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Bayesian Restructuring Technology Acceptance Model (TAM) with Moderating Lecture Self-Managing in E-Learning Adoption

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ABSTRACT

High-quality lecturing is pivotal in advancing the Sustainable Development Goals (SDGs) through both traditional and digital education approaches. In E-learning, lecturers play a fundamental role in influencing adoption and effectiveness. This study introduces a restructured Technology Acceptance Model (TAM) by incorporating Lecture Self-Managing (LSM) as a moderating variable, enhancing its applicability to E-learning contexts. Bayesian Structural Equation Modelling (SEM) was employed to assess the performance of the restructured TAM compared to the original framework. The revised TAM was implemented within an E-learning system, with data collected through structured surveys from lecturers actively engaged in E-learning over one semester. The findings revealed that LSM significantly moderated the relationships between Subjective Norm (SN) and Perceived Ease of Use (PE), as well as SN and Perceived Usefulness (PU), with a BIC of 11,974.18—lower than the BIC of 12,009.42 when LSM was considered an external variable. These results indicate that integrating LSM as a moderating factor within TAM enhances the assessment of E-learning effectiveness. The innovation of lecturer-managed learning content within LSM can enrich and improve the success of E-learning implementation.

1. Introduction

E-learning refers to the utilisation of digital media and internet networks for the delivery of instructional content and interaction between educators and students [1]. Ensuring high-quality learning through E-learning is particularly vital in higher education, as it fosters competitive academic environments [2] and contributes to the development of highly skilled graduates [3]. Additionally, it enhances individual capabilities across cognitive, affective, and psychomotor domains [4]. The adoption of E-learning represents a significant educational innovation aimed at improving learning quality and supporting the attainment of the Sustainable Development Goals (SDGs). E-learning platforms are equipped with various features designed to facilitate learning. However, despite its numerous advantages, the integration of E-learning into higher education remains limited [3], necessitating an in-depth examination of its acceptance within this sector.

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The Technology Acceptance Model (TAM) is a widely employed theoretical framework for assessing technology adoption, including in the context of E-learning [5]. Initially proposed by [6], TAM has demonstrated its effectiveness in evaluating technology acceptance, with prior studies [5; 7; 8] confirming its ability to explain 40% of system usage [9]. The model is centred around three key constructs—Intentions to Use, Perceived Usefulness (PU), and Perceived Ease of Use (PE)—which collectively shape user behavior [10]. These constructs are interrelated in a sequential manner, forming the Graphical Causal Model. Given TAM's hierarchical structure, Structural Equation Modelling (SEM) is an appropriate analytical technique for its assessment. SEM is a multivariate statistical method that integrates regression and factor analysis, enabling the simultaneous estimation of relationships between variables [11; 12]. It conceptualises models through latent variables measured via specific indicators [13]. However, SEM analysis necessitates compliance with several assumptions, including the multivariate normality of latent variables, linear relationships between indicator and latent variables, as well as a sufficiently large sample size [14]. In practice, real-world data frequently fail to meet these assumptions, requiring alternative analytical methods capable of addressing such violations. The Bayesian SEM approach effectively resolves these issues, as it does not rely on conventional SEM assumptions. When combined with the Markov Chain Monte Carlo (MCMC) method, Bayesian SEM proves particularly effective in handling small sample sizes due to its independence from asymptotic theory. Furthermore, the estimated parameter values of latent variables can be obtained through the Gibbs Sampler method for posterior simulation using MCMC, simplifying the estimation process compared to traditional techniques [14; 15].

E-learning systems exhibit distinct characteristics compared to other digital platforms, with certain users functioning as system extensions. Numerous studies have explored different aspects of E-learning adoption, acceptance, and effectiveness. Angela et.al. and Baber investigated user acceptance of E-learning, likely employing established models such as TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT) [16; 17]. Humida et.al. examined student perceptions and challenges associated with E-learning, considering demographic and regional variations [18]. Concurrently, research by Hussein and Sukendro et.al. identified barriers to E-learning implementation, encompassing technological infrastructure, user motivation, and institutional support, particularly in underprivileged regions [19; 20]. Ibrahim et.al. (2021) assessed the effectiveness of E-learning in higher education, focusing on student engagement and faculty preparedness, while Ibrahim et.al. (2018) analysed E-learning satisfaction using metrics such as usability, interactivity, and learner autonomy [21; 22]. Iqbal and Arisman explored user perceptions of online learning platforms, concentrating on usability and engagement [23], whereas Kang and Shin investigated the psychological aspects of E-learning, including motivation, cognitive load, and engagement [24].

Recent studies, such as those conducted by Mashroofa et.al. and Natasia et.al., examined post-pandemic trends in E-learning, highlighting the influence of emerging technologies and generational differences in adoption [3; 25]. Ritter focused on instructional design principles and their effects on digital learning [26], while Saputera et.al. investigated institutional readiness and policy implications for E-learning implementation [27]. Sukendro et.al. further explored challenges in developing countries, particularly concerning accessibility and the digital divide [20]. Conversely, Yodha et.al. assessed engagement metrics in virtual learning environments, analysing factors such as course completion rates and user participation [28]. Zardari et.al. investigated the broader implementation of technology-enhanced learning across various educational settings [29]. Despite extensive research on E-learning adoption, engagement, and implementation, prior studies have not explicitly examined the role of users as system extensions or the implications of this dynamic within learning environments. This underscores the necessity for a revised or expanded Technology Acceptance Model that integrates the diverse roles of users and their interactions within E-learning systems.

2. Literature Review

2.1. Technology Acceptance Model

Davis introduced the Technology Acceptance Model (TAM) to examine the behavioural and motivational factors influencing the adoption and utilisation of Information Technology (IT) [10]. TAM is derived from the Theory of Reasoned Action (TRA), which posits that an individual's perceptions shape their attitudes and subsequent behaviours. In this context, users' attitudes towards IT influence their acceptance of technological systems, with their decisions primarily driven by the perceived benefits of technology. Ultimately, the perceived usefulness and ease of use of IT are considered key determinants of user acceptance [8]. Initially, Davis formulated TAM with five interconnected factors related to technology acceptance. However, after empirical validation, he refined the model, concluding that three key constructs—Intentions to Use, Perceived Usefulness (PU), and Perceived Ease of Use (PEU)—were sufficient to accurately predict user behavior [10]. Research by Teo et al. identified TAM as one of the most effective models for predicting technology adoption [5]. Since its introduction, TAM has been widely tested across various studies, demonstrating its ability to explain approximately 40% of system usage [9]. TAM is rooted in Ajzen's Theory of Planned Behaviour (TPB) and Fishbein and Ajzen's TRA, which describe individuals' behavioural intentions based on their beliefs and attitudes towards technology [30].

TAM postulates that two primary constructs—PU and PEU—shape an individual's acceptance of IT. TRA provides TAM with a theoretical foundation to establish causal relationships between PU, PEU, user attitudes, intentions, and technology adoption behaviour. However, TAM extends beyond TRA, offering a broader application to computer usage behavior [5]. TAM is widely regarded as a simple yet effective model for understanding technology adoption. It has been extensively applied across various technologies, including computer adoption, object-oriented technology, and internet usage, as well as in diverse contexts such as different time periods and cultural settings. Additionally, numerous studies have incorporated various control factors to enhance TAM's applicability in distinct technological environments. Here are examples of research projects based on the TAM:

1. Rafikasari et al. investigated the acceptance of E-learning using TAM. The study incorporated four primary TAM variables: perceived usefulness (PU), perceived ease of use (PE), behavioural intention (BI), and actual use (AU). Additionally, the research included external variables such as subjective norms (SN), training (T), experience (E), facilitating conditions (FC), and lecture self-managing (LSM). In this study, LSM was treated as an external variable, with results indicating that it did not significantly influence either PU or PE [31].
2. Teo et al. examined computer adoption among staff members at Singapore's National Institute of Education. Their study utilised three primary TAM variables—PU, PEU, and computer attitude (CA). Additionally, SN and FC were incorporated as external variables. The study applied structural equation modelling (SEM) using the Amos 6.0 software. The findings demonstrated that PU, PEU, SN, and FC significantly contributed to CA [5].
3. Lee, Kim, Rhee, and Trimi analysed external factors in TAM through a case study on object-oriented technology. Data were collected from members of the Association of Information Technology Professionals (AITP) across four US states. The study employed TAM with four core variables: usefulness, ease of use, intention, and actual use. Six external factors—innovativeness, training, experience, access, support, and group size—were examined concerning their influence

on usefulness and ease of use. While the initial hypothesis suggested that all external variables would simultaneously affect both constructs, the final analysis revealed that only group size and access had a significant impact on usefulness, whereas support was the sole factor significantly influencing ease of use [32].

4. Kim, Park, and Lee investigated internet acceptance in Korea, incorporating nine variables: experience, self-efficacy, task equivocality, task independence, organisational support, usefulness, ease of use, subjective norms, and actual usage. The findings indicated that ease of use was strongly associated with experience, self-efficacy, and organisational support. Moreover, internet usage was primarily driven by usefulness and ease of use, while subjective norms had a minimal effect on actual usage [33].

Two primary variables in TAM influence individual adoption of information system technology: PU and PEU. External factors affecting these variables include SN [34], FC [35], innovativeness, training, and experience [32]. Additional influencing factors comprise compatibility, computer anxiety, self-efficacy, enjoyment, computing support, and experience [36].

2.2. Role of Lecture Self-Managing (LSM) in TAM

LSM refers to lecturers' ability to supervise and regulate the learning process within an E-learning framework, ensuring instructional activities align with institutional standards and pedagogical objectives. This concept encompasses the ability to update, modify, and enhance educational resources to improve student engagement and comprehension, alongside managing course structures. Effective LSM enables lecturers to independently oversee online learning environments, making critical decisions on course design, content delivery, assessment methods, and student interactions. This autonomy is particularly vital in digital education, where the absence of physical classroom dynamics necessitates structured yet adaptable management. Agustina emphasised that the effectiveness of E-learning platforms largely depends on lecturers' ability to manage course materials, implement instructional strategies, and foster interactive learning environments [1].

Additionally, LSM involves overseeing key instructional components, such as student assessments, assignment distribution, feedback mechanisms, and real-time content modifications, ensuring that the online learning experience remains pedagogically sound, relevant, and interactive. In an online setting, student motivation, performance, and engagement are directly influenced by lecturers' capacity to manage these aspects effectively. The adaptability and technological competence of educators significantly impact the success of E-learning, as supported by various studies [37]. For instance, a meta-analysis conducted by the U.S. Department of Education found that students receiving instruction through traditional face-to-face methods performed slightly better than those engaged in online learning [38]. Lecturers with high levels of self-management are more likely to effectively adopt, integrate, and sustain digital learning technologies. Thus, LSM is not merely a technical skill set but a crucial factor in determining technology acceptance strategies. Institutions must prioritise training and support programmes to enhance lecturers' self-management capabilities as reliance on E-learning platforms grows. This includes equipping them with interactive learning strategies, assessment tools, and digital literacy skills to ensure a seamless and effective online teaching experience. By improving LSM, institutions can foster a more sustainable and engaging E-learning ecosystem, ultimately enhancing technology adoption rates, instructional quality, and overall student learning experiences [1].

2.3. Bayesian Structural Equation Modelling

SEM allows variables to be directly observed through indicators and indirectly through latent constructs, enabling simultaneous correlation analysis. Raykov and Marcoulides defined latent variables as theoretical constructs that are not directly observable within a population or sample. According to Raykov and Marcoulides , SEM models are often poorly defined and difficult to measure due to three key aspects: the inability to be measured indirectly, potential measurement issues affecting all observed variables, particularly independent variables, and their suitability for generating matrices that establish correlations and covariances among variables. SEM can be constructed using path analysis and CFA. Raykov and Marcoulides regarded both CFA and path analysis as integral components of SEM. Path analysis identifies correlations between observed variables; although some scholars do not classify it as part of SEM, its importance is widely acknowledged. CFA, on the other hand, examines relationships between multiple latent constructs, which are measured using observable indicators [39]. Bollen characterised latent variables as unobservable factors and differentiated between exogenous and endogenous latent variables. While endogenous variables are influenced by external factors, exogenous variables remain unaffected. Bollen formulated an equation model to represent these variables as follows:

$$\boldsymbol{\eta} = \boldsymbol{B\eta} + \boldsymbol{\Gamma\xi} + \boldsymbol{\zeta} \tag{1}$$

with:

$\boldsymbol{B} =$ The $m \times m$ coefficient matrix represents the relationships between endogenous latent variables

$\boldsymbol{\Gamma} =$ The $m \times n$ coefficient matrix represents the relationship between exogenous variables and latent variables

$\boldsymbol{\xi} =$ Vector of exogenous variables of size $q \times 1$

$\boldsymbol{\eta} =$ Vector of endogenous variables of size $p \times 1$

$\boldsymbol{\zeta} =$ Vector of error in the equation of size $p \times 1$

q = The number of exogenous variables is denoted as q, where q is equal to n

p = The number of endogenous variables is equal to the number of exogenous variables, denoted as p=m.

with assumptions: $E(\boldsymbol{\eta}) = 0; E(\boldsymbol{\xi}) = 0; E(\boldsymbol{\zeta}) = 0$. The $\boldsymbol{\zeta}$ is not associated with $\boldsymbol{\xi}$; and the matrix $(\boldsymbol{I} - \boldsymbol{B})$ is nonsingular [40].

In addition to latent variables, in SEM, observation variables are also known as manifest variables, measures/measurables, indicators, and proxies. Observation variables are divided into exogenous and endogenous latent variables, formulated in the following equation:

$$\boldsymbol{x} = \boldsymbol{\Lambda_x \xi} + \boldsymbol{\delta} \tag{2}$$

$$\boldsymbol{y} = \boldsymbol{\Lambda_y \eta} + \boldsymbol{\varepsilon} \tag{3}$$

with:

$\boldsymbol{y} =$ The $p \times 1$ indicator vector of $\boldsymbol{\eta}$,

$\boldsymbol{x} =$ The $q \times 1$ indicator vector of $\boldsymbol{\xi}$,

$\boldsymbol{\varepsilon} =$ The $p \times 1$ measurement error for ***y***,

$\boldsymbol{\delta} =$ The $q \times 1$ measurement error for ***x***,

In CFA, $\boldsymbol{\xi}$ distributes $N(0, \boldsymbol{\Phi})$. $\boldsymbol{\Phi}$ has a definite positive covariance matrix. The variance and covariance matrix of **x** can be stated as follows:

$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda\Phi\Lambda^T} + \boldsymbol{\Psi_\varepsilon} \tag{4}$$

Common names for the previously described SEM model include standard SEM and LISREL (Linear Structural Relationship) model. Accurate results from standard SEM require several assumptions to be met, including a large sample size, a multivariate normal distribution for latent variables, and linear relationships between indicator variables and other latent variables [41]. Bayesian SEM shares many features with standard SEM, such as structural equations and observation variables. The following equations represent the observation variables, similar to Equations (2) and (3):

$$\boldsymbol{y_i} = \boldsymbol{\Lambda\omega_i} + \boldsymbol{\varepsilon_i} \quad (5)$$

The vector $\boldsymbol{\omega_i}$ defined as $\left(\boldsymbol{\eta}_i^T, \boldsymbol{\xi}_i^T\right)$, where $\boldsymbol{\eta_i}$ is an endogenous latent variable vector of size q_1×1, and ξ_i is an exogenous latent variable vector of size q_2×1. The structural equation that describes the relationship between the endogenous latent variable and exogenous latent variables is:

$$\boldsymbol{\eta_i} = \boldsymbol{\Pi\eta_i} + \boldsymbol{\Gamma\xi_i} + \boldsymbol{\delta_i} \quad (6)$$

The parameter matrix of the regression coefficient is denoted as $\boldsymbol{\Pi}_{q_1\times q_1}$ and $\boldsymbol{\Gamma}_{q_1\times q_2}$are parameter. The error vector is represented as $\boldsymbol{\delta}_i$ with size q_1×*1*.

The CFA model, which is an expanded form of Exploratory Factor Analysis (EFA), includes Equations (2) for the exogenous latent model and (3) for the endogenous latent model. Exogenous latent components and the CFA model can be correlated, assuming that $\boldsymbol{\xi}$ distributed in $N\left[\mathbf{0},\boldsymbol{\Phi}_{\xi}\right]$ with $\boldsymbol{\Phi}_{\xi}$ a positive definite matrix and $\boldsymbol{\xi}$ to be independent of $\boldsymbol{\delta}$. The covariance matrix of $\mathbf{x}$ is:

$$\boldsymbol{\Sigma}_x = \boldsymbol{\Lambda}_x\boldsymbol{\Phi}_{\xi}\boldsymbol{\Lambda}_x^T + \boldsymbol{\Psi}_{\delta} \quad (7)$$

Similarly, for endogenous latent variables where $\boldsymbol{\eta}$ distributed in $N\left[\mathbf{0},\boldsymbol{\Phi}_{\xi}\right]$ and assumed that $\boldsymbol{\eta}$ to be independent of $\boldsymbol{\varepsilon}$. The covariance matrix of $\mathbf{y}$ is as follows:

$$\boldsymbol{\Sigma}_y = \boldsymbol{\Lambda}_y\boldsymbol{\Phi}_{\eta}\boldsymbol{\Lambda}_y^T + \boldsymbol{\Psi}_{\varepsilon} \quad (8)$$

3. Research Methodology

3.1. Research Model

This study applied TAM to assess the acceptance of E-learning technology in higher education. The TAM structure was adapted from [6], [32], [34], [42], [43], and [44], as illustrated in Fig. 1.

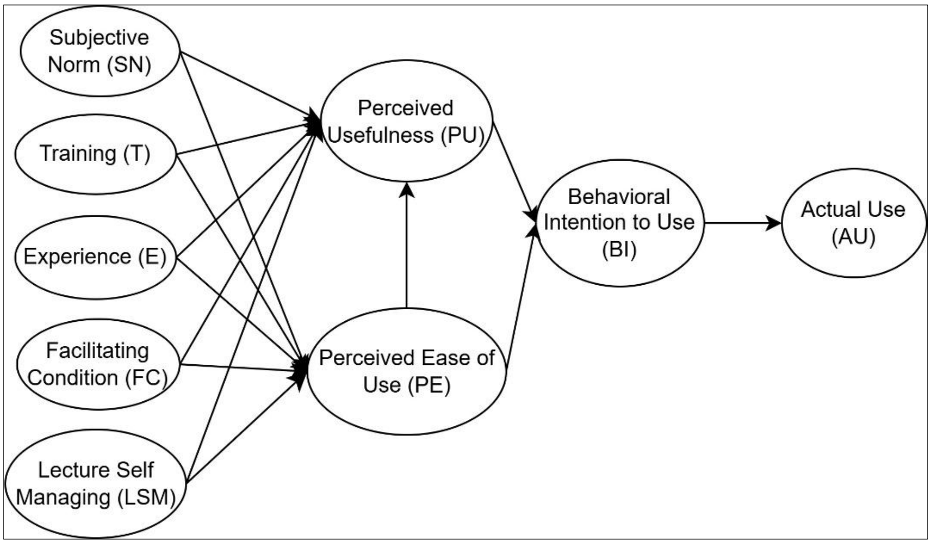


Fig. 1. TAM Original Model

The restructured TAM in this study modifies the model proposed by Rafikasari, Iriawan, and Otok, where LSM was initially treated as an external variable. The revised structure incorporates LSM as a moderating variable, as depicted in Fig. 2. Further analysis contrasts the TAM model introduced by Rafikasari, Iriawan, and Otok, termed the Original Model, with the Modified TAM Model integrating LSM as a moderating variable [31].

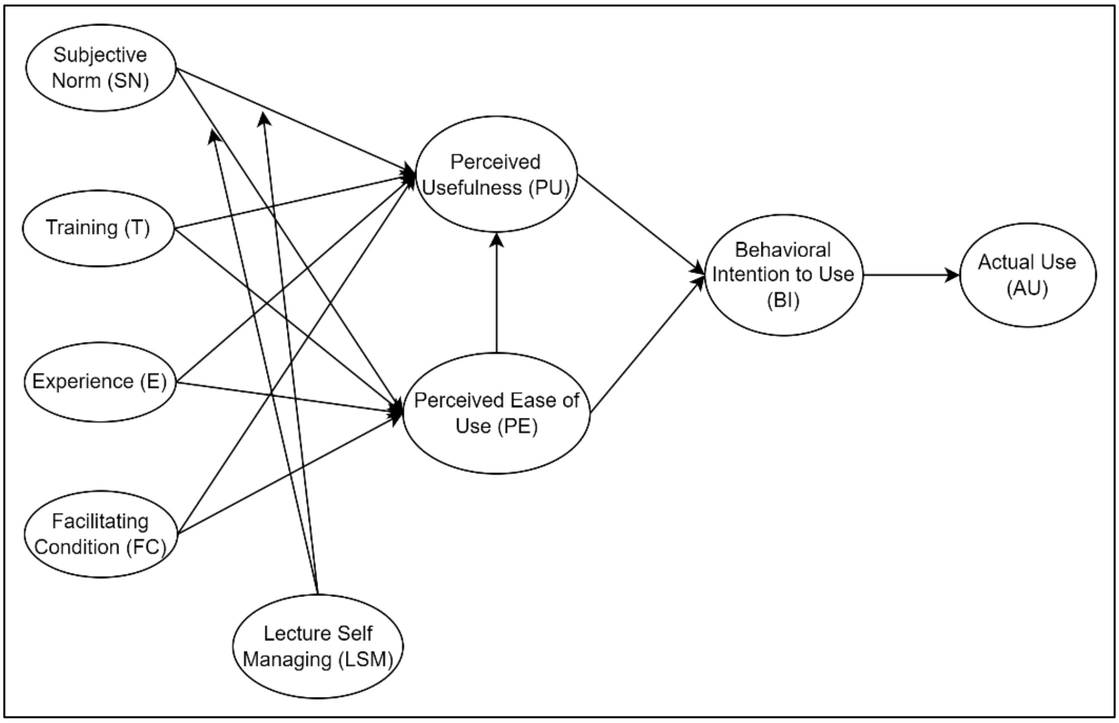


Fig. 2. TAM Modified Model in This Study

LSM variable is used to accommodate users who also act as system add-ons. Lecturers or teaching staff who are users with more authority than students can manage the E-learning process by updating materials, giving assignments, and providing assessments, all accessible to students [1; 45-47]. The inclusion of the LSM variable is intended to moderate the level of acceptance and use of E-learning.

3.2. Research Design

TAM necessitates the application of SEM as a suitable statistical method. To perform SEM analysis, specific conditions must be satisfied, including the assumption that latent variables follow a normal multivariate distribution, the presence of linear relationships between indicator and latent variables, and sufficient sample size [48]. Experts recommend adjusting the sample size according to the estimation method. ADF estimation requires a minimum sample size of 1000 [49] or even 2000 [49]. ML estimation demands at least five times the number of estimated parameters, including errors [50], and up to ten times the number of parameters for data with high kurtosis [48]. In practice, meeting these assumptions is often challenging. Bayesian SEM overcomes these limitations by relaxing standard assumptions. This study employs Bayesian estimation with the MCMC method to assess the restructured TAM, as demonstrated by Lee [14].

3.3. Data Collection and Sample

This study utilised primary data collected through questionnaires or online surveys. The respondents comprised 240 lecturers and students from UIN Sayyid Ali Rahmatullah Tulungagung, selected through non-probability sampling. The questionnaire, consisting of 31 questions as outlined in Table 1, included statements serving as indicators for both external and main variables in TAM. Responses were recorded using a five-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree." The collected data were analysed using the Bayesian SEM method. With the inclusion of indicator variables for each latent construct, the TAM model depicted in Fig. 2 is extended into the structural model illustrated in Fig. 3. Given the 31 survey questions, the model comprises 31 indicator variables.

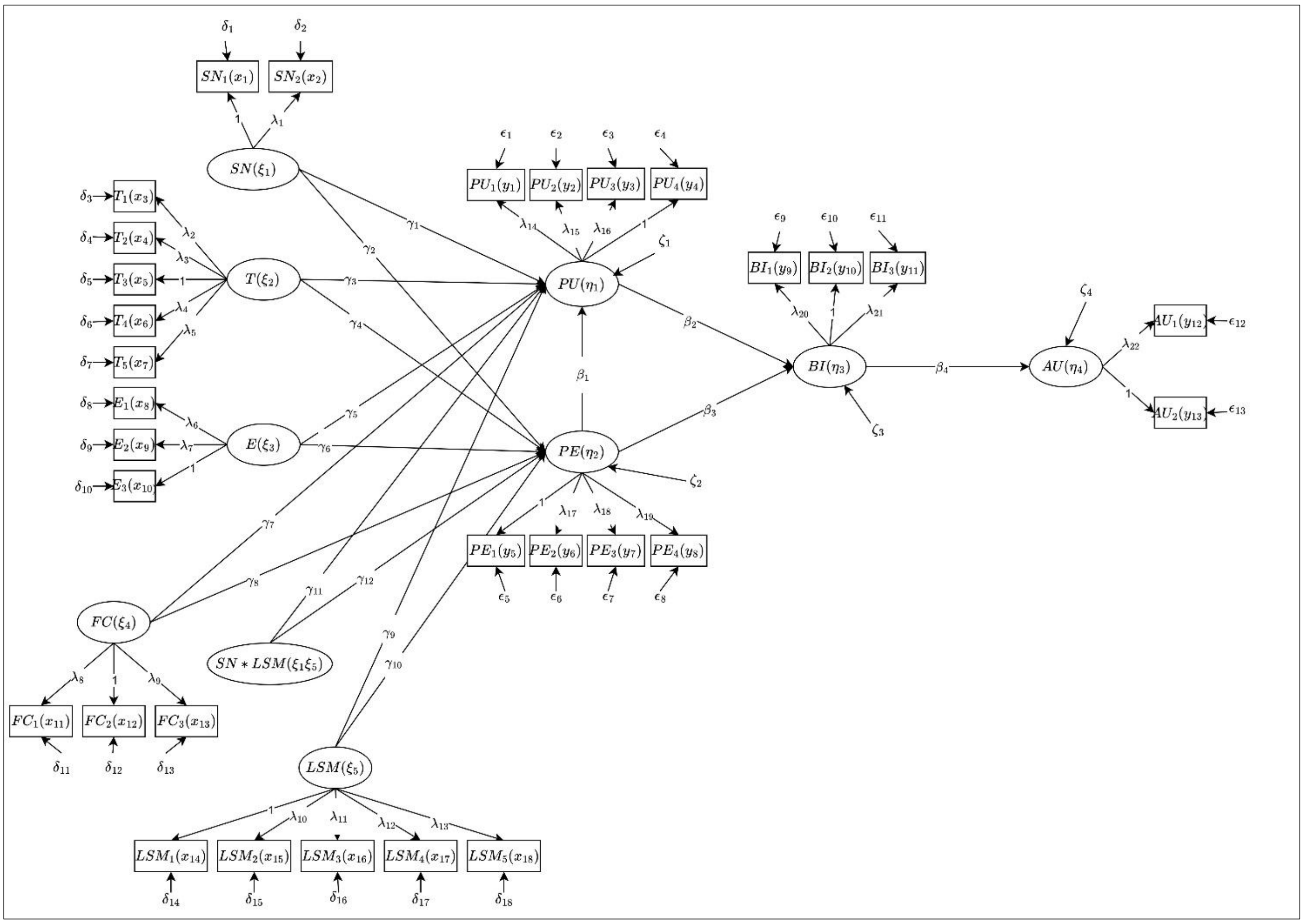


Fig. 3. Structural Model of This Study

Table 1
Measurement Items for Variable in TAM

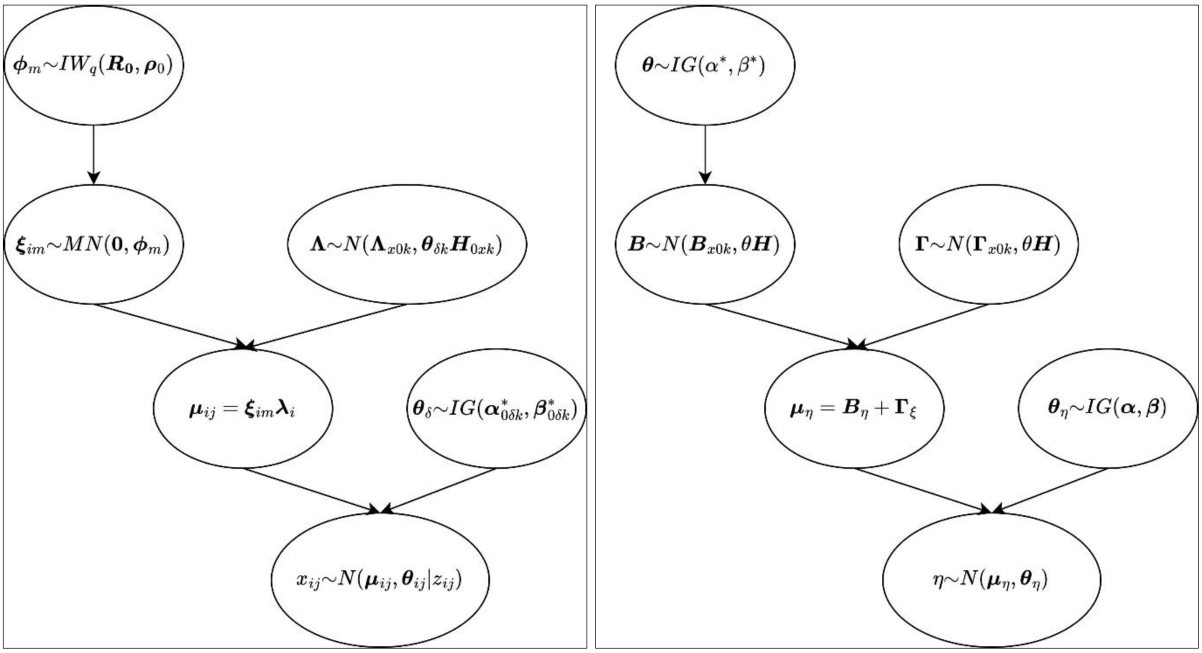
Variable	Measurement Item	Code
Subjective Norm (SN)	I am active in lecture activities through E-learning because there is someone who encourages me	SN1
	I am active in lecture activities through E-learning because of the support of someone influential on campus	SN2
Training (T)	E-learning operations training (tutorial) is available to improve one's abilities in online lecture activities through E-learning	T1
	My understanding level of E-learning substantially increased after reading and viewing tutorial videos	T2
	Having a tutorial on using E-learning convinced me to use E-learning	T3
	The tutorial provided is adequate and detailed	T4
	There is an admin/tutor who helps me when I have problems interacting with E-learning	T5
Experience (E)	Experience in interacting with E-learning (in the semester)	E1
	I am used to carrying out lecture activities through E-learning	E2
	After using E-learning, I think that using E-learning is important	E3
Facilitating Condition (FC)	Assistance was readily accessible to me when I required direction in utilizing E-learning.	FC1
	When I required assistance with E-learning, I was provided with precise directions to guide me	FC2
	When I require assistance with E-learning, there are individuals accessible to offer support	FC3
Lecture Self-Managing (LSM)	Lecturers can manage the learning process by following the existing structure of E-learning	LSM1
	Lecturers can update learning materials to make it easier for students to understand the material	LSM2
	Lecturers can prepare assignment agenda deadlines	LSM3
	Lecturers manage attendance on E-learning well	LSM4
	Lecturers upload lecture materials through E-learning	LSM5
	Using E-learning will enhance my performance	PU1

Perceived Usefulness (PU)	Utilizing E-learning will enhance my efficiency in lecture activities	PU2
	Using E-learning will enhance my efficiency	PU3
	E-learning is an effective tool for enhancing lecture activities	PU4
Perceived Ease of Use (PE)	I found my experience with E-learning to be straightforward	PE1
	I find E-learning to be a convenient tool for accomplishing my desired tasks	PE2
	Engaging with E-learning necessitates minimal exertion	PE3
	E-learning is user-friendly	PE4
Behavioural Intention (BI)	I intend to use E-learning in every lecture activity whenever possible	BI1
	Should I be asked about my opinion of using E-learning, I would say it is beneficial	BI2
	In the future, I intend to use E-learning in learning activities regularly	BI3
Actual Use (AU)	Average E-learning usage in hours per week	AU1
	Average frequency of use	AU2

4. Results and Discussion

4.1. Bayesian SEM Analysis

The questionnaire results showed a total of 240 respondents participated in this study. The data obtained were analyzed using SEM and transformed into a continuous dataset with a Normal distribution (mean 0, standard deviation 1). In this study, a threshold score was determined before conducting Bayesian estimation using SEM. The subsequent stage included determining the prior distribution used, with the structure and parameter presented in Fig. 4 and Table 2, respectively.



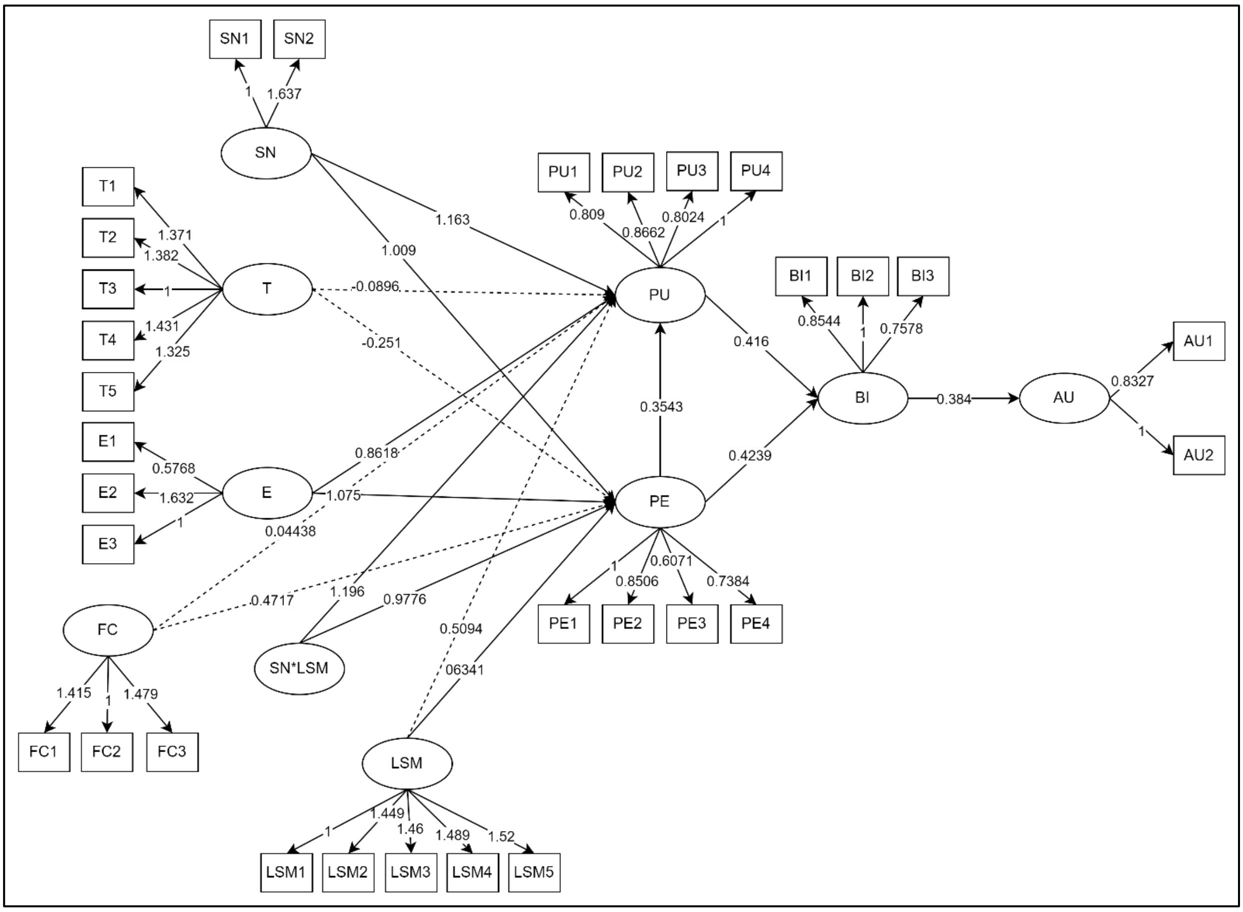
(a) (b)

Fig. 4. Prior Distribution Structure for (a) Measurement and (b) Structural Equation

The estimation results obtained parameter estimation of λ on TAM model using WinBUGS. All significant values fell within the range of 0.5768 – 1.637, confirming that all indicators effectively captured and represented the underlying factors being assessed. SEM in Fig. 3 is estimated using the Bayesian technique, with the parameter estimation results presented in Table 3, with variable interrelationships illustrated in Fig. 5.

Table 2
Parameter of Prior Distribution

No	Parameter Model
1	$\boldsymbol{\Theta}_{\delta} \sim \mathrm{IG}(10,8)$
2	$\boldsymbol{\Theta}_{\varepsilon} \sim \mathrm{IG}(10,8)$
3	$\left[\boldsymbol{\Lambda}_{x} \middle| \boldsymbol{\theta}_{\delta}\right] \sim \mathrm{N}\left[0.6; 4\boldsymbol{\theta}_{\varepsilon}\right]$
4	$\left[\boldsymbol{\Lambda}_{y} \middle| \boldsymbol{\theta}_{\delta}\right] \sim \mathrm{N}\left[0.6; 4\boldsymbol{\theta}_{\varepsilon}\right]$
5	$\boldsymbol{\xi} \sim \mathrm{MN}\left(0, \boldsymbol{\varphi}\right)$
6	$\boldsymbol{\varphi} \sim IW\left(\begin{bmatrix} 8.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 8.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 8.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 8.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 8.0 \end{bmatrix}, 240\right)$
7	$\boldsymbol{\Theta}_{\eta} \sim \mathrm{IG}(10,8)$
8	$\boldsymbol{\beta} \sim \mathrm{N}(1.1; 10.0\boldsymbol{\theta})$
9	$\boldsymbol{\gamma} \sim \mathrm{N}(1.5; 9.0\boldsymbol{\theta})$
10	$\boldsymbol{\theta} \sim \mathrm{IG}(10,8)$



Note:
--- : non-significant relationship —— : significant relationship

Fig. 5. SEM TAM Estimation Result for E-learning Adoption

Fig. 5 indicates that SN and E significantly influenced PU and PE. The mandatory use of E-learning at UIN Sayyid Ali Rahmatullah Tulungagung, particularly when in-person meetings were not feasible, reinforced SN's impact. Users also perceived E-learning as facilitating the learning process. E positively influenced PU and PE by enhancing perceptions of ease and benefits. However, FC and T had no significant effect on PU and PE, as their adequacy did not impact interaction and participation in E-learning.

Table 3
Estimation Parameter Result

Parameter	Estimate	SD	Credible Interval (CI) 2.5%	97.5%
β_1 (PE→PU)	0.3543	0.1215	0.1165	0.6017
β_2 (PU→BI)	0.4160	0.1050	0.2055	0.6175
β_3 (PE→BI)	0.4239	0.1076	0.2220	0.6440
β_4 (BI→AU)	0.3840	0.0659	0.2627	0.5211
γ_1 (SN→PU)	1.1630	0.2861	0.5799	1.7030
γ_2 (SN→PE)	1.0090	0.3070	0.3700	1.5800
γ_3 (T→PU)	-0.0896	0.3234	-0.7439	0.5495
γ_4 (T→PE)	-0.2510	0.3385	-0.8846	0.4529
γ_5 (E→PU)	0.8618	0.2913	0.2507	1.3820
γ_6 (E→PE)	1.0750	0.2569	0.5309	1.5590
γ_7 (FC→PU)	0.0444	0.3488	-0.6791	0.6779
γ_8 (FC→PE)	0.4717	0.3372	-0.2454	1.0850
γ_9 (LSM→PU)	0.5094	0.2632	-0.0456	1.0120
γ_{10} (LSM→PE)	0.6341	0.2748	0.0736	1.1540
γ_{11} (SN*LSM→PU)	1.1960	0.3941	0.3267	1.9000
γ_{12} (SN*LSM→PE)	0.9776	0.4649	0.0161	1.7820
λ_1	*1.0000	-	-	-
λ_2	1.6370	0.3483	0.9196	2.2700
λ_3	1.3710	0.1310	1.1310	1.6420
λ_4	1.3820	0.1327	1.1330	1.6520
λ_5	*1.0000	-	-	-
λ_6	1.4310	0.1280	1.1950	1.6960
λ_7	1.3250	0.1315	1.0820	1.5930
λ_8	0.5768	0.1665	0.2634	0.9169
λ_9	1.6320	0.1805	1.3000	2.0130
λ_{10}	*1.0000	-	-	-
λ_{11}	1.4150	0.1456	1.1550	1.7280
λ_{12}	*1.0000	-	-	-
λ_{13}	1.4790	0.1472	1.2160	1.8060
λ_{14}	*1.0000	-	-	-
λ_{15}	1.4490	0.1245	1.2100	1.7100
λ_{16}	1.4600	0.1310	1.2080	1.7270
λ_{17}	1.4890	0.1307	1.2460	1.7630
λ_{18}	1.5200	0.1274	1.2760	1.7720
λ_{19}	0.8090	0.0617	0.6953	0.9362
λ_{20}	0.8662	0.0616	0.7541	0.9942
λ_{21}	0.8024	0.0618	0.6825	0.9277
λ_{22}	*1.0000	-	-	-
λ_{23}	*1.0000	-	-	-
λ_{24}	0.8506	0.0629	0.7315	0.9815
λ_{25}	0.6071	0.0614	0.4903	0.7316
λ_{26}	0.7384	0.0669	0.6146	0.8717
λ_{27}	0.8544	0.0669	0.7286	0.9924
λ_{28}	*1.0000	-	-	-
λ_{29}	0.7578	0.0698	0.6271	0.9023
λ_{30}	0.8327	0.1195	0.6145	1.0720
λ_{31}	*1.0000	-	-	-

Note:
: not-significant
: moderating effect

Several studies have explored moderating factors in TAM concerning E-learning adoption. Tarhini, Hone, and Liu examined age and gender as moderators of students' intentions to use E-learning, highlighting the significance of PU, PE, SN, and self-efficacy [51]. Liao et al. extended TAM by integrating it with VAM, assessing e-WOM's moderating role in shaping attitudes, perceived value, and intention toward E-learning [52]. Rafikasari, Iriawan, and Otok evaluated TAM's effectiveness using PU, PE, BI, and AU, with SN, T, E, FC, and LSM as external variables [31]. Although LSM was classified as external, it had no direct impact on PU or PE. However, no prior research has examined LSM as a moderator. Table 4 illustrates LSM's moderating effect, showing a significant influence on PE, as lecturers' ability to manage E-learning—through content enrichment, assignments, and assessments—enhanced learning. The interaction between SN and LSM significantly affected both PE and PU, indicating LSM's role in moderating these relationships. The credible interval values [0.3267, 1.9000] and [0.0161, 1.7820] in Table 4 confirm LSM's moderating effect, while the external variable's interval [-0.0456, 1.0120] included zero, rendering it non-significant. These findings affirm LSM's role as a moderator, reinforcing its importance in E-learning adoption frameworks. Thus, incorporating LSM into TAM better reflects lecturers' contributions as system facilitators.

Table 4
LSM's Moderating Effect

Relationship	Estimate	SD	Credible Interval (CI)	
			2.5% CI	97.5% CI
SN→PU (Moderated by LSM)	1.1960	0.3941	0.3267	1.9000
SN→PE (Moderated by LSM)	0.9776	0.4649	0.0161	1.7820

Most lecturers and students view E-learning apps as productivity-enhancing tools due to their convenience and user-friendly interfaces. Clear and seamless interactions with these applications further support their adoption. Lecturers' ability to manage learning within E-learning environments plays a vital role in their effective use. Beyond being users, lecturers actively shape the learning process, determining engagement levels and influencing habitual E-learning usage in each course, ultimately fostering more effective learning experiences.

4.2. Selection of the Best Model

To determine the superior model, the Bayesian Information Criterion (BIC) scores of the Original TAM and the Restructured TAM are compared. The model with the lower BIC score is preferred and recommended for implementation. The BIC scores for the Original TAM [31] and the Restructured Model are calculated as follows:

$$\begin{aligned}\mathrm{BIC}_{Original} &= D + k\log(n)\\ &= 11750 + 127\log(240)\\ &= 12052.286\end{aligned}$$

$$\begin{aligned}\mathrm{BIC}_{Restructured} &= D + k\log(n)\\ &= 11710 + 133\log(240)\\ &= 12026.568\end{aligned}$$

where,

D : deviance
k : numbers of parameters
n : numbers of observation

The substantial difference of 25.718 between the two BIC scores suggests that the Restructured TAM outperforms the Original TAM, making it the preferred model for E-learning adoption analysis.

4.3. Theoretical and Practical Implication

By incorporating LSM as a significant moderating component, this study enriches TAM theoretically, highlighting lecturers' role in enhancing and applying E-learning. The model provides deeper insights into technology adoption by emphasising lecturers' management of digital learning environments. Institutions should offer training to strengthen lecturers' self-management skills in online education, equipping them with the expertise to navigate, customise, and optimise digital platforms. This approach ensures the seamless and effective integration of technology into pedagogical practices.

5. Conclusions

In conclusion, the restructured TAM, used to evaluate E-learning adoption at UIN Sayyid Ali Rahmatullah Tulungagung, was modified to include LSM as a moderating variable. The model comprised 31 indicator variables measuring key constructs, assessing the impact of PU and PE on BI and AU to determine E-learning acceptance. SN, E, and LSM significantly influenced PE and PU, with LSM moderating the relationships between SN and both PE and PU. The restructured TAM with LSM as a moderating factor effectively accommodated lecturers as system facilitators. Enhancing lecturers' ability to manage online learning is essential for maximising E-learning benefits. Institutions should implement targeted training to equip lecturers with the skills necessary for managing digital classrooms. Additionally, evidence-based policies should be developed to encourage active lecturer engagement in online education. Infrastructure improvements are also needed to ensure seamless pedagogical integration and user-centred autonomy. Future research should explore the influence of cultural factors on online course adoption, variations in LSM implementation across universities, and the long-term impact of lecture self-management on student performance. Examining these aspects will provide deeper insights into how institutional and contextual factors shape the effectiveness and integration of E-learning frameworks.

Author Contributions

The project benefitted from the contributions of the following individuals: E.F.R. contributed to several aspects of the project, including ideation, methodology, software development, validation, formal analysis, inquiry, resource management, data curation, original draft preparation, writing review and editing, visualization, project administration, and funding acquisition. N.I. and B.W.O. provided supervision and also contributed to validation, formal analysis, investigation, project administration, and funding acquisition. All authors reviewed and consented to the final version of the manuscript that has been published.

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Conflicts of Interest

The authors declare no conflicts of interest. The UIN Sayyid Ali Rahmatullah Tulungagung as the owner of this e-learning system had no say in conceptualizing the study, gathering, analyzing, or interpreting data, writing the report, or deciding to publish the results.

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