for explaining individual acceptance of digital technologies. TAM emphasizes that users' perceptions regarding the usefulness of a system and the ease with which it can be used play a central role in shaping their attitudes and behavioral intentions toward technology adoption. Numerous empirical studies have consistently demonstrated that individuals are more likely to adopt emerging technologies when they perceive clear performance benefits and minimal effort associated with system usage. As a result, TAM has been extensively applied in educational contexts to analyze the adoption of digital learning platforms, online learning systems, and various AI-supported educational tools [7], [8], [9]. However, prior studies also indicate that TAM alone may not fully capture the influence of broader contextual and institutional conditions. Recent developments in the literature further suggest that the explanatory power of TAM can be enhanced by incorporating contextual and affective variables such as enjoyment, social influence, and habitual use. These extensions acknowledge that technology adoption is not purely a rational cognitive process but is also influenced by users' emotional responses, prior experiences, and institutional environments. Particularly within complex digital learning ecosystems, individual perceptions are often shaped by broader contextual conditions that influence how technologies are introduced, supported, and governed within educational institutions [10], [11], [12], [13].

In the context of higher education, TAM has frequently been used to examine user acceptance of emerging pedagogical innovations, including flipped classroom models, metaverse-based learning environments, and generative AI tools. While these studies provide valuable insights into individual cognitive mechanisms that influence technology adoption, they also reveal an important limitation: user perceptions alone may not sufficiently capture the influence of broader institutional and environmental conditions that enable or constrain AI adoption at the organizational level. This indicates the need for a more integrative perspective that links individual perceptions with institutional contexts. In many higher education environments, the availability of technological infrastructure, institutional policies, and leadership support significantly influences how new technologies are introduced and adopted by academic stakeholders [14], [15], [16].

To better understand technology adoption from an organizational perspective, the Technology Organization Environment (TOE) framework has been widely used to analyze how institutional capabilities, governance mechanisms, and external environmental pressures shape organizational decisions regarding technology implementation. The TOE framework highlights that technological readiness, organizational resources, leadership commitment, and environmental conditions collectively influence the adoption and diffusion of digital innovations. This framework has been widely applied in studies examining the adoption of complex digital systems that require institutional coordination, resource allocation, and collaboration among multiple stakeholders, making it particularly relevant for understanding AI implementation within higher education institutions [17], [18], [19].

Recent studies have attempted to integrate TAM and TOE in order to capture both individual and institutional determinants of technology adoption. Combining these two frameworks allows researchers to examine how institutional conditions shape individual perceptions and behavioral intentions toward technology use. Nevertheless, much of the existing literature tends to treat institutional factors as direct antecedents of technology usage intentions without sufficiently explaining the intermediate mechanisms through which organizational and environmental contexts influence individual acceptance processes. As a result, the underlying pathways linking institutional conditions and individual acceptance remain insufficiently theorized [20], [21], [22], [23].

A growing body of research on AI adoption in higher education further indicates that many studies focus primarily on individual-level outcomes, such as attitudes toward AI or intention to use AI tools among students and faculty members. While such studies provide valuable insights into user perceptions, they often overlook how institutional conditions contribute to the readiness of academic environments to adopt AI technologies. In particular, the concept of AI readiness has rarely been explicitly modeled as a mediating or intermediate mechanism through which technological, organizational, and environmental conditions shape individual acceptance of AI systems. This gap limits a comprehensive understanding of how institutional drivers translate into individual adoption behavior [16], [23]. Another important gap concerns the limited empirical evidence from developing regions and non-metropolitan higher education environments. In many developing-country contexts, disparities in digital infrastructure, human resource capacity, and institutional governance can significantly influence technology adoption dynamics. Higher education institutions located outside major metropolitan areas may face unique challenges related to resource availability, technological capacity, and

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institutional support, which may lead to adoption patterns that differ from those observed in more technologically advanced academic ecosystems. Consequently, findings derived from global AI adoption studies may not always be directly generalizable without empirical validation in specific regional contexts [1], [24], [25].

From a methodological standpoint, many technology acceptance studies focus primarily on the statistical significance of structural relationships while paying relatively limited attention to broader model evaluation criteria such as predictive relevance, explanatory power, and overall model robustness. In contrast, the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach emphasizes a balanced evaluation that considers theoretical consistency, predictive capability, and practical relevance, making it particularly suitable for exploratory and integrative models such as those combining TAM and TOE frameworks [26], [27], [28]. This approach is therefore appropriate for capturing both explanatory and predictive aspects of AI adoption models. Empirical studies conducted in the Indonesian context using TAM-based and satisfaction-oriented models have shown that factors such as system quality, interface responsiveness, and institutional support play important roles in influencing user satisfaction and technology usage in digital public services and academic information systems. However, these studies have rarely extended their analytical scope to investigate AI adoption in higher education using an explicitly integrated TAM–TOE framework that places AI readiness as a central construct linking institutional conditions with individual technology acceptance [20], [29], [30].

In summary, previous studies provide strong evidence that TAM effectively explains individual technology acceptance, while TOE offers a comprehensive framework for understanding institutional and environmental determinants of technology adoption. Nevertheless, there remains a limited number of studies that explicitly integrate these two frameworks through the mediating role of AI readiness as a bridge between institutional drivers and individual acceptance mechanisms, particularly in higher education institutions located in developing regions. Therefore, this study develops and empirically examines an integrative TAM–TOE model by positioning AI readiness as an intermediate construct linking institutional contexts and individual acceptance mechanisms. Specifically, this research aims to (1) examine the influence of TOE contexts on AI readiness, (2) analyze how AI readiness and TAM constructs jointly shape attitudes and behavioral intentions toward AI use, and (3) evaluate the structural model quality and predictive relevance to inform evidence-based strategies for more adaptive and sustainable AI implementation in higher education institutions.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is widely used to explain individual acceptance of digital technologies. It posits that perceived usefulness and perceived ease of use influence users' attitudes and behavioral intentions toward technology adoption [7], [8], [9]. Numerous studies have confirmed the robustness of TAM across various contexts, including e-learning and AI-based systems. However, TAM primarily focuses on individual perceptions and does not fully capture the influence of broader institutional and environmental conditions. This limitation becomes particularly relevant in higher education, where technology adoption is often shaped by organizational support, infrastructure, and governance mechanisms.

2.2. Technology Organization Environment (TOE) Framework

The Technology Organization Environment (TOE) framework explains technology adoption from an organizational perspective by considering technological, organizational, and environmental contexts [17], [18], [19]. In higher education, TOE is particularly relevant because adoption decisions depend on institutional readiness, resource availability, and external pressures. Nevertheless, TOE-based studies often emphasize direct effects of contextual factors without adequately explaining how these factors influence individual perceptions and behaviors. This creates a gap in understanding the linkage between institutional conditions and individual acceptance.

2.3. Integrating TAM and TOE

To address these limitations, recent studies have attempted to integrate TAM and TOE to capture both individual and institutional determinants of technology adoption. This integration enables a more comprehensive analysis of how contextual factors shape user perceptions and behavioral intentions. However, prior integrative studies often treat institutional factors as direct predictors, without clearly explaining the mechanism through which these factors influence individual acceptance. As a result, the relationship between institutional context and user perception remains insufficiently explained.

2.4. AI Readiness as an Intermediate Construct

AI readiness reflects the extent to which institutions and users are prepared to adopt artificial intelligence technologies. In higher education, this includes technological infrastructure, organizational support, and user capability. In this study, AI readiness is conceptualized as an intermediate construct that bridges institutional conditions (TOE) and individual acceptance (TAM). This perspective provides a clearer explanation of how contextual factors translate into user perceptions and behavioral intentions.

2.5. Hypotheses Development

The adoption of artificial intelligence (AI) in higher education is not determined solely by the availability of advanced technologies, but also by the interaction between institutional readiness and individual acceptance mechanisms. Unlike conventional information systems, AI technologies introduce higher levels of complexity, uncertainty, and ethical considerations, which require both organizational preparedness and users' cognitive readiness to ensure sustainable adoption. Consequently, understanding AI adoption in higher education necessitates an integrative perspective that simultaneously captures institutional driving factors and individual behavioral responses. To address this complexity, the present study integrates the Technology Acceptance Model (TAM) and the Technology, Organization, Environment (TOE) framework, positioning AI readiness as a central construct that links institutional conditions to individual acceptance outcomes. The TOE framework posits that organizational innovation adoption is shaped by technological characteristics, organizational conditions, and environmental pressures. In the context of AI adoption in higher education, environmental context reflects external forces such as government regulations, accreditation requirements, competitive pressure among universities, and societal expectations regarding digital transformation. These external pressures often act as catalysts that encourage institutions to explore and prepare for AI adoption. Prior studies suggest that favorable environmental conditions increase organizational awareness and strategic orientation toward emerging technologies, thereby strengthening institutional readiness. Based on this rationale, it is expected that:

H3 : Environmental Context has a positive effect on AI Readiness.

Organizational context represents internal institutional conditions, including organizational structure, human resource capability, governance mechanisms, and strategic alignment. Higher education institutions with flexible structures, innovation-oriented cultures, and adequate organizational capacity are more likely to develop readiness for AI implementation. Organizational readiness theory emphasizes that without sufficient internal support and alignment, advanced technologies are unlikely to be effectively adopted. In line with these arguments, the study hypothesizes that:

H4 : Organizational Context has a positive effect on AI Readiness.

Technological context refers to the availability, compatibility, and perceived maturity of technological infrastructure within the institution. In AI adoption, this includes data infrastructure, computing capacity, system interoperability, and technological expertise. Institutions with robust technological foundations are better positioned to experiment with and scale AI applications. Thus, the following hypothesis is proposed:

H8 : Technological Context has a positive effect on AI Readiness.

Top management support is widely recognized as a critical success factor in organizational innovation adoption. Strategic commitment, resource allocation, and leadership support from senior management signal institutional seriousness toward AI initiatives and reduce uncertainty among organizational members. In higher education, leadership endorsement is essential to legitimize AI adoption and integrate it into institutional strategies. Therefore, the following hypothesis is advanced:

H9 : Top Management Support has a positive effect on AI Readiness.

AI readiness reflects an institution's overall preparedness to adopt and utilize AI technologies effectively. Institutions with higher levels of AI readiness are expected to provide enabling conditions that enhance users' perceptions of AI usefulness. When institutional systems, policies, and infrastructure are aligned, AI applications are more likely to be perceived as beneficial in supporting academic and administrative tasks. Accordingly, the following hypothesis is proposed:

H1 : AI Readiness has a positive effect on Perceived Usefulness.

Within the TAM framework, perceived ease of use and perceived usefulness represent key cognitive beliefs that shape users' attitudes and behavioral intentions toward technology adoption. Perceived ease of use refers to the extent to which users believe that interacting with AI systems requires minimal effort. In higher education, AI tools that are intuitive and user-friendly are more likely to foster positive attitudes toward AI usage. Therefore, the following hypothesis is formulated:

H5 : Perceived Ease of Use has a positive effect on Attitude Toward AI.

Perceived ease of use also influences perceived usefulness, as systems that are easier to use enable users to exploit AI functionalities more effectively. When AI tools reduce cognitive and operational burdens, users are more likely to recognize their performance-enhancing potential. Thus, the following hypothesis is proposed:

H6 : Perceived Ease of Use has a positive effect on Perceived Usefulness.

Perceived usefulness reflects users' beliefs that AI adoption can improve teaching effectiveness, research productivity, or administrative efficiency. According to TAM, perceived usefulness is a direct determinant of behavioral intention, as users are more inclined to adopt technologies that provide tangible benefits. Accordingly, the following hypothesis is advanced:

H7 : Perceived Usefulness has a positive effect on Behavioral Intention.

Attitude toward AI represents users' overall evaluative judgment regarding the use of AI technologies in academic contexts. A positive attitude indicates acceptance and openness toward AI-driven change. In accordance with TAM principles, a more positive attitude toward AI is anticipated to enhance users' intention to adopt and sustain its use. Therefore, the following hypothesis is proposed:

H2 : Attitude Toward AI has a positive effect on Behavioral Intention.

Digital literacy reflects users' ability to understand, evaluate, and effectively utilize digital technologies. In the context of AI adoption, users with higher digital literacy are better equipped to translate positive attitudes into actual behavioral intentions. Thus, digital literacy is expected to strengthen the relationship between attitude toward AI and behavioral intention. Accordingly, the following hypothesis is formulated:

H10 : Digital Literacy moderates the relationship between Attitude Toward AI and Behavioral Intention.

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In addition, top management support may interact with technological context in shaping AI readiness. Even when technological infrastructure is available, insufficient leadership support may hinder institutional preparedness. Conversely, strong managerial support can amplify the impact of technological capabilities on AI readiness. Therefore, the final hypothesis is proposed:

H11 : Top Management Support moderates the relationship between Technological Context and AI Readiness.

3. METHODS

This research employs a quantitative survey-based approach to examine both institutional and individual factors influencing the adoption of artificial intelligence (AI) in higher education. The survey method was selected because it enables the systematic collection of users' perceptions, attitudes, and readiness toward emerging technologies while allowing empirical testing of causal relationships among latent constructs within a complex structural model. To analyze the proposed integrative and prediction-oriented research model, this study applies Partial Least Squares Structural Equation Modeling (PLS-SEM), which is widely used for analyzing complex models involving multiple latent constructs and can be applied without strict distributional assumptions [27], [31].

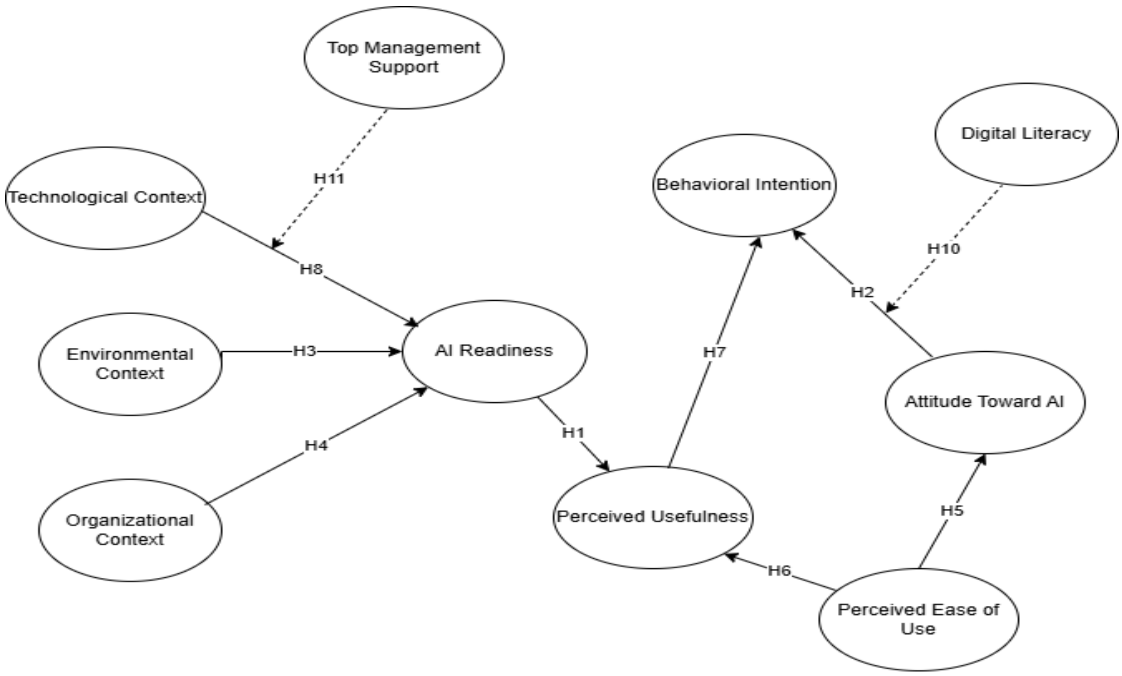

Figure 1. Research Conceptual Framework

The research model was developed by integrating the Technology Acceptance Model (TAM) and the Technology, Organization, Environment (TOE) framework to provide a more comprehensive explanation of AI adoption in the higher education context. TAM represents individual-level determinants reflecting users' cognitive and attitudinal processes, including perceived usefulness, perceived ease of use, attitude toward AI usage, and behavioral intention. In contrast, the TOE framework captures institutional-level determinants consisting of technological context, organizational context, and environmental context that influence an institution's readiness to adopt AI. The integration of these two frameworks enables a holistic analysis in which institutional conditions are not treated as direct predictors of individual behavior but instead function as antecedents that shape AI readiness conditions, which subsequently influence individual acceptance mechanisms, as illustrated in Figure 1.

3.1. Research Procedure and Data Collection

The study began with a systematic literature review to ensure that all constructs included in the research model were grounded in well-established conceptual and operational definitions and aligned with prior empirical studies. This review provided the theoretical basis for selecting TAM as the primary framework for explaining individual-level technology acceptance and TOE as the framework for capturing institutional readiness conditions associated with AI adoption in higher education environments. The research instrument was developed in the form of a structured questionnaire using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Measurement items representing the TAM constructs included perceived usefulness, perceived ease of use, attitude toward AI usage, and behavioral intention to adopt AI. Meanwhile, the TOE constructs were operationalized through indicators representing technological readiness, organizational support, and environmental influences. The measurement items were adapted from previously validated instruments to ensure content validity and measurement consistency across constructs.

Prior to the main data collection, a pilot test was conducted involving a small group of respondents ($n \approx 30$) who had experience in using digital technologies in academic environments. The pilot test aimed to assess item clarity, reliability, and contextual relevance. The results indicated that all items were understandable and relevant, with minor revisions made to improve wording clarity. Data collection was conducted between

October 2025 and December 2025 using a purposive sampling technique. Respondents consisted of lecturers, students, and administrative staff who had experience or basic knowledge related to AI and digital technologies in higher education. The respondents were drawn from multiple higher education institutions located in different regions, ensuring variability in institutional characteristics and improving the generalizability of the findings.

Participation in this study was voluntary, and respondents were informed about the purpose of the research prior to completing the questionnaire. No personally identifiable information was collected, and all responses were treated anonymously. This study did not involve sensitive data and therefore did not require formal ethical approval; however, the research procedures followed general ethical standards for social science research. Prior to the main analysis, the collected data were screened to ensure completeness and quality. Missing data were handled using listwise deletion, while outliers were assessed using standardized residuals and Mahalanobis distance to ensure data normality and consistency. Responses containing incomplete questionnaires or inconsistent patterns were removed. After the screening process, a total of 366 valid responses were retained for further analysis. The demographic characteristics of the respondents are presented in Table 1. The distribution of respondents indicates diversity in institutional roles, age groups, regional affiliations, and levels of experience in using AI technologies. Such diversity reflects the heterogeneity of AI users in higher education institutions and contributes to the external validity of the study's findings. Overall, the majority of respondents fall within the productive age range and possess academic backgrounds that enable them to critically assess both the potential benefits and the challenges associated with AI adoption in higher education.

Table 1. Demographic Characteristics of Respondents

Variable	Category	Frequency (n)	Percentage (%)
Respondent Status	Lecturers	125	34.2
	Students	172	47.0
	Administrative Staff	69	18.9
Study Program/ Unit	Information Systems	178	48.6
	Informatics Engineering	129	35.2
	Non-specific	59	16.1

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Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	182	49.7
	Female	184	50.3
Age Group (years)	< 25	118	32.2
	25–35	103	28.1
	36–45	120	32.8
	> 45	25	6.8
Duration of AI Technology Use	< 6 months	40	10.9
	6–12 months	124	33.9
	1–2 years	130	35.5
	> 2 years	72	19.7
Region of Institutional Affiliation	Sumbawa	73	19.9
	West Lombok	99	27.0
	Central Lombok	126	34.4
	East Lombok	68	18.6

3.2. Data Analysis Technique

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) by following a two-stage evaluation procedure consisting of measurement model evaluation and structural model evaluation [28], [32]. In the measurement model evaluation stage, convergent validity was assessed using outer loadings and Average Variance Extracted (AVE). Construct reliability was evaluated using composite reliability and Cronbach's alpha. Discriminant validity was assessed using the Fornell Larcker criterion and the heterotrait monotrait ratio (HTMT), where HTMT values below 0.90 indicate adequate discriminant validity [27], [33]. In the structural model evaluation stage, hypothesis testing was conducted using bootstrapping procedures. The strength of relationships was evaluated using effect size (f^2), while multicollinearity was assessed using Variance Inflation Factor (VIF).

To ensure robustness, the predictive relevance of the model was also evaluated using the Stone–Geisser Q^2 value, which indicates the model's predictive capability. To minimize potential common method bias, procedural remedies such as anonymity and clear questionnaire wording were implemented. Additionally, Harman's single-factor test was conducted, and the results indicated that no single factor accounted for more than 50%

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of the total variance, suggesting that common method bias is not a serious concern. The explanatory power of the model was evaluated using R^2 values. Model evaluation was conducted by considering both statistical significance and predictive relevance to ensure that the findings provide meaningful theoretical and practical implications.

4. RESULTS AND DISCUSSION

4.1. Measurement Model

The measurement model was evaluated to ensure the adequacy of the constructs in terms of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity prior to testing the structural relationships. Following the recommended two-step approach in PLS-SEM, the assessment of the measurement model was conducted using indicator loadings, reliability coefficients, Average Variance Extracted (AVE), the Heterotrait–Monotrait ratio (HTMT), and the Fornell–Larcker criterion. Indicator reliability was assessed by examining the outer loadings of each measurement item. As presented in Table 2 and visually illustrated in Figure 2, all indicators exhibit outer loading values above the recommended threshold of 0.70, indicating that each indicator contributes substantially to its corresponding latent construct.

Table 2. Measurement Scales of Research Constructs

Construct	Indicator Code	Measurement Item	Outer Loadings
Perceived Usefulness (PU)	PU1	AI improves task completion speed	0.782
	PU2	AI enhances work and learning quality	0.887
	PU3	AI increases work efficiency	0.885
	PU4	AI provides academic benefits	0.805
Perceived Ease of Use (PEOU)	PEOU1	AI is easy to learn	0.810
	PEOU2	AI is easy to use	0.862
	PEOU3	AI interaction is clear	0.850
	PEOU4	AI is easily accessible	0.869
Attitude Toward AI (ATT)	ATT1	AI use is positive	0.811
	ATT2	Using AI is enjoyable	0.846
	ATT3	Interest in learning AI	0.813
	ATT4	Positive view of AI in higher education	0.711

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Construct	Indicator Code	Measurement Item	Outer Loadings
Behavioral Intention (BI)	BI1	Intention to continue using AI	0.815
	BI2	Will recommend AI to others	0.810
	BI3	Plan to increase AI use	0.859
	BI4	Will use AI if available	0.785
Technological Context (TC)	TC1	Adequate AI infrastructure	0.737
	TC2	AI-compatible information systems	0.897
	TC3	Availability of technical support	0.917
Organizational Context (OC)	OC1	Leadership supports AI adoption	0.910
	OC2	Policies support digital transformation	0.926
	OC3	Human resources are AI-ready	0.860
	OC4	Innovation-oriented organizational culture	0.822
Environmental Context (EC)	EC1	Government policy supports AI use	0.909
	EC2	Global trends encourage AI adoption	0.922
	EC3	External collaboration supports AI	0.784
AI Readiness (AR)	AR1	Individual readiness to use AI	0.844
	AR2	Institutional AI-supportive policies	0.846
	AR3	Openness toward AI use	0.846
	AR4	Digital infrastructure supports AI	0.856
Digital Literacy (DL)	DL1	Basic digital skills proficiency	0.768
	DL2	Experience with digital and AI tools	0.764
	DL3	Ability to evaluate AI outputs	0.770
	DL4	Understanding of AI ethics	0.840
	DL5	Confidence in using AI	0.788
Top Management Support (TMS)	TMS1	Resource allocation for AI	0.758
	TMS2	Strategic direction for AI	0.932
	TMS3	Leadership-driven AI innovation	0.967

This result confirms that the indicators reliably represent their underlying constructs and that no indicator removal was required in the measurement model. Table 2 presents the measurement items and their corresponding outer loading values. All constructs are measured using multiple indicators, reflecting their multidimensional nature within the integrated TAM–TOE model. The loading values demonstrate that each item has a strong

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association with its respective construct, indicating satisfactory indicator reliability across all constructs included in the study.

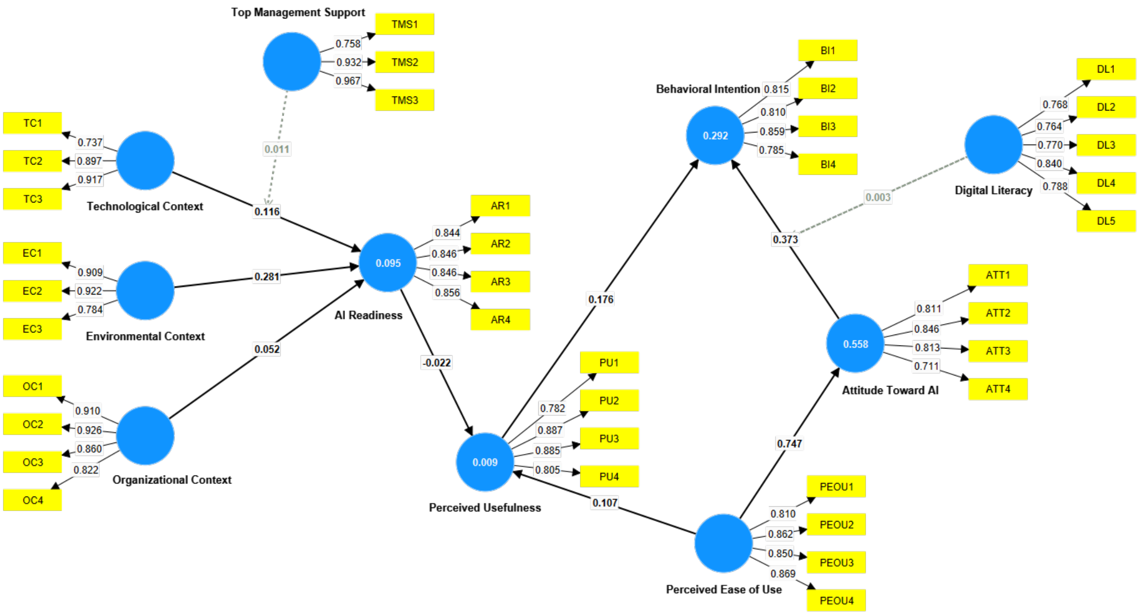

Figure 2. Results of PLS-SEM Analysis

Convergent validity was further evaluated using the Average Variance Extracted (AVE). As shown in Table 3, all constructs demonstrate AVE values exceeding the recommended minimum threshold of 0.50, indicating that each construct explains more than half of the variance of its indicators. This result confirms that the latent constructs capture sufficient variance from their respective measurement items and therefore demonstrate adequate convergent validity.

Table 3. Reliability and Convergent Validity of the Measurement Model

Construct	(CA)	ρA	(CR)	AVE
AI Readiness	0.870	0.875	0.911	0.719
Attitude Toward AI	0.806	0.812	0.874	0.635
Behavioral Intention	0.836	0.844	0.890	0.669
Digital Literacy	0.846	0.850	0.890	0.619
Environmental Context	0.846	0.875	0.906	0.764
Organizational Context	0.908	0.995	0.932	0.776
Perceived Ease of Use	0.869	0.870	0.911	0.719
Perceived Usefulness	0.862	0.877	0.906	0.707

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Construct	(CA)	ρA	(CR)	AVE
Technological Context	0.814	0.857	0.889	0.730
Top Management Support	0.900	0.985	0.919	0.793

Note(s): CA = Cronbach's alpha; ρA = Dijkstra–Henseler's rho; CR = Composite reliability; AVE = Average variance extracted.

Internal consistency reliability was examined using Cronbach's alpha (CA), Dijkstra–Henseler's rho (ρA), and Composite Reliability (CR). As reported in Table 3, all constructs exhibit CA, ρA, and CR values above the recommended cutoff value of 0.70, indicating satisfactory internal consistency among the measurement items. Several constructs, including AI Readiness, Top Management Support, and Organizational Context, demonstrate particularly high reliability values, reflecting strong internal consistency across their respective indicators. These results indicate that the measurement scales employed in this study are reliable and stable for measuring the constructs included in the integrated TAM–TOE framework.

Discriminant validity was first assessed using the Heterotrait–Monotrait ratio (HTMT), which is considered a stringent criterion for evaluating construct distinctiveness in PLS-SEM analysis. As presented in Table 4, the majority of HTMT values fall below the conservative threshold of 0.85, indicating that most constructs are empirically distinct from one another. However, a few construct pairs show HTMT values slightly above this conservative cutoff, particularly between Perceived Ease of Use and Attitude Toward AI, Digital Literacy and Perceived Usefulness, and Technological Context and Top Management Support. Despite these values exceeding the strict 0.85 criterion, they remain within the more liberal threshold of 0.90 that is commonly accepted in PLS-SEM studies[26], [27]. Therefore, the results still indicate an acceptable level of discriminant validity, although the conceptual proximity between these constructs should be interpreted with caution.

To further confirm discriminant validity, the Fornell–Larcker criterion was applied. As shown in Table 5, the square root of the AVE for each construct (displayed along the diagonal) is greater than the correlations with other constructs in the model. This finding indicates that each construct shares more variance with its own indicators than with

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other constructs, thereby satisfying the Fornell–Larcker criterion and providing additional support for discriminant validity.

Tabel 4. Discriminant Validity Assessment (HTMT Criterion)

Construct	AR	ATT	BI	DL	EC	OC	PEOU	PU	TC	TMS	DLx ATT	TMS xTC
AR												
ATT	0.792											
BI	0.427	0.521										
DL	0.058	0.182	0.427									
EC	0.329	0.074	0.103	0.054								
OC	0.097	0.120	0.282	0.473	0.085							
PEOU	0.695	0.891	0.449	0.145	0.032	0.128						
PU	0.052	0.177	0.420	0.867	0.055	0.551	0.110					
TC	0.123	0.199	0.370	0.660	0.105	0.585	0.151	0.811				
TMS	0.053	0.097	0.302	0.651	0.072	0.516	0.046	0.732	0.871			
DL x ATT	0.058	0.029	0.010	0.065	0.029	0.074	0.037	0.064	0.099	0.023		
TMS x TC	0.032	0.042	0.157	0.258	0.051	0.243	0.055	0.356	0.463	0.398	0.015	

Note(s): AR= AI Readiness; ATT= Attitude Toward AI; BI= Behavioral Intention; DL= Digital Literacy; EC= Environmental Context; OC= Organizational Context; PEOU= Perceived Ease of Use.

Table 5. Discriminant Validity – Fornell Larcker Criterio

Construct	AR	ATT	BI	DL	EC	OC	PEOU	PU	TC	TMS
AR	0.848									
ATT	0.663	0.797								
BI	0.364	0.427	0.818							
DL	0.042	0.151	0.370	0.787						
EC	0.289	0.042	0.039	-0.020	0.874					
OC	0.095	0.120	0.244	0.408	0.079	0.881				
PEOU	0.606	0.747	0.382	0.116	-0.009	0.122	0.848			
PU	0.043	0.150	0.367	0.735	-0.016	0.483	0.094	0.841		
TC	0.106	0.159	0.303	0.532	0.075	0.502	0.124	0.655	0.854	
TMS	0.039	0.084	0.268	0.563	0.057	0.448	0.040	0.642	0.679	0.890

Note(s): AR= AI Readiness; ATT= Attitude Toward AI; BI= Behavioral Intention; DL= Digital Literacy; EC= Environmental Context; OC= Organizational Context; PEOU= Perceived Ease of Use.

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Overall, the results of the measurement model assessment indicate that the constructs in the integrated TAM–TOE model demonstrate satisfactory levels of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The consistency between the numerical results reported in Tables 2–5 and the standardized outer loadings depicted in Figure 2 further supports the robustness of the measurement model. Given that the measurement model demonstrates acceptable psychometric properties, the analysis can proceed to the evaluation of the structural model and hypothesis testing.

4.2. Structural Model

The structural model evaluation was conducted to examine the explanatory power of the proposed model, test the significance of the hypothesized relationships among the latent constructs, and evaluate the predictive relevance of the model. The results of the structural model assessment are summarized in Table 6 and Table 7, which present the coefficients of determination (R^2), predictive relevance (Q^2), path coefficients (β), t-values, p-values, effect sizes (f^2), and variance inflation factors (VIF).

Table 6. Structural Model Quality and Predictive Relevance

Construct	R^2	R^2 **adjusted**	Q^2	**T values**	**P values**
AI Readiness	0.095	0.082	0.061	2.485	0.013
Attitude Toward AI	0.558	0.557	0.351	10.851	0.000
Behavioral Intention	0.292	0.284	0.186	6.193	0.000
Perceived Usefulness	0.009	0.004	0.004	0.807	0.420

Note(s): R^2 = Variance explained; Adjusted R^2 = Adjusted coefficient of determination; Q^2 = Predictive relevance (Stone–Geisser criterion).

Table 6 reports the explanatory power and predictive relevance of the endogenous constructs in the model. The construct Attitude Toward AI demonstrates the strongest explanatory power, with an R^2 value of 0.558, indicating that approximately 55.8% of the variance in users' attitudes toward AI is explained by its predictors in the model, particularly perceived ease of use. This result indicates that users' cognitive evaluations of AI usability play a dominant role in shaping positive attitudes toward AI adoption in higher education. The corresponding Q^2 value of 0.351 further confirms strong predictive relevance for this construct.

The construct Behavioral Intention shows an R^2 value of 0.292, suggesting that approximately 29.2% of the variance in users' intention to adopt AI is explained by attitude toward AI and perceived usefulness. Although this level of explanatory power can be considered moderate, the Q^2 value of 0.186 indicates that the model possesses adequate predictive capability in explaining behavioral intention at the individual level.
In contrast, AI Readiness exhibits a relatively low R^2 value of 0.095, indicating that the TOE-related institutional factors included in the model explain only 9.5% of the variance in institutional readiness for AI adoption. Nevertheless, the Q^2 value of 0.061 indicates that the construct still retains predictive relevance, albeit limited. This finding suggests that institutional AI readiness may be influenced by additional contextual factors that are not fully captured by the technological, organizational, and environmental variables included in the current model.

Similarly, the construct Perceived Usefulness shows a very low explanatory power with an R^2 value of 0.009 and a Q^2 value of 0.004, indicating that the predictors included in the model provide only minimal explanation of perceived usefulness. This result suggests that perceptions regarding the usefulness of AI among higher education stakeholders may still be evolving and may depend on other determinants beyond institutional readiness and ease of use, particularly in contexts where AI adoption remains in relatively early stages of institutional integration.

Table 7. Structural Model Results and Hypothesis Testing

Hypothesis/ Relationships	**β**	**T-value**	**P-values**	**f^2**	**VIF**	**Supported**
H1: AR -> PU	- 0.020	0.344	0.731	0.000	1.579	No
H2: ATT -> BI	0.370	5.914	0.000	0.191	1.028	Yes
H3: EC -> AR	0.280	4.444	0.000	0.086	1.008	Yes
H4: OC -> AR	0.050	0.850	0.395	0.002	1.380	No
H5: PEOU-> ATT	0.750	21.56	0.000	1.261	1.000	Yes
H6: PEOU -> PU	0.110	1.774	0.076	0.007	1.579	No

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Hypothesis/ Relationships	β	T-value	P-values	f^2	VIF	Supported
H7: PU -> BI	0.180	2.373	0.018	0.020	2.180	Yes
H8: TC -> AR	0.120	1.348	0.178	0.007	2.176	No
H9: TMS -> AR	-0.070	0.743	0.457	0.003	1.927	No
H10: DL x ATT -> BI	0.000	0.039	0.969	0.000	1.005	No
H11: TMS x TC -> AR	0.01	0.272	0.786	0.000	1.220	No

Note(s): AR= AI Readiness; ATT= Attitude Toward AI; BI= Behavioral Intention; DL= Digital Literacy; EC= Environmental Context; OC= Organizational Context; PEOU= Perceived Ease of Use.

The hypothesis testing results presented in Table 7 indicate that four out of eleven hypotheses are supported, while the remaining seven hypotheses are not statistically significant.

At the individual level, the relationship between Attitude Toward AI and Behavioral Intention (H2) is positive and statistically significant ($\beta = 0.370$; $p < 0.001$), indicating that a more favorable attitude toward AI increases users' intention to adopt AI technologies in higher education contexts. The associated effect size ($f^2 = 0.191$) suggests a moderate practical impact, highlighting the importance of attitudinal acceptance in shaping behavioral intention. At the institutional level, the relationship between Environmental Context and AI Readiness (H3) is the only institutional path that is statistically supported ($\beta = 0.280$; $p < 0.001$). This finding indicates that external pressures and environmental drivers such as government regulations, global technological trends, and external collaborations play a meaningful role in encouraging higher education institutions to prepare for AI adoption. Compared with internal organizational conditions, these external environmental influences appear to exert stronger pressure for institutional readiness toward AI implementation.

The strongest relationship observed in the model is the path from Perceived Ease of Use to Attitude Toward AI (H5), with a path coefficient of $\beta = 0.75$ and a very large effect size ($f^2 = 1.261$). This result suggests that the usability and accessibility of AI technologies represent the most influential determinant of positive attitudes toward AI adoption. In academic environments, AI systems that are perceived as intuitive and easy to use are more likely to generate favorable perceptions among users. The relationship between Perceived Usefulness and Behavioral Intention (H7) is also positive and statistically significant (β = 0.18; p = 0.018), although the effect size is relatively small. This finding indicates that perceived usefulness contributes to the formation of behavioral intention, but its influence appears to be weaker compared with the effect of attitudinal factors. Several theoretically expected relationships are not supported by the empirical data. The path from AI Readiness to Perceived Usefulness (H1) is not statistically significant, suggesting that institutional readiness does not directly translate into users' perceptions regarding the usefulness of AI technologies. Similarly, the relationship between Perceived Ease of Use and Perceived Usefulness (H6) is not significant, indicating that ease of use alone does not necessarily lead users to perceive AI technologies as useful in academic contexts.

At the institutional level, the relationships between Organizational Context and AI Readiness (H4), Technological Context and AI Readiness (H8), and Top Management Support and AI Readiness (H9) are not statistically significant. These findings suggest that internal institutional conditions may not yet play a decisive role in shaping readiness for AI adoption within the sampled higher education institutions. Instead, institutional preparedness for AI may be influenced by broader environmental dynamics and external technological developments. The moderating effects hypothesized in the model are also not supported. The interaction effect between Digital Literacy and Attitude Toward AI on Behavioral Intention (H10) is not significant, indicating that variations in digital literacy among respondents do not significantly strengthen the relationship between attitudes toward AI and behavioral intention. Similarly, the interaction between Top Management Support and Technological Context on AI Readiness (H11) does not show a significant effect. All reported VIF values are below the recommended threshold, indicating that multicollinearity does not pose a problem in the structural model. This finding confirms that the estimated path coefficients are statistically stable and suitable for interpretation.

The structural model results suggest that AI adoption in higher education is primarily driven by individual-level cognitive and attitudinal factors, particularly perceived ease of use and attitude toward AI. Institutional-level determinants appear to exert a more limited influence in the current model, with environmental context emerging as the only institutional factor that significantly contributes to AI readiness. These findings provide an empirical basis for further discussion regarding the relative importance of individual perceptions and institutional conditions in shaping AI adoption dynamics within higher education institutions.

4.3. Discussion

This study investigates how institutional conditions and individual perceptions jointly shape the adoption of artificial intelligence (AI) in higher education using an integrative TAM–TOE framework. The findings reveal a differentiated pattern of relationships between institutional determinants, individual cognitive perceptions, and behavioral intentions toward AI adoption. Overall, the results indicate that individual-level cognitive and attitudinal mechanisms play a more prominent role in shaping AI adoption behavior than institutional readiness factors, while environmental pressures emerge as the most influential institutional determinant. This pattern is consistent with recent studies in developing-country contexts, which emphasize that individual perceptions often dominate adoption behavior when institutional systems are still evolving (e.g., digital transformation in emerging economies).

1) Institutional-Level Determinants of AI Readiness

At the institutional level, the relationship between Environmental Context and AI Readiness (H3) is the only path that is empirically supported. This finding indicates that external forces including government policies, national digital transformation initiatives, global technological developments, and collaboration networks serve as key drivers encouraging higher education institutions to acknowledge and prepare for AI adoption. This result is consistent with prior studies in higher education and developing regions, which show that regulatory pressure and external ecosystems play a dominant role in accelerating digital adoption (e.g., TOE-based studies in public sector and education contexts). In contrast, the relationships between Organizational Context and AI Readiness (H4) and Technological Context and AI Readiness (H8) are not statistically significant. The absence of a significant organizational effect suggests that internal factors such as institutional culture, governance structures, and human resource capacity have not yet translated into concrete institutional readiness for AI implementation. This finding aligns with recent research indicating that in early-stage digital transformation, organizational structures often lag behind technological awareness, particularly in developing-country higher education institutions.

Similarly, the non-significant relationship between technological context and AI readiness suggests that the presence of technological infrastructure alone does not guarantee institutional preparedness. This result supports prior findings that distinguish between technology availability and effective utilization, where infrastructure without strategic alignment fails to produce meaningful adoption outcomes. The hypothesis concerning Top Management Support and AI Readiness (H9) is also not supported. While previous studies frequently report a significant role of leadership in digital transformation, the present findings suggest that such effects may not emerge strongly in early adoption stages or in institutions where leadership support has not yet been operationalized into concrete policies and resource commitments. Furthermore, the interaction effect between Top Management Support and Technological Context (H11) is not significant. This contrasts with some prior studies that highlight synergistic effects between leadership and infrastructure, indicating that such interactions may require more mature institutional environments to become effective.

2) Relationship Between Institutional Readiness and Individual Perceptions

The hypothesis AI Readiness → Perceived Usefulness (H1) is not supported, indicating that institutional readiness does not directly influence users' perceptions of AI usefulness. This finding is consistent with recent studies suggesting that users evaluate technology primarily based on direct experience rather than institutional signals, especially in early adoption contexts. In contrast to studies conducted in more mature digital environments where institutional readiness significantly shapes user perceptions, the present result suggests that such effects may not yet be fully realized in developing-country higher education settings. Users' perceptions of usefulness appear to depend more strongly on task relevance and observable benefits rather than on institutional preparedness.

3) Individual Cognitive and Attitudinal Mechanisms

At the individual level, the results strongly support the core mechanisms proposed by TAM. The relationship between Perceived Ease of Use and Attitude Toward AI (H5) represents the strongest path in the model. This finding is consistent with a large body of TAM-based research in educational technology, which emphasizes usability as a key driver of positive user attitudes.

Interestingly, the relationship between Perceived Ease of Use and Perceived Usefulness (H6) is not supported. This result contrasts with traditional TAM assumptions but aligns with recent studies in AI adoption contexts, where usefulness is more strongly influenced by perceived performance outcomes rather than ease of use alone. The relationship between Perceived Usefulness and Behavioral Intention (H7) is positive and statistically significant, although with a relatively small effect size. This finding is partially consistent with prior studies, which often report a strong influence of perceived usefulness; however, the weaker effect observed in this study suggests that affective factors such as attitude may play a more dominant role in emerging technology contexts. The most influential behavioral pathway is observed in Attitude Toward AI → Behavioral Intention (H2), confirming that users' evaluative judgments toward AI are critical in shaping adoption intention. This result reinforces recent findings that highlight the growing importance of affective and experiential factors in technology adoption, particularly in AI-driven systems.

4) Moderating Effects and Boundary Conditions

The moderating effect of Digital Literacy on the relationship between Attitude Toward AI and Behavioral Intention (H10) is not supported. This finding contrasts with several prior studies that identify digital literacy as a significant moderator; however, it may be explained by the relatively homogeneous level of digital competence among respondents in this study. This result also suggests that digital literacy may function more as a baseline requirement rather than a differentiating factor in contexts where users already possess sufficient technological familiarity. The absence of significant moderation effects suggests that the core TAM relationships remain dominant in explaining AI adoption intentions in higher education. Contextual capability factors such as digital literacy may become more influential only under conditions of greater variability or increased technological complexity. Taken together, the findings reveal that AI adoption in higher education is primarily driven by individual perceptions and attitudes rather than institutional readiness mechanisms. Environmental pressures encourage institutions to recognize the importance of AI adoption, but internal organizational conditions and leadership support have not yet translated into strong institutional readiness. These findings are consistent with prior research in developing-country contexts, where technology adoption often follows a bottom-up pattern driven by user acceptance rather than top-down institutional strategies. These results reflect a transitional stage of AI adoption in higher education, where institutional structures are still evolving and individual acceptance is largely shaped by usability perceptions and affective responses. Consequently, efforts to promote AI adoption may benefit from prioritizing user-centered system design, practical demonstrations of AI benefits, and gradual institutional alignment between technological infrastructure, governance frameworks, and organizational strategies.

4.4. Theoretical Implications

This study offers several important theoretical implications for the literature on technology adoption, particularly in the context of artificial intelligence (AI) in higher education. By integrating the Technology Acceptance Model (TAM) with the Technology, Organization, Environment (TOE) framework, this research advances existing adoption theories by demonstrating how institutional and individual factors operate through distinct and asymmetrical mechanisms in shaping AI adoption intentions.

1) Advancing a Multilevel Perspective on AI Adoption

A key theoretical contribution of this study lies in strengthening the multilevel perspective on AI adoption. The empirical findings reveal that institutional-level factors and individual-level cognitive mechanisms do not exert equivalent or directly additive effects. While environmental context significantly influences institutional AI readiness, organizational and technological contexts do not consistently predict readiness. In contrast, individual acceptance of AI is primarily explained by cognitive–affective processes articulated in TAM, particularly perceived ease of use and attitude toward AI. These findings extend prior adoption research by suggesting that, within higher education, institutional factors function mainly as *enabling conditions* rather than as direct behavioral determinants. This supports the argument that AI adoption is a staged process in which structural and regulatory readiness precedes but does not guarantee individual acceptance. The study therefore reinforces the necessity of multilevel theoretical frameworks that distinguish between institutional preparedness and user-level adoption behavior.

2) Reconceptualizing Institutional AI Readiness

This research also contributes to theory by reconceptualizing the role of institutional AI readiness. Contrary to dominant assumptions in organizational readiness and innovation diffusion literature, AI readiness does not exert a significant effect on perceived usefulness. This finding challenges the notion that institutional preparedness automatically translates into positive user perceptions regarding the value of new technologies. Theoretically, this suggests that AI readiness should be understood as a macro-structural construct reflecting strategic orientation, regulatory alignment, and external pressures, rather than as a direct antecedent of individual cognitive evaluations. As such, the study extends readiness theory by differentiating *institutional readiness* from *perceived technological value*, highlighting the need for additional mediating mechanisms to bridge these conceptual levels.

3) Reinforcing the Central Role of Attitude in TAM

Another important theoretical implication concerns the reaffirmed centrality of attitude toward technology in the TAM framework. The findings demonstrate that perceived ease of use exerts a strong influence on attitude, which in turn becomes the most powerful predictor of behavioral intention to adopt AI. Perceived usefulness, while significant, plays a secondary role relative to affective evaluation. This result enriches TAM-based literature by indicating that, for emerging and complex technologies such as AI, affective and evaluative components of user perception may outweigh purely instrumental considerations. Theoretically, this suggests that the relative salience of TAM constructs is context-dependent and influenced by the novelty and perceived complexity of the technology under investigation.

4) Boundary Conditions of Digital Literacy and Top Management Support

The study further contributes to theory by identifying boundary conditions for commonly assumed moderators in technology adoption research. The absence of a significant moderating effect of digital literacy on the relationship between attitude and behavioral intention indicates that positive attitudes toward AI can motivate adoption intentions even among users with varying levels of digital competence. This finding refines existing assumptions that digital literacy necessarily amplifies acceptance mechanisms in advanced technology contexts. Similarly, the non-significant role of top management support both as a direct predictor and as a moderating variable challenges prevailing

TOE-based arguments that position leadership support as a primary driver of technological readiness. These results imply that, in the early stages of AI adoption, symbolic or declarative managerial support may be insufficient to shape institutional readiness unless it is accompanied by concrete structural and operational changes.

5) Contributions to AI Adoption Research in Higher Education

Overall, this study advances the theoretical understanding of AI adoption in higher education by empirically demonstrating that adoption is a complex socio-technical phenomenon characterized by asymmetric interactions between institutional conditions and individual acceptance processes. The integrated TAM–TOE model examined in this research is not merely additive; rather, it reveals theoretical tensions between macro-level readiness and micro-level acceptance. By highlighting these asymmetries, the study calls for more context-sensitive, dynamic, and multilevel adoption models that explicitly account for the transformation mechanisms linking institutional readiness and individual acceptance. Consequently, this research provides a robust theoretical foundation for future studies seeking to refine AI adoption frameworks and to explore mediating and moderating pathways in digitally transforming higher education environments.

4.5. Practical Implications

The findings of this study provide several important practical implications for higher education institutions seeking to design, implement, and manage artificial intelligence (AI) adoption in a sustainable and effective manner. By distinguishing between institutional readiness and individual acceptance mechanisms, this research offers actionable insights for university leaders, policymakers, and educational technology developers.

1) Prioritizing User-Centered AI Adoption Strategies

One of the most salient practical implications is the central role of individual cognitive and affective factors in shaping AI adoption intentions. The strong influence of perceived ease of use on attitude toward AI, and subsequently on behavioral intention, indicates that AI adoption initiatives in higher education should prioritize user-centered design and usability considerations. Institutions should ensure that AI tools are intuitive, transparent, and aligned with academic workflows to reduce perceived complexity and resistance. From a managerial perspective, this finding suggests that investments in sophisticated AI infrastructure alone are insufficient if users perceive AI systems as

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difficult to learn or operate. Training programs, hands-on workshops, and guided onboarding processes should therefore be designed to emphasize simplicity, practical relevance, and immediate academic benefits. Such initiatives can foster positive attitudes toward AI and increase the likelihood of sustained adoption across teaching, research, and administrative activities.

2) Reframing Institutional Readiness Beyond Infrastructure

The results also indicate that institutional AI readiness does not automatically translate into higher perceived usefulness among users. This has important implications for institutional strategy. Universities should avoid equating readiness solely with technological infrastructure, policy formulation, or strategic declarations. Instead, readiness initiatives should be operationalized through concrete support mechanisms that are visible and directly experienced by users, such as accessible AI services, responsive technical support, and clear usage guidelines. Policymakers and institutional leaders should therefore focus on translating macro-level readiness into micro-level value creation. This may involve aligning AI initiatives with pedagogical objectives, research productivity goals, and administrative efficiency targets that are meaningful to academic staff. By explicitly demonstrating how AI supports daily academic tasks, institutions can bridge the gap between institutional preparedness and individual perceptions of usefulness.

3) Leveraging Environmental Drivers for Strategic Alignment

The significant influence of environmental context on institutional AI readiness highlights the importance of external pressures and opportunities in shaping adoption strategies. Government policies, regulatory frameworks, and global technological trends play a crucial role in motivating institutions to prepare for AI adoption. Practically, higher education institutions should actively monitor and align their AI strategies with national digital transformation agendas, accreditation requirements, and international best practices. Engagement in external collaborations such as partnerships with industry, research consortia, and international networks can further strengthen institutional readiness. These collaborations not only provide access to resources and expertise but also legitimize AI initiatives within the academic community. Institutional leaders should therefore view environmental pressures not as constraints, but as strategic enablers for accelerating AI readiness and innovation.

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4) Rethinking the Role of Leadership and Digital Literacy

The non-significant effects of top management support and the moderating role of digital literacy offer critical insights for practice. While leadership commitment remains symbolically important, the findings suggest that declarative support alone is insufficient to drive AI readiness or adoption. Practical leadership engagement should be reflected in tangible actions, such as allocating dedicated resources, revising academic policies, and embedding AI competencies into institutional development plans. Similarly, the absence of a significant moderating effect of digital literacy implies that positive attitudes toward AI can emerge even among users with varying levels of technical competence. This suggests that institutions should not delay AI initiatives until uniformly high levels of digital literacy are achieved. Instead, AI tools can be introduced incrementally, accompanied by continuous capacity-building efforts that evolve alongside usage experiences.

5) Implications for Sustainable AI Implementation in Higher Education

Taken together, these findings underscore the importance of adopting a balanced and phased approach to AI implementation. Institutions should simultaneously strengthen institutional readiness and cultivate positive user attitudes through usability-focused design, targeted training, and meaningful application of AI in academic contexts. By doing so, higher education institutions can move beyond symbolic adoption toward substantive and sustainable integration of AI technologies. Overall, the practical implications of this study emphasize that successful AI adoption in higher education is not merely a technological challenge, but a socio-technical transformation that requires alignment between institutional structures, environmental forces, and individual acceptance processes.

5. CONCLUSION

This study examines the adoption of artificial intelligence (AI) in higher education using an integrative TAM–TOE framework. The findings indicate that AI adoption is primarily driven by individual-level factors, particularly perceived ease of use and user attitudes, which emerge as the most influential determinants of behavioral intention. At the institutional level, environmental context is identified as the only significant driver of AI readiness, highlighting the role of external pressures such as policy direction and

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technological trends. In contrast, organizational, technological, and leadership factors show limited influence, suggesting that institutional readiness for AI adoption is still in an early stage of development. The study contributes to the literature by demonstrating that AI readiness functions as an intermediate construct linking institutional conditions and individual acceptance, while also highlighting the dominant role of user-centered perceptions in shaping AI adoption in higher education. From a practical perspective, these findings suggest that higher education institutions should prioritize user-oriented strategies, such as improving system usability and providing practical exposure to AI applications, while gradually strengthening institutional alignment and governance mechanisms. This study is subject to several limitations. The relatively modest explanatory power of some constructs suggests that additional contextual factors may influence AI adoption. Furthermore, the cross-sectional design limits the ability to capture temporal dynamics. Future research is encouraged to adopt longitudinal approaches and explore additional institutional and contextual variables to provide a more comprehensive understanding of AI adoption in higher education.

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