Journal of Applied Data Sciences
Vol. 6, No. 4, December 2025, pp. 3046-3059

ISSN 2723-6471
3046

Acceptance and Success Model for AI Use in Higher Education: Development, Instrument Decomposition, and Its Triangulation Testing

A'ang Subiyakto[1,*], Muhammad Q. Huda[2], Nashrul Hakiem[3], Hendra B. Suseno[4], Viva Arifin[5], Agus N. Azmi[6], Asrul Sani[7], Dwi Yuniarto[8], Muhammad S. Hartawan[9], Agung Suryatno[10], Muji Muji[11], Fachrul Kurniawan[12], Ririen Kusumawati[13], Naeem A. Balogun[14], Abd. Rahman Ahlan[15]

[1, 2, 3]*Department of Information Technology, UIN Syarif Hidayatullah Jakarta, South Tangerang, 15412, Indonesia*

[4, 5]*Department of Informatics Engineering, UIN Syarif Hidayatullah Jakarta, South Tangerang, 15412, Indonesia*

[6]*Department of International Relationship, UIN Syarif Hidayatullah Jakarta, South Tangerang, 15412, Indonesia*

[7]*Department of Information Technology, National University, Jakarta, 12520, Indonesia*

[8]*Department of Information Systems, Universitas Sebelas April, Sumedang, 54323, Indonesia*

[9]*Department of Information Systems, Universitas Krisnadwipayana, Jakarta, 13077, Indoensia*

[10]*School of Science and Technology, Asia e University, Kuala Lumpur, 47500, Malaysia*

[11]*Doctoral Program of Management Science, Universitas Tarumanagara, Jakarta, 11440, Indonesia*

[12, 13]*Department of Informatics, UIN Maulana Malik Ibrahim Malagng, Malang, 65144, Indonesia*

[14]*Department of Information Technology, Confluence University of Science and Technology, Kogi State, 264103, Nigeria*

[15]*Department of Information Systems, International Islamic University Malaysia, Kuala Lumpur, 50728, Malaysia*

(Received: April 10, 2025; Revised: July 05, 2025; Accepted: October 01, 2025; Available online: November 15, 2025)

Abstract

Prior social computing studies described that the performance of technology products is about how the product use benefits the users, including Artificial Intelligence (AI). To have an impact, ensuring how AI is used is a prerequisite after the development. Furthermore, its use is also influenced by how users accept AI. This study aimed to develop an acceptance and success model of AI use in the higher education world from the user perspective, to decompose the model into its instrument level, and to test the validity and reliability of the research instrument. The researchers developed the model by adopting and combining the Technology Acceptance Model (TAM) and the Information System Success Model (ISSM) and adapting the proposed model in the context of AI use in higher education learning. The measurement items were derived from definitions of the variables and indicators of the model. The instrument was tested sequentially using triangulation methods. The quantitative testing was online survey with about 51 respondents and the qualitative one was interview involving five experts. This study may contribute methodologically as one of the guidance for novice scholars in similar works. It may relate to the clarity of the research procedure and the implementation of the mixed testing methods. Of course, the assumptions, samples, and data used in the study cannot be generalized for the other studies. Referring to the model development, the proposed model may not cover the other factors related to the ethical, cultural, and organizational barriers for adopting AI. These barriers may also affect its acceptance and success. Thus, the adoption of the factors related the barriers may also be interesting to study further.

Keywords: AI, Acceptance And Success Model, Model Development, Instrument Decomposition, Instrument Testing, Triangulation Method

1. Introduction

It is undeniable that the use of AI is one of the hot topics of academic discussion in this early post-pandemic era [1], [2]. In the higher education context, utilization brings many benefits, such as personalization of learning, administrative

***Corresponding author: A'ang Subiyakto (aang_subiyakto@uinjkt.ac.id)**
DOI: https://doi.org/10.47738/jads.v6i4.619

ISSN 2723-6471

efficiency, analysis of student performance, and improvement of assessment quality [3], [4], [5]. On the other hand, Jin, et al. [3], Suryanarayana, et al. [4], and Wang, et al. [5] elucidated that risks of the technology use may also need serious attention related to data privacy issues, potential algorithm bias, reduced human interaction, dependence on technology, and high costs. In brief, the wise and ethical use of AI is essential to obtain optimal benefits, minimize risks, and have an impact on learning success.

It is common in nature that scholars of education studies seem to explain the use of AI from the educational points of view around the implementation, impact, law, and teaching issues [3], [4], [5], [6]. Meanwhile, researchers in the computer science area tend to discuss AI from the technical perspective, in terms of form, development, and delivery [7], [8]. The studies that discuss AI from the user perspective may still rarely be discussed by researchers. Previous social computing research explained that to ensure the impact of the use of a technology product, the guarantee of the technology use is a prerequisite after the development [9], [10], [11]. Furthermore, the use of technology products by its users is also influenced by how they accept the product [11], [12]. This may also apply to the use of AI in the higher education world [13]. The above-mentioned phenomena were interesting for the researchers to understand further in the context of how to develop the acceptance and success model of AI in the higher education world from the perspective of the users. In addition, the validity and reliability of a research instrument are essential because it directly affects the quality of the research findings [14], [15]. Validity refers to the extent to which a research model measures or describes what it is supposed to measure. Reliability indicates the consistency of the model and the measuring instrument used. Gee, et al. [16] indicated that both aspects determine how a study impacts knowledge development theoretically and the practical application of its results in the real world.

This study aimed to develop the acceptance and success model of AI usage, to break down the proposed model into the research instrument level, and to examine the validity and reliability of the instrument. Besides conducting library studies as the basis of model development, the researchers used survey and expert judgment for testing the instrument in this study. It was hoped that the model and questionnaire developed be the input for further studies. In the methodological issues, even though the stages of model development, operationalization, and instrument testing may become common issues for expert researchers, a clear elucidation related to the three stages above may be very useful for students and novice researchers. Also, the methodological literature seems rarely published. The clarity of the model development, operationalization, and instrument testing may also be methodological guidance for similar works [17]. Three questions were proposed for guiding the research implementation, i.e., (1) How to develop the use and success model of AI in the higher education world? (2) How to break down the above-developed model into the form of data collection instruments? And (3) Are the used indicators in the model reliable and valid?

The following sections elucidate sequentially three points. The methodological section describes the design, sample, method, technique, instrument, and procedure of the study. The result and discussion section show the results of the three last main phases. The authors discussed the results by comparing them with the prior studies to show the contribution and implication of the study. Finally, this article is closed by the conclusion section.

2. Methodology

The researchers designed this study within five main stages (figure 1). They developed the proposed model within four substages (P2), decomposed the model into the instrument by defining each variable and indicator, adopted and adapted the definitions to be a measurement statement referring to the research context (P.3), and tested the developed instrument using triangulation method (P.4) [17], [18]. In terms of the mixed methods, the authors tested sequentially the item instruments through the quantitative (P.4.1) and qualitative (P.4.2) stages. In the interpretation stage (P.4.3), they confirmed sequentially the statistical and interpretative analysis results with the prior research findings adopted in the previous stages (figure 2). The statistical testing used around 51 data, including about 46 undergraduate students and five academicians with doctoral degrees. Meanwhile, the qualitative one was the interview responses of the five academicians. The researchers selected the samples by considering their key informant aspects, e.q., the experience, education, motivation, and expertise of the AI use [17].

ISSN 2723-6471

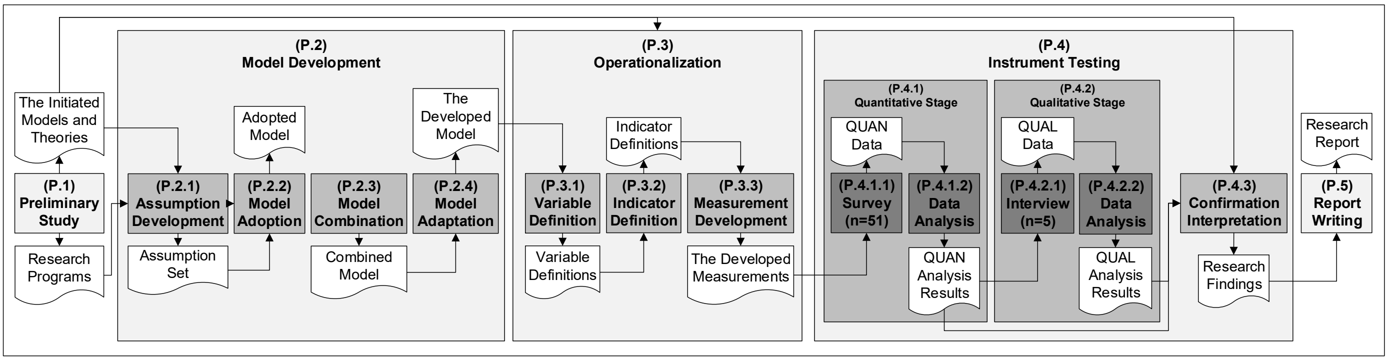

Figure 1. Research procedure

Figure 2 shows the interpretation stage. The researchers confirmed sequentially the statistical and interpretative analysis results with the prior research findings adopted in the previous stages following the prior triangulation method studies [17], [18].

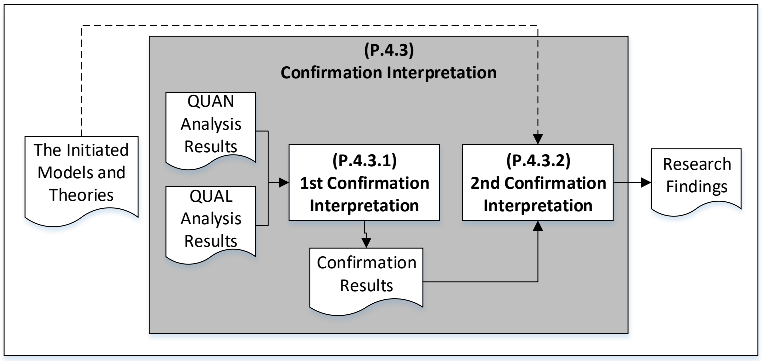

Figure 2. Procedure of the interpretation meta-inference

The authors analyzed the statistical data using four measurement model assessments with SmarPLS 4 software [19]. (1) The indicator reliability assessment employed a threshold value of 0.7 for the item loading of each indicator and the Composite Reliability (CR) value of each variable. (2) The internal consistency reliability assessment used the comparisons between the cross-loading value of each indicator in certain variables with indicators outside of the variable to those indicators that fulfilled the threshold value. (3) The convergent validity assessment used a threshold value of 0.7 for the Average Variance Extracted (AVE) value of each variable. (4) The discriminant validity assessment employed the AVE square root cross-loading matrix. Meanwhile, the authors analyzed the qualitative data using a thematic analysis matrix with the structured tabulation feature in MS. Excel 2016 [20].

The scholars identified seven interpretative points that were frequently mentioned by the interviewees regarding their judgments in response to the questionnaire check request, including the typos in writing statements, use of complex language, use of compound sentence structures, use of non-uniform sentence types, presence of double-barreled questions, ambiguity of statements, and the biased statements. The scholars then interpreted by confirming the results of the statistical and interpretative analyses with the previous theories to develop the triangulation inferences (figure 2). The sequential design of this mixed method testing was hoped to cover the comprehensiveness, completeness, coherency cohesiveness, and validity aspects of the developed questionnaires [17], [18], [21], [22].

3. Results and Discussion

Referring to the research procedure (figure 1), there are results of the model development, its operationalization, and the instrument evaluations. Firstly, the acceptance and success model of AI use in the higher education world was developed as a response to debates among academics regarding the benefits and risks of technology use [1], [3], [4], [6]. It is undeniable that the usage has brought significant benefits in higher education learning [3], [4], [5]. However, the negative impacts have been a concern for observers of the tertiary education sectors [6]. Previous social computing studies suggest that to succeed and obtain optimal benefits from the use of a technological product, the aspect of user acceptance is also a determining variable [9], [10], [11]. How will a technology have an optimal impact if the technology is not fully used? Furthermore, a technological product tends not to be fully used if its users do not accept it [11], [12].

Accordingly, the authors develop the acceptance and success model of AI use in tertiary learning within four sub-stages. First, the assumption development sub-stage (P.2.1). The authors analogized the acceptance and success model of AI use in the context of information processing theory within the Input, Process, and Output (IPO) dimensions (figure 3) [23], [24], [25]. Second, the model adoption sub-stage (P.2.2). They adopted two popular models, i.e., ISSM [26], [27], [28], [29] and TAM [12], [30], [31]. The previous studies elucidated that the success model consists of three dimensions, i.e., the system creation, its use, and the implementation impacts [26], [27], [28], [29]. Third, the model combination sub-stage (P.2.3). By considering the relationship phenomenon between the acceptance and use aspects of a technology product, the researchers then combined variables of TAM in the context of representing the system use a variable of ISSM (figure 3).

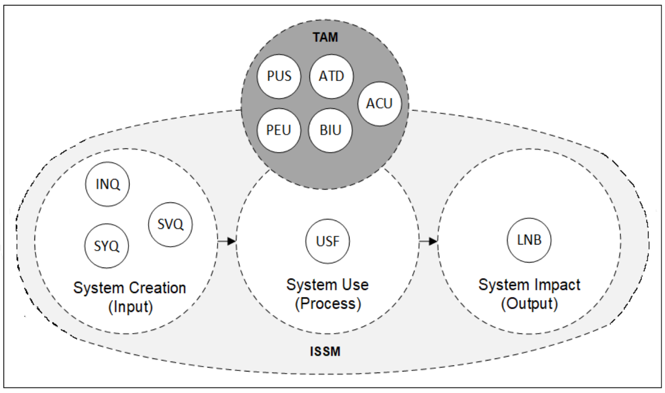

Figure 3. Model development assumption

Figure 4 shows the developed model with 23 hypotheses which are proposed referring to previous studies [12], [26], [27], [28], [29], [30], [31]. Fourth, the authors adapted names of each adopted variable referring to the phenomenon of AI use in the higher education world (figure 4). This adaptation aspect has also been implemented in the operationalization stage, especially in the variable and indicator definitions and measurement development. In short, the developed model and its hypothesis paths have been inputs of the operationalization stage.

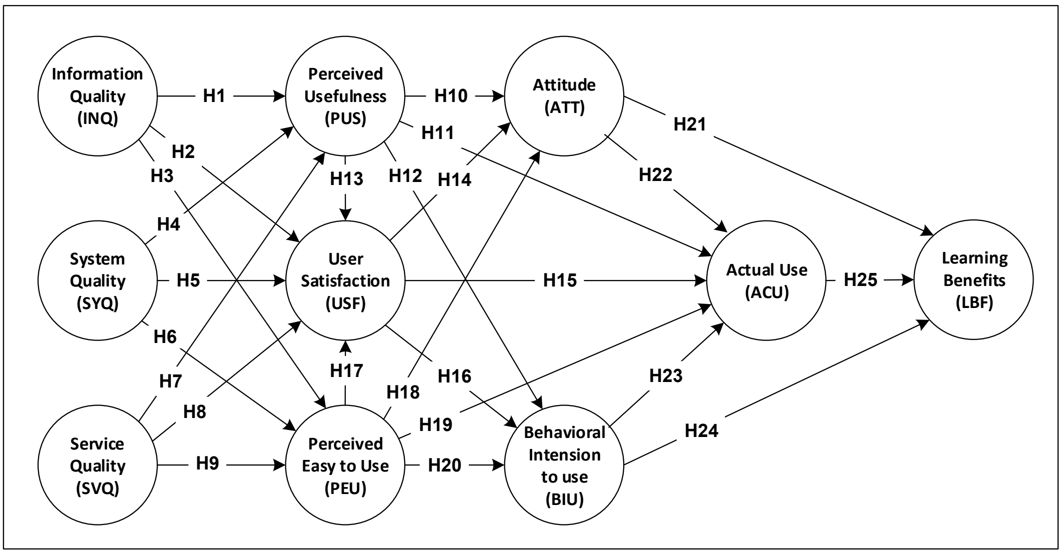

Figure 4. The developed research model and its hypotheses [3], [4], [5], [6], [12], [26], [27], [28], [29], [30], [31].

Secondly, referring to the previous model development stage, table 1 and table 2 present the variable definitions and indicators of each variable respectively. The variables and indicators were adopted from the previous studies [12], [26],

[27], [28], [29], [30], [31] and adapted following the research phenomenon [3], [4], [5], [6]. The researchers adopted the variable and indicator definitions used in the proposed research model from similar studies and adapted the definitions in terms of the acceptance and success of AI use in the higher education world. Table 1 shows list of variables adopted in the research model and each of its definition by adapting the research phenomenon.

Table 1. List of variable definitions [3], [4], [5], [6], [12], [26], [27], [28], [29], [30], [31].

Code	Definition
INQ	The degree to which the information is provided by AI applications for supporting academic activities.
SYQ	The overall performance of the AI application affects the user experience in the learning process.
SVQ	The extent to which AI application services meet the expectations and needs of users during learning activities.
PUS	The degree to which users believe that using AI applications enhances their learning outcomes and academic work.
PEU	The degree to how easily users can learn, interact, and navigate the AI applications without much effort.
USF	The overall contentment of users with the AI application for facilitating learning activities.
ATD	The user's positive or negative feelings and beliefs of AI applications for supporting learning and self-development.
BIU	The strength of users' intention and commitment to continue using AI applications in future learning activities.
ACU	The degree to which AI applications are integrated into their daily academic routines.
LNB	The positive outcomes are derived from using AI applications in learning and academic work.

Table 2 presents indicators of each variable which are adopted in the research model.

Table 2. Indicators of each variable [3], [4], [5], [6], [12], [26], [27], [28], [29], [30], [31].

Var	Indicators
INQ	Relevance (INQ1), Accuracy (INQ2), Completeness (INQ3), Consistency (INQ4), Timeliness (INQ5), Reliability (INQ6), Accessibility (INQ7)
SYQ	Reliability (SYQ1), Responsiveness (SYQ2), Flexibility (SYQ3), Efficiency (SYQ4), Availability (SYQ5), Security (SYQ6), Easiness (SYQ7)
SVQ	Responsiveness (SVQ1), Competency (SVQ2), Reliability (SVQ3), Empathy (SVQ4), Availability (SVQ5), Communication (SVQ6), Solution (SVQ7)
PUS	Learning Performance (PUS1), Time efficiency (PUS2), Productivity (PUS3), Work Quality (PUS4), Ease of Access (PUS5), Independent Learning (PUS6), Analytical Capabilities (PUS7)
PEU	Ease of Use (PEU1), Interface Intuitiveness (PEU2), Ease of Learning (PEU3), Ease of Access (PEU4), Assistance Effectiveness (PEU5), Ease of Integration (PEU6), Adaptation Speed (PEU7)
USF	Overall Satisfaction (USF1), Functional Satisfaction (USF2), Performance Satisfaction (USF3), Satisfaction Expectations (USF4), Ease of Use Satisfaction (USF5), Support Satisfaction (USF6), Content Satisfaction (USF7)
ATD	Positive Attitude to Use (ATD1), Personal Benefit (ATD2), Satisfaction of Use (ATD3), Desire to Continue Use (ATD4), Social Influence (ATD5), Learning Suitability (ATD6), Long-Term Benefits (ATD7)
BIU	Continuity (BIU1), Frequency Use (BIU2), Commitment (BIU3), Substitutive Tendency (BIU4), Motivation to Use (BIU5), Environment Influence (BIU6), Trust (BIU7)
ACU	Frequency Use (ACU1), Duration Use (ACU2), Intensity Use (ACU3), Activity Type (ACU4), Learning Integration (ACU5), Planning Compliance (ACU6), Quality Use (ACU7)
LNB	Material Understanding (LNB1), Skills Improvement (LNB2), Knowledgeability (LNB3), Learning Independence (LNB4), eLearning Motivation (LNB5), Resources Accessibility (LNB6), Learning Effectiveness (LNB7)

Table 3 elucidates definitions of each indicator which are adopted from the prior studies [27], [28], [29], [30], [31] and adapted following the research phenomenon [3], [4], [5], [6].

Table 3. Definitions of each indicator [3], [4], [5], [6], [12], [26], [27], [28], [29], [30], [31].

Indicators	Definitions
Relevance (INQ1)	The degree to which the information generated by AI is relevant to the learning topics.
Accuracy (INQ2)	The degree to which the information provided by AI is correct and error-free for learning activities.
Completeness (INQ3)	The degree to the information provided by AI covers the important details needed in learning.
Consistency (INQ4)	The degree to which the information provided by AI is consistent academically with knowledge.
Timeliness (INQ5)	The degree to the information provided by AI is always up-to-date in learning.
Reliability (INQ6)	The degree to the information provided by AI is reliable for use in learning.
Accessibility (INQ7)	The degree to which the information from the AI is easy to access whenever the user needs it.
Reliability (SYQ1)	The degree in AI is reliable for learning activities.
Responsiveness (SYQ2)	The degree to which AI responds quickly without significant delays in the learning activities.
Flexibility (SYQ3)	The degree to which AI can be customized to suit my preferences and needs in the learning process.

 ISSN 2723-6471

Efficiency (SYQ4)	The degree to which AI uses resources efficiently.
Availability (SYQ5)	The degree that AI is always available and accessible at all times during the learning activities.
Security (SYQ6)	The degree to which AI is safe from threats in learning activities.
Easiness (SYQ7)	The degree that AI has an easy-to-use interface for learning activities.
Responsiveness (SVQ1)	The degree of responsiveness of the AI services to questions and issues quickly in learning.
Competency (SVQ2)	The degree that competency of the AI services is sufficient to resolve issues in the learning activities.
Reliability (SVQ3)	The degree of reliability of the AI services in the learning activities.
Empathy (SVQ4)	The degree of attention and suitability of the AI services to user needs in the learning activities.
Availability (SVQ5)	The degree of the AI available services according to the needs of its users in the learning activities.
Communication (SVQ6)	The degree that communication of the AI services is clear, timely, and accurate in learning.
Solution (SVQ7)	The degree to which the AI services provide solutions according to the needs of its users in learning.
Learning Performance (PUS1)	The degree to which the AI helps me understand the material better in the learning activities.
Time efficiency (PUS2)	The degree to which the AI reduces the time it takes to complete assignments in the learning activities.
Productivity (PUS3)	The degree to which the AI makes it possible to complete assignments in the same amount of time.
Work Quality (PUS4)	The degree to which AI helps me produce better, higher-quality work in learning activities.
Ease of Access (PUS5)	The degree to which the AI provides the information I need quickly and easily in activities.
Independent Learning (PUS6)	The degree to which the AI allows for self-study without always needing help from a teacher in learning.
Analytical Capabilities (PUS7)	The degree to which AI helps users develop better analytical skills in learning activities.
Ease of Use (PEU1)	The degree to which the AI is easy to understand and use without much effort.
Interface Intuitiveness (PEU2)	The degree to which AI interface capability allows users to understand and interact without guidance.
Ease of Learning (PEU3)	The degree to which the AI interface is intuitive and easy to navigate without guidance.
Ease of Access (PEU4)	The degree to which users can easily learn to use the AI.
Assistance Effectiveness (PEU5)	The degree to which the AI features are easy to access in its use.
Ease of Integration (PEU6)	The degree that AI easy to be integrated with the other applications
Adaptation Speed (PEU7)	The degree that AI needs time efficiently to be adopted.
Overall Satisfaction (USF1)	The degree of user satisfaction with the overall AI in supporting learning activities.
Functional Satisfaction (USF2)	The degree of user satisfaction with the functions of the AI in supporting learning activities.
Performance Satisfaction (USF3)	The degree of user satisfaction with the performance of the AI in supporting learning activities.
Satisfaction Expectations (USF4)	The degree of user satisfaction with the support of the AI in learning according to their expectations.
Ease of Use Satisfaction (USF5)	The degree of user satisfaction with the ease of understanding the AI in learning activities.
Support Satisfaction (USF6)	The degree of satisfaction with the technical support availability for the AI in learning activities.
Content Satisfaction (USF7)	The degree of user satisfaction with the content of the AI in learning activities.
Positive Attitude to Use (ATD1)	The degree to how to have a positive attitude towards the AI use in learning activities.
Personal Benefit (ATD2)	The degree to which the use of AI provides significant benefits for learning and self-development.
Satisfaction of Use (ATD3)	The degree of satisfaction of using AI in supporting their learning activities.
Desire to Continue Use (ATD4)	The degree that the strong desire of users to continue using AI in learning activities.
Social Influence (ATD5)	The degree of social influence influences the use of AI in learning activities.
Learning Suitability (ATD6)	The degree that the extent to which AI is by learning preferences and needs.
Long-Term Benefits (ATD7)	The degree that the use of AI will provide long-term benefits in learning.
Continuity (BIU1)	The degree that a strong desire to use AI in learning activities.
Frequency Use (BIU2)	The degree of repetition use of AI in learning activities.
Commitment (BIU3)	The degree of commitment to use AI in learning activities.
Substitutive Tendency (BIU4)	The degree that the tendency to use AI to replace conventional methods in learning activities.
Motivation to Use (BIU5)	The degree of motivation to use AI applications in learning activities.
Environment Influence (BIU6)	The degree of influence of social environment on the use of AI in learning activities.
Trust (BIU7)	The degree to which users believe that AI applications are useful in learning activities.
Frequency Use (ACU1)	The degree of the use repetition of the AI applications in learning activities.
Duration Use (ACU2)	The degree that the duration of the use of AI applications in learning activities.
Intensity Use (ACU3)	The degree of the use intensity of the AI applications in learning activities.
Activity Type (ACU4)	The degree of the use diversity of the AI applications in learning activities.
Learning Integration (ACU5)	The degree to the integration of the use of AI applications in the routine of learning activities.

ISSN 2723-6471

Planning Compliance (ACU6)	The degree of compliance with the plan for using AI in learning activities.
Quality Use (ACU7)	The degree to the use quality of AI applications in learning activities.
Material Understanding (LNB1)	The degree of the AI applications is used to improve the understanding of materials in learning activities.
Skills Improvement (LNB2)	The degree to which AI applications are used to improve technical skills in learning activities.
Knowledgeability (LNB3)	The degree to the use of AI applications improves the ability to apply knowledge in learning activities.
Learning Independence (LNB4)	The degree to which the use of AI applications improves learning independence in learning activities.
eLearning Motivation (LNB5)	The degree of the use of AI applications to improve learning motivation in learning activities.
Resources Accessibility (LNB6)	The degree that the use of AI applications in accessing learning resources during learning.
Learning Effectiveness (LNB7)	The degree to which the use of AI applications improves learning effectiveness.

Table 4 elucidates the measurement items which are adopted from the prior studies [27], [28], [29], [30], [31] and adapted following the research phenomenon [3], [4], [5], [6].

Table 4. List of measurement items [3], [4], [5], [6], [12], [26], [27], [28], [29], [30], [31].

Code	Measurement Items
INQ1	I find that the information generated by the AI application is relevant to my learning topics and academic assignments.
INQ2	I am confident that the information provided by the AI application is always correct and error-free in my learning activities.
INQ3	I find that the information provided by the AI application covers all the important details I need for assignments and learning.
INQ4	I see that the information provided by the AI application does not show any inconsistencies or contradictions.
INQ5	I feel that the information provided by the AI application is always up-to-date and relevant to the latest developments.
INQ6	I believe that the information provided by the AI application is reliable for my academic assignments and decision-making.
INQ7	I can easily access information from the AI application whenever I need it in my learning activities.
SYQ1	I find that the AI application is always reliable in supporting my learning activities.
SYQ2	I see that the AI application responds quickly without significant delays in my learning activities.
SYQ3	I can customize the AI application to suit my preferences and needs in the learning process.
SYQ4	I feel that the AI application uses resources efficiently.
SYQ5	I find that the AI application is always available and accessible at all times during my learning activities.
SYQ6	I feel that the AI application is safe from threats in my learning activities.
SYQ7	I find that the AI application has an easy-to-use interface for my learning activities.
SVQ1	I find that the AI application services respond to my questions and issues quickly in my learning activities.
SVQ2	I believe that the competency of the AI application services is sufficient to resolve issues I encounter in my learning activities.
SVQ3	I find the AI application services to be reliable in my learning activities.
SVQ4	I find that the AI application services pay attention to and meet my needs in my learning activities.
SVQ5	I find that the AI application services are always available when I need them in my learning activities.
SVQ6	I feel that the communication from the AI application services is clear, timely, and accurate in my learning activities.
SVQ7	I find that the AI application services provide solutions according to my needs in my learning activities.
PUS1	I feel that the AI application helps me better understand the material in my learning activities.
PUS2	I feel that the AI application reduces the time it takes me to complete assignments in my learning activities.
PUS3	I find that the AI application allows me to complete more assignments in the same amount of time.
PUS4	I feel that the AI application helps me produce better, higher-quality work in my learning activities.
PUS5	I find that the AI application provides the information I need quickly and easily in my learning activities.
PUS6	I feel that the AI application allows me to self-study without always needing help from a teacher in my learning activities.
PUS7	I feel that the AI application helps me develop better analytical skills in my learning activities.
PEU1	I find that the AI application is easy to understand and use without much effort.
PEU2	I feel that the AI application's interface allows me to understand and interact with the system naturally without guidance.
PEU3	I find that the AI application's interface is intuitive and easy to navigate without requiring additional guidance.
PEU4	I can easily learn how to use the AI application.
PEU5	I find that the AI application's features are easy to access during use.
PEU6	I feel that the help and guidance provided by the AI application are effective.
PEU7	I find that help and guidance are always available when I use the AI application.
USF1	I am satisfied with the overall AI application in supporting my learning activities.
USF2	I am satisfied with the functions of the AI application in supporting my learning activities.
USF3	I am satisfied with the performance of the AI application in supporting my learning activities.

ISSN 2723-6471

USF4	I am satisfied with the support the AI application provides for my learning, meeting my expectations.
USF5	I am satisfied with the ease of understanding the AI application in my learning activities.
USF6	I am satisfied with the availability of technical support for the AI application in my learning activities.
USF7	I am satisfied with the content provided by the AI application in my learning activities.
ATD1	I have a positive attitude toward using the AI application in my learning activities.
ATD2	I feel that using the AI application provides significant benefits for my learning and self-development.
ATD3	I am satisfied with using the AI application to support my learning activities.
ATD4	I have a strong desire to continue using the AI application in my learning activities.
ATD5	I feel that social influence affects my use of the AI application in my learning activities.
ATD6	I find that the AI application aligns with my learning preferences and needs.
ATD7	I believe that using the AI application will provide long-term benefits for my learning.
BIU1	I have a strong desire to use the AI application in my learning activities.
BIU2	I frequently use the AI application repeatedly in my learning activities.
BIU3	I am committed to using the AI application in my learning activities.
BIU4	I tend to use the AI application to replace conventional methods in my learning activities.
BIU5	I am motivated to use the AI application in my learning activities.
BIU6	I feel that my social environment influences my use of the AI application in my learning activities.
BIU7	I believe that the AI application is useful for my learning activities.
ACU1	I frequently use the AI application repeatedly in my learning activities.
ACU2	I use the AI application for extended periods during my learning activities.
ACU3	I use the AI application with high intensity in my learning activities.
ACU4	I use the AI application in diverse ways during my learning activities.
ACU5	I integrate the use of the AI application into my learning routine.
ACU6	I follow the planned usage of the AI application in my learning activities.
ACU7	I use the AI application with high quality in my learning activities.
LNB1	I use the AI application to improve my understanding of materials in my learning activities.
LNB2	I use the AI application to improve my technical skills in my learning activities.
LNB3	I use the AI application to improve my ability to apply knowledge in my learning activities.
LNB4	I use the AI application to enhance my learning independence in my learning activities.
LNB5	I use the AI application to improve my learning motivation in my learning activities.
LNB6	I use the AI application to access learning resources during my learning activities.
LNB7	I use the AI application to improve the effectiveness of my learning.

Thirdly, results of the statistical analysis show that 16 of 70 indicators are rejected because they failed to fulfill statistically the threshold values. Table 5, and table 6 present results of the measurement model assessments. Table 5 show the indicator reliability assessment results with the item loadings of each indicator and the CR values of each variable fulfilled the threshold value of 0.7 [19].

Table 5. Results of the indicator reliability assessment

Variable	CR	AVE	Indicator	Indicator Cross Loading									
				ACU	ATD	BIU	INQ	LNB	PEU	PUS	SVQ	SYQ	USF
ACU	0.96	0.81	ACU1	0.88									
			ACU2	0.89									
			ACU3	0.93									
			ACU4	0.91									
			ACU5	0.92									
			ACU6	0.87									
			ACU7	Reject									
ATD	0.94	0.83	ATD1		0.71								
			ATD2		0.93								
			ATD3		Reject								
			ATD4		Reject								
			ATD5		Reject								
			ATD6		0.92								

 ISSN 2723-6471

			ATD7	0.89								
BIU	0.90	0.65	BIU1		0.87							
			BIU2		0.82							
			BIU3		0.82							
			BIU4		Reject							
			BIU5		0.76							
			BIU6		Reject							
			BIU7		0.75							
INQ	0.90	0.61	INQ1			0.74						
			INQ2			0.75						
			INQ3			0.81						
			INQ4			0.79						
			INQ5			0.76						
			INQ6			0.82						
			INQ7			Reject						
LNB	0.92	0.71	LNB1				Reject					
			LNB2				0.82					
			LNB3				0.86					
			LNB4				0.83					
			LNB5				0.81					
			LNB6				Reject					
			LNB7				0.89					
PEU	0.92	0.67	PEU1					0.78				
			PEU2					0.79				
			PEU3					0.86				
			PEU4					0.94				
			PEU5					0.78				
			PEU6					0.77				
			PEU7					Reject				
PUS	0.90	0.65	PUS1						0.78			
			PUS2						0.81			
			PUS3						0.82			
			PUS4						0.80			
			PUS5						0.84			
			PUS6						Reject			
			PUS7						Reject			
SVQ	0.93	0.65	SVQ1							0.81		
			SVQ2							0.79		
			SVQ3							0.72		
			SVQ4							0.86		
			SVQ5							0.83		
			SVQ6							0.78		
			SVQ7							0.85		
SYQ	0.89	0.74	SYQ1								Reject	
			SYQ2								0.87	
			SYQ3								Reject	
			SYQ4								0.86	
			SYQ5								Reject	
			SYQ6								Reject	
			SYQ7								0.85	
USF	0.93	0.65	USF1									0.84
			USF2									0.83

	USF3	0.91
	USF4	0.72
	USF5	0.80
	USF6	0.76
	USF7	0.76

Meanwhile, results of the indicator validity assessments show that the AVE values of each variable fulfilled the threshold value of 0.7 (tabel 5) with the AVE square root cross-loading matrix standardization (table 6).

Table 6. Results the AVE square root cross-loading assessment

Variable	ACU	ATD	BIU	INQ	LNB	PEU	PUS	SVQ	SYQ	USF
ACU	0.90									
ATD	0.29	0.91								
BIU	0.76	0.47	0.80							
INQ	0.52	0.32	0.46	0.78						
LNB	0.38	0.47	0.46	0.38	0.84					
PEU	0.40	0.39	0.54	0.35	0.50	0.82				
PUS	0.67	0.59	0.71	0.50	0.48	0.45	0.81			
SVQ	0.49	0.53	0.59	0.67	0.44	0.59	0.69	0.81		
SYQ	0.50	0.73	0.63	0.59	0.48	0.63	0.76	0.77	0.86	
USF	0.34	0.56	0.48	0.53	0.48	0.61	0.66	0.74	0.71	0.81

Following the statistical rejections of the measurement model assessments, the researchers interpreted the interview responds of the five participants. The authors found recommendations for revising the eight of 16 rejected instruments, i.e., SYQ1, SYQ2, SYQ6, PUS6, BIU4, BIU6, ATD4, and LNB1 (table 7). In the interpretation step, the researchers confirmed results of the quantitative and qualitative analyses with the previous literature used in the model development step for justifying the instrument evaluation results. Table 7 shows the inferential confirmation results between the statistical, interpretative, and theoretical points. This confirmation table presents eight indicator rejection recommendations, i.e., INQ7, SYQ5, PUS7, PEU7, ACU7, ATD3, ATD5, and LNB6. In brief, it can be seen that besides the outer model having statistically psychometric properties following the measurement model assessment results, results of the triangulation instrument testing may also be a comprehensive consideration in terms of the mixed-method testing implemented in the study.

Table 7. Results of the interpretation stage

Indicator	Interpretation		Previous Studies	Recommendation
	Qualitative	Quantitative		
INQ7	Rejected	Rejected	Weak	Rejected
SYQ1	Rejected	Revised	Strong	Revised
SYQ3	Rejected	Revised	Strong	Revised
SYQ5	Rejected	Rejected	Weak	Rejected
SYQ6	Rejected	Revised	Strong	Revised
PUS6	Rejected	Revised	Strong	Revised
PUS7	Rejected	Rejected	Weak	Rejected
PEU7	Rejected	Rejected	Weak	Rejected
BIU4	Rejected	Revised	Strong	Revised
BIU6	Rejected	Revised	Strong	Revised
ACU7	Rejected	Rejected	Weak	Rejected
ATD3	Rejected	Rejected	Strong	Rejected
ATD4	Rejected	Revised	Strong	Revised

ISSN 2723-6471

ATD5	Rejected	Rejected	Strong	Rejected
LNB1	Rejected	Revised	Strong	Revised
LNB6	Rejected	Rejected	Strong	Rejected

To discuss the above-mentioned results of this study, there are three highlighted points referring to the three research questions. First, the proposed model was developed by using IPO analogy [23], [24], [25], adopting two reputable models (i.e., ISSM and TAM) [3], [4], [5], [6], [12], [26], [27], [28], [29], [30], [31], combining both models based the causal relation concept of the acceptance, use, and success phenomena of a technology product [9], [10], [11], [12], and adapting the combination model in terms of AI use in higher education learning [11], [12], [13]. Second, the model was then decomposed into the research instrument by defining each variable and indicator of the model and formulating each indicator definition into a measurement statement item. Third, the triangulation confirmation analysis results recommended eight indicator rejections (i.e., INQ7, SYQ5, PUS7, PEU7, ACU7, ATD3, ATD5, and LNB6). However, the researchers argue that the rejections can be accounted for in terms of the quality of the proposed models and tools. The interesting discussion of this study is about how to justify the quality of the proposed model and its instrument.

Referring to the quality aspects of medical studies described by Eddy [32], the following descriptions may help to describe the reliability and validity aspects of this study's results. First, clarity, transparency, and trust issues are three essential interrelated elements that develop the reliability perception of a study. A clear and understandable process description of the model development, its decomposition to the instrument level, and the instrument testing in this study are expected to help others understand the information and intent conveyed. In addition, this study also shows the transparency issue, and openness of information related to the process, decisions, and results achieved. In short, both clarity and transparency issues of this study show the point of honesty which in turn fosters the trust aspect of the further study implementation [14], [15], [16], [33]. Second, the validity aspect of this study can be seen through reverse tracing whether the study results have represented the phenomena underlying the study implementation. The developed research model has represented the phenomena of the acceptance and success of AI use in the higher education world. The instrument has been developed referring to indicators and variables of the proposed model. The valid and reliable measurements resulting in the instrument testing can be traced through its triangulation inferences. In short, the output of this study can be confirmed by its input.

In summary, both reliability and validity elucidations of this study may be two of the consideration points for further studies. The elucidations may be negligible for the experts, but the presentations may be helpful for the beginner as one of the methodological guidance on how to develop a social computing model, decompose the model into its instrument level, and test the instruments using a mixed-method inquiry. On the other side, this study has limitations in terms of the assumptions in the model development step, samples, and data used in the study. Salman, et al. [33] and Romano, et al. [34] indicated that the subjectivities of the researchers and participants influence bias of the data and results in a study. Thus, the findings cannot be generalized to the other studies. Considering the use of TAM and ISSM for developing the acceptance and success model of AI use here, they only tend to cover the individual perspective of AI adoption [3], [4], [5], [6], [12], [26], [27], [28], [29], [30], [31]. This may affect the acceptance and success phenomena. The other factors related to the ethical, cultural, and organizational barriers to adopting AI may also affect the phenomena. Therefore, the adoption of other models related to these may also be interesting to study further.

4. Conclusion

The acceptance of AI affected its implementation performance among higher education institutions in terms of a technology success model. This study has developed the acceptance and success model of AI usage, decomposed the proposed model into the research instrument level, and tested the validity and reliability of the instrument. Referring to the research design, this study proposed the acceptance and success model of AI use in the higher education world and its data collection instrument. The authors adopted TAM and ISSM, combined both models, and adapted them to the higher education use context. The researchers employed a concurrent mixed method for testing the developed instrument in particular. In the statistical examination sub-stage rejected 16 of 70 indicators for presenting the psychometric property of the outer model. However, the triangulation confirmation substage proposed only eight indicator rejections by considering the quantitative and qualitative results and the previous studies used in the study. The interesting issue of this study is around the reliability and validity elucidation aspects of the model and its instrument developments. Besides this may be useful for beginners in methodological terms, the limitations around the scholar's subjectivity and the sampled data may be two considerations for similar studies.

5. Declarations

6.1. Author Contributions

Conceptualization: A.S., M.Q.H., N.H., and H.B.S.; Methodology: M.Q.H.; Software: A.S.; Validation: A.S., M.Q.H., N.H., and H.B.S.; Formal Analysis: A.S., M.Q.H., N.H., and H.B.S.; Investigation: A.S.; Resources: M.Q.H.; Data Curation: M.Q.H.; Writing—Original Draft Preparation: A.S., M.Q.H., N.H., and H.B.S.; Writing—Review and Editing: M.Q.H., A.S., N.H., and H.B.S.; Visualization: A.S.; All authors (A.S., M.Q.H., N.H., H.B.S., V.A., A.N.A., A.Sa., D.Y., M.S.H., A.Su., M.M., F.K., R.K., N.A.B., and A.R.A.) have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

This research supported by the Centre of Research and Publication, UIN Syarif Hidayatullah Jakarta.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] T. K. F. Chiu, Q. Xia, X. Zhou, C. S. Chai, and M. Cheng, "Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education," *Computers and Education: Artificial Intelligence,* vol. 4, no. 1, pp. 1-18, 2023/01/01/ 2023.

[2] R. C. Climent, D. M. Haftor, and M. W. Staniewski, "AI-enabled business models for competitive advantage," *Journal of Innovation & Knowledge,* vol. 9, no. 3, pp. 1-22, 2024/07/01/ 2024

[3] Z. Jin, S. B. Goyal, and A. S. Rajawat, "The Informational Role of Artificial Intelligence in higher Education in the New era," *Procedia Computer Science,* vol. 235, no. 1, pp. 1008-1023, 2024/01/01/ 2024

[4] K. S. Suryanarayana, V. S. P. Kandi, G. Pavani, A. S. Rao, S. Rout, and T. Siva Rama Krishna, "Artificial Intelligence Enhanced Digital Learning for the Sustainability of Education Management System," *The Journal of High Technology Management Research,* vol. 35, no. 2, p. 100495, 2024/11/01/ 2024

[5] S. Wang, F. Wang, Z. Zhu, J. Wang, T. Tran, and Z. Du, "Artificial intelligence in education: A systematic literature review," *Expert Systems with Applications,* vol. 252, no. 1, pp. 1-17, 2024/10/15/ 2024

[6] A. O. Tzirides, "Combining human and artificial intelligence for enhanced AI literacy in higher education," *Computers and Education Open,* vol. 6, no. 1, pp. 1-24, 2024/06/01/ 2024

[7] M. C. Laupichler, A. Aster, J. Schirch, and T. Raupach, "Artificial intelligence literacy in higher and adult education: A scoping literature review," *Computers and Education: Artificial Intelligence,* vol. 3, no. 1, pp. 1-21, 2022/01/01/ 2022

[8] W. Sun, A. Tohirovich Dedahanov, W. P. Li, and H. Young Shin, "Sanctions and opportunities: Factors affecting China's high-tech SMEs adoption of artificial intelligence computing leasing business," *Heliyon,* vol. 10, no. 16, pp. 1-20, 2024/08/30/ 2024

[9] J. Varajão, J. C. Lourenço, and J. Gomes, "Models and methods for information systems project success evaluation – A review and directions for research," *Heliyon,* vol. 8, no. 12, pp. 1-17, 2022/12/01/ 2022

[10] F. Sunmola and G. L. Lawrence, "Key Success Factors for Integration of Blockchain and ERP Systems: A Systematic Literature Review," *Procedia Computer Science,* vol. 232, no. 1, pp. 775-782, 2024/01/01/ 2024

[11] G. Tetik, S. Türkeli, S. Pinar, and M. Tarim, "Health information systems with technology acceptance model approach: A systematic review," *International Journal of Medical Informatics,* vol. 190, no. 1, pp. 1-16, 2024/10/01/ 2024

[12] C. Wang, "An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce," *Heliyon,* vol. 9, no. 8, pp. 1-19, 2023/08/01/ 2023

[13] S. C. Kong, Y. Yang, and C. Hou, "Examining teachers' behavioural intention of using generative artificial intelligence tools for teaching and learning based on the extended technology acceptance model," *Computers and Education: Artificial Intelligence,* vol. 2024, no. Nov., pp. 1-28, 2024/11/01/ 2024

[14] O. Antsygina, S. Rollo, N. McRae, J.-P. Chaput, and M. S. Tremblay, "Reliability and validity of instruments containing reported sleep measures among children from birth to <5 years of age: A systematic review," *Sleep Medicine Reviews,* vol. 79, no. Feb., pp. 1-23, 2025/02/01/ 2025

[15] J. A. M. Bom, D. C. Voormolen, W. B. F. Brouwer, E. W. de Bekker-Grob, and J. van Exel, "Construct Validity, Reliability, and Responsiveness of the 10-Item Well-Being Instrument for Use in Economic Evaluation Studies," *Value in Health,* vol. 27, no. 7, pp. 871-878, 2024/07/01/ 2024

[16] P. M. Gee, A. Clift, J. Osteyee, E. B. P. C. R. Katz, and D. Collingridge, "Fall risk instrument for pediatric behavioral health patients (BHFR-P©): A validity and reliability study," *Journal of Pediatric Nursing,* vol. 69, no. 1, pp. 118-120, 2023/03/01/ 2023

[17] C Wallwey and R. L. Kajfez, "Quantitative research artifacts as qualitative data collection techniques in a mixed methods research study," *Methods in Psychology,* vol. 8, no. Nov., pp. 1-15, 2023/11/01/ 2023

[18] H. Taherdoost, "What are different research approaches? Comprehensive Review of Qualitative, quantitative, and mixed method research, their applications, types, and limitations," *Journal of Management Science & Engineering Research,* vol. 5, no. 1, pp. 53-63, 2022

[19] J. Hair and A. Alamer, "Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example," *Research Methods in Applied Linguistics,* vol. 1, no. 3, pp. 1-27, 2022/12/01/ 2022

[20] R. M. Belcher, B. Shultz, J. Mucksavage, E. Herrera, and S. Benken, "Qualitative analysis of preparation and planning habits of students with low-performance on high-stakes practice examinations (pre-NAPLEX®)," *Currents in Pharmacy Teaching and Learning,* vol. 16, no. 10, pp. 1-20, 2024/10/01/ 2024

[21] A. Subiyakto, R. Rosalina, M. C. Utami, N. Kumaladewi, and S. J. Putra, "The psychometric and interpretative analyses for assessing the end-user computing satisfaction questionnaire," in *2017 5th International Conference on Cyber and IT Service Management, CITSM 2017*, vol. 2017, no. 1, pp. 1-6, 2017

[22] A. Subiyakto, M. R. Juliansyah, M. C. Utami, and A. Susanto, "Combining the Statistical and Interpretative Analyses for Testing E-Commerce Customer Loyalty Questionnaire," in *2018 6th International Conference on Cyber and IT Service Management, CITSM 2018*, vol. 2018, no. 1, pp. 1—6, 2019

[23] M. Tiwari, D. J. Bryde, nF. Stavropoulou, R. Dubey, S. Kumari, and C. Foropon, "Modelling supply chain Visibility, digital Technologies, environmental dynamism and healthcare supply chain Resilience: An organisation information processing theory perspective," *Transportation Research Part E: Logistics and Transportation Review,* vol. 188, no. Aug., pp. 1-13, 2024/08/01/ 2024

[24] O. O. Mwambe, "Deployment of information processing theory to support adaptive e-learning systems: Feasibility study," *Computers in Human Behavior Reports,* vol. 14, no. May, pp. 1-20, 2024/05/01/ 2024

[25] S. Yadav, "The interplay effects of digital technologies, green integration, and green innovation on food supply chain sustainable performance: An organizational information processing theory perspective," *Technology in Society,* vol. 77, no. 1, pp. 1-15, 2024/06/01/ 2024

[26] M. K. Al-Kofahi, H. Hassan, R. Mohamad, T. Intan, and M. Com, "Information systems success model: A review of literature," *International Journal of Innovation, Creativity and Change,* vol. 12, no. 8, pp. 1-12, 2020

[27] I. Y. Alyoussef, "Acceptance of e-learning in higher education: The role of task-technology fit with the information systems success model," *Heliyon,* vol. 9, no. 3, pp. 1-21, 2023/03/01/ 2023

[28] G. Banafo Akrong, S. Yunfei, and E. Owusu, "Development and validation of an improved DeLone-McLean IS success model - application to the evaluation of a tax administration ERP," *International Journal of Accounting Information Systems,* vol. 47, no. Sec., pp. 1-19, 2022/12/01/ 2022

[29] A. Jeyaraj, "DeLone & McLean models of information system success: Critical meta-review and research directions," *International Journal of Information Management,* vol. 54, no. 1, pp. 1-19, 2020/10/01/ 2020

[30] Y. T. Prasetyo, "Determining factors Affecting acceptance of e-learning platforms during the COVID-19 pandemic: Integrating Extended technology Acceptance model and DeLone & Mclean is success model," *Sustainability,* vol. 13, no. 15, pp. 1-15, 2021

[31] A. Sulhi, N. A. B. Yahaya, and A. Subiyakto, "Acceptance of Information Technology Security Among Universities: a Model Development Study," *Journal of Applied Data Sciences,* Article vol. 4, no. 4, pp. 363-371, 2023

[32] D. M. Eddy, W. Hollingworth, J. J. Caro, J. Tsevat, K. M. McDonald, and J. B. Wong, "Model Transparency and Validation:A Report of the ISPOR-SMDM Modeling Good Research Practices Task Force–7," *Medical Decision Making,* vol. 32, no. 5, pp. 733-743, 2012, doi: 10.1177/0272989x12454579.

[33] I. Salman, P. Rodríguez, B. Turhan, A. Tosun, and A. Güreller, "What Leads to a Confirmatory or Disconfirmatory Behavior of Software Testers?," *IEEE Transactions on Software Engineering,* vol. 48, no. 4, pp. 1351-1368, 2022, doi: 10.1109/TSE.2020.3019892.

[34] S. Romano, D. Fucci, G. Scanniello, M. T. Baldassarre, B. Turhan, and N. Juristo, "On researcher bias in Software Engineering experiments," *Journal of Systems and Software,* vol. 182, no. Dec., pp. 1-18, 2021/12/01/ 2021