

# Does The Lecturers' Innovativeness Drive Online-Learning Adoption In Higher Education? A Study based on Extended TAM

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**Abstract**— Adoption and intention to utilize Online learning is an emerging field of study in educational research. Despite a large body of research on online learning acceptance, more is needed to know about the factors that impact lecturers' intentions to continue utilizing online learning. This study's goal was to present empirical data on the acceptability of online learning. The proposed model was derived from TAM. Several hypotheses were created using the TAM Model, utilizing lecturers' personal innovativeness as an external factor. This study employed SEM-PLS to examine the utilization of technology among 180 lecturers. The findings indicated that the model effectively forecasted the inclination to persist in utilizing e-learning. The innovativeness of lecturers had a substantial influence on PU, PEOU, and intention to sustain the use of e-learning. PU was the main factor that determined the intention to keep utilizing e-learning. The presence of PEOU had a substantial impact on PU, enabling PU to facilitate the connection between LPI and PEOU with CI. Nevertheless, PEOU did not.

**Keywords:** lecturers' innovativeness, perceived usefulness, e-learning, TAM

## I. INTRODUCTION

With the conclusion of the Covid-19 pandemic, the government has moved to resume face-to-face schooling in primary, secondary, and higher education. At the level of universities, the transition back to in-person learning brings with it a range of new infrastructure problems, as well as the difficulty of adapting the online learning model, which has been seen as convenient for almost two years. Consequently, numerous universities still employ a combination of in-person and online instruction. Online learning is an educational approach that utilizes the internet and digital media to provide information. Online learning methods are considered more attractive to contemporary students, who are known to prefer technological devices.

Since online learning relies heavily on technology, a process is needed to ensure that people can adopt it. This is because user acceptance plays a crucial role in a technology's success or failure [1]. It is therefore essential to comprehend the elements

that may motivate people to use online learning.

Prior literature had established the existence of various theories and models about the acceptance of technology, one of which is the Technological Acceptance Model (TAM). TAM is considered a very pertinent structure for understanding how individuals engage with and adopt technological advancements due to its ability to accurately describe and predict the behaviors of end-users of information technology [2], [3].

When integrating online learning, Lecturers and students must radically alter their methods of communication, assessments, and information delivery. Many lecturers have challenges and restrictions while utilizing online learning, particularly fully online [4]. Many lecturers still have low technological literacy. Therefore, lecturers' readiness and innovative behavior are considered essential elements in determining the success of online learning implementation [3]. Personal innovativeness is a basic personality characteristic that is typically distributed and can be viewed as a willingness to adapt. The ability to accept, adapt, and survive in a new learning context is the component of change readiness [4]. Furthermore, Personal innovativeness is considered a crucial aspect in fostering a positive attitude regarding the acceptance and implementation of novel technology [5].

Individuals with innovativeness react differently to changes based on specific features or tendencies. It emphasizes the importance of being adaptive and adaptable to change by taking different risks than most others. As a result, Lecturers with high personal innovation tend to embrace new ideas and concepts early than their peers, as they are more receptive to change. Some earlier research on personal innovativeness and the TAM model have conducted in online learning [4], [7]–[9]. However, most of them focus on the student's side. Based on this, the research integrated the innovativeness component of the lecturers using the TAM model as a foundation. Personal innovativeness refers to an individual's inclination to embrace change and explore the possibilities of information technology through experimentation [5]. Individual curiosity plays a crucial

role in personal invention and greatly influences the intention to use information technologies [5], [6]. This study will specifically investigate the mechanisms involved in personal innovation during learning activities. Researchers also seek to investigate the elements that inspire lecturers to continue adopting online learning.

Several studies have been carried out to investigate the determinants of lecturers' inclination towards adopting online learning in developed nations. However, in developing countries like Indonesia, where the spread of technology is still in its early phase, further research is required to identify the factors that drive technology diffusion. Previous research has primarily focused on early adoption, while this study focuses on post-adoption, which has received little attention. The objective of this study was to augment the current understanding of e-learning in the post-adoption phase. Additionally, it seeks to provide university administration with valuable insights into the determinants that impact lecturers' acceptance of online learning in Indonesia. Thus, Understanding the characteristics that motivate lecturers to use e-learning might help higher education administrators build effective e-learning programs.

## II. LITERATURE REVIEW

### A. Online learning

The term online learning is a form of education that is accomplished via the use of the internet and takes place in a digital classroom internet [10]. Meanwhile, Online learning refers also to the use of electronic equipment, like computers and mobile phones, to facilitate the educational process [[11]. Online learning enables lecturers in different locations to communicate with students online and to teach flexibly, at their own pace. In addition, lecturers no longer have distance or time limits, and They have convenient and affordable access to a variety of information and educational resources [12], [13]. Online learning can mitigate the issue of uneven allocation of resources and enhance their utilization [14]. Although online learning offers numerous advantages and a remarkable history of success, it has been challenging to persuade more teachers to transition to the method. Hence, It is crucial to examine the aspects that influence lecturers' utilization of online learning.

### B. Technological Acceptance Model (TAM)

The TAM framework is widely recognized as the predominant method for studying the ways in which individuals engage in and get advantages from emerging technological advancements. TAM has received significant empirical validation and has been extensively employed by scholars in the information systems discipline [5], [15], [16]. There are two beliefs that are important to consider: perceived usefulness (PU) and perceived ease of usage. TAM is a widely established framework that describes the effectiveness of utilizing IT. Davies is credited as the creator of this notion[2]. TAM, similar to TRA and TPB, places emphasis on the capacity to accurately forecast and explain the acceptance of a particular innovation. Nevertheless, TAM was primarily designed for use in information technology (IT) settings. TAM is largely recognized as the most superior framework for understanding technology adoption in information systems [17]. Perceived

ease of use (PEOU) is included as a predictor of attitudes in the model. Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) pertain to an individual's expectation that utilizing a specific technology will not require physical or mental exertion [18].

Both PEOU and PU prioritize user comfort as a crucial factor in assessing the usability of technology. The TAM paradigm posits that users' perceptions of a system's usability and usefulness have a substantial impact on their behavioral intentions (BI) and attitudes towards system adoption or rejection. According to TAM, user acceptability of technological systems is influenced by extrinsic factors such as PU and PEOU [19]. Hence, this research employed TAM as the foundation of the model and incorporated an additional component, specifically Lecturers' innovativeness in technology, to improve the comprehension of the intention to persist in utilizing e-learning.

### C. Lecturers' Personal Innovativeness

According to Agarwal and Prasad (1998), personal innovation is an individual's openness to considering change and engaging in experimentation with information. Personal innovation encompasses a person's curiosity, which greatly influences their drive to utilize information systems [5], [6]. Rogers' theory of the diffusion of innovation posits that individuals who possess robust personal innovation traits are more inclined to embrace progress [5]. The tendency of innovative consumers to adopt a variety of technical advances is often recognized as a personality trait. This research was adapted from Agarwal and Prasad's 1999 research which consists of the following six items:

1. *When I come across information on new mobile technology, I actively seek potential applications for it.*
2. *I have no interest in delving into emerging a mobile technology.*
3. *I typically take the initiative to experiment with novel information technologies.*
4. *I enjoy delving into novel information technologies.*
5. *I am highly interested in experimenting with a novel technology.*
6. *Generally, I enjoy utilizing emerging technology.*

### D. Perceived ease of use (PEOU)

PEOU stands for the cognitive process individuals use to make judgments while using technological equipment [2]. The lecturers' propensity to employ e-learning as a novel mode of instruction can be affected by the impression of the platform's usability. If lecturers have a positive impression of the platform's usability, they will be more inclined to employ it efficiently. PEOU relates to the degree to which an individual believes that the utilization of technological equipment will streamline thair task [2]. PEOU refers to the level of ease with which a system can be comprehended or operated. If users perceive e-learning as beneficial but are unable to utilize it due to its complexity or if they consider enhancement in performance to be insufficient in comparison to the effort required, they are unlikely to make use of it. PEOU is the belief that utilizing a specific technology requires minimal exertion[2]. This implies that if the system is designed to be

easily used by the user, the level of exertion required to run it will be diminished. On the other hand, if the system is complex, the required workload will be greater. The presence of this emotion will impact user behavior.

Several studies suggested that PEOU affected usage intention [20]–[22]. When lecturers felt comfortable, they were considerably more likely to adopt e-learning. Aside from that, the convenience of access to teaching in online learning would motivate lecturers to continue using the platform.

#### E. Perceived usefulness (PU)

Previous studies have identified perceived utility as a significant indicator among the various qualities that could impact technology adoption. The qualities relate to an individual's understanding of the importance of a system. Researchers have been looking into the effect of perceived utility in system use since the 1970s [2]. Davis, Bagozzi, and Warshaw [15] confirmed PU's validity and reliability as an indicator for predicting future intention to embrace technology.

#### F. Continued intention

Behavioral intention to use is an individual's inclination or motivation to engage in a specific conduct [2]. An individual will engage in a behavior if they possess the inclination or purpose to do so. Prior research had demonstrated that behavioral intention was a reliable indicator of technology adoption among system users. A person's behavioral intentions can be measured by how strong their intention is to engage in certain actions. Within the context of this study, the phrase behavioral intentions specifically pertained to long-term behavioral intentions. The success of an innovation system depends not only upon the first adoption but also on what happens after the adoption stage. Continuing intention refers to an individual's resolve to perform actions that they have already completed currently [23]. The term "intention to continue using," also referred to as the continuing intention to use signifies a robust inclination to persist in employing a system [5], [18], [24]. Continuance intention is commonly used to forecast the likelihood of someone continuing a particular activity in different contexts [25]. Prior research indicated that continued use is more than just a repeat of the adoption decision. In addition, some important components in studies on adoption may alter or lose their meaning in continuing intention study, whereas other aspects might evolve [26].

#### G. Research framework and Hypothesis Development

Lecturers' innovativeness, perceived ease of use, perceived usefulness and behavioral intention

Agarwal and Prasad [5] claim that people who are more personally innovative are more likely to embrace innovations at an earlier stage in accordance with Rogers' theory of the spread of innovation. In order to accurately forecast an individual's response to a new idea, it is necessary to redefine this notion within a particular domain, rather than globally. LPI is a person's capacity to willingly and effectively accept and incorporate new information technology.

Individuals possessing elevated levels of LPI are anticipated to cultivate more favorable opinions regarding innovation and

exhibit more affirmative intentions towards the use of modern IT/IS. The LPI is highly successful in assessing innovation adoption since it measures an individual's natural tendency to experiment with new technologies across a variety of acceptance domains. According to Wang[27], personal innovativeness had an impact on how individuals subjectively perceive new technology, specifically in terms of ease of use and usefulness. Prior studies have demonstrated that personal innovativeness had an impact on POEU, PU and intention to use [27]–[30]. So, the hypothesis proposed:

*H1: Lecturers' innovativeness in technology influences perceptions of ease*

*H2: Lecturers' innovativeness in technology influences perceived usefulness*

*H3: Lecturers' innovativeness in technology influences the continuance intention using e-learning*

*PEOU on perceived usefulness (PU) and intention to use*

. Therefore, perceived usefulness is a potential intermediary between the perceived ease of use and user intentions.

According to Davis, PU is the extent to which a person think a system would improve their job [2]. When considering new technology-based applications, a significant determinant in their acceptance is the perceived ease of use [24]. This refers to the extent to which a user thinks that the system will require minimal effort to operate [2]. Several research have demonstrated that the perceived ease of use of an e-learning platform had an impact on the intention to utilize it [27], [29], [31]–[33]. Consequently the better the PEOU of e-learning platform, the higher the intention to use it, increasing the possibility that the system will be employed. Furthermore, it is believed that PEOU in the e-learning environment had an indirect impact on the intention to use, mediated by PU [34], [35]. Therefore, PU is a potential mediator between PEOU and the user intentions.

*H4. Perceived ease of use influences the intention to use.*

*H5. Perceived usefulness is positively correlated with the perceived ease of use.*

*Perceived usefulness (PU) and intent to use*

Perceived usefulness, as described by Davis, referred to an individuals' belief that utilizing a given system will enhance their job. [2]. It was a crucial predictor of intention, motivating consumers to embrace creative and user-friendly technology, thus granting them greater autonomy [36]. In fact, a person's tendency to utilize a particular information system for their activities is determined by their impression of its usefulness [37], [38]. Previous research had demonstrated that PU had a significant and favorable effect on individuals' intent to use e-learning [27], [34], [35], [39], [40]. As a result, The level of usability of an e-learning system directly correlates with its usage rate.

H6: PU influences intentions to use online learning.  
 H7: PU serves as a mediator of the link between LPI, PEO, and CI

III. RESEARCH METHODOLOGY

The study included 180 randomly selected instructors from a private university in east Jakarta. The lecturers were informed of the study approach; Their involvement was optional, and all information was gathered in an anonymized manner. All of the participating lecturers have previously used online learning. We altered some constructs from previously validated instruments to create a study instrument on online learning acceptability. We used [2] davis items for PU and PEOU, as well as Taylor and Todd's [41] items for continuance Intention to Use. Personal innovativeness (LPI) is borrowed from Agarwal and Prasad [5]. The analysis conducted in this investigation was a first-order confirmatory method. The author used Smart PLS 3.2 software to generate a path diagram based on study variables and indicators for data analysis. The Structural Equation Model requires the creation of a path diagram based on the causal links identified.

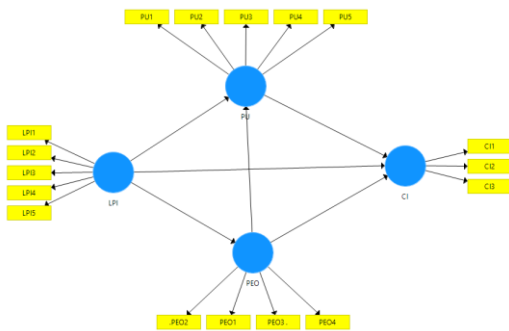


Fig 1. The path diagram of research.

III. RESULTS AND DISCUSSION

A. Respondent characteristics

TABLE I. Demographic Profile

	Frequency	Percent
<b>Gender</b>		
Male	91	50.6
Female	89	49.40
Total	180	100.0
<b>Age</b>		
25-35	52	28.9
36-45	61	33.9
46-55	47	26.1
>55	20	11.1
total	180	100.0
<b>Education</b>		
S2	145	80.6
S3	35	19.4
Total	180	100.0

Table 1 presents the demographic breakdown of respondents based on gender, with males comprising 50.6% of

the total and females comprising 49.4%. The largest group of respondents, comprising 33.9%, fell within the age range of 36-45 years. The second largest group, accounting for 28.9%, comprised respondents aged 23-35. The remaining respondents were divided between those aged 46-55 years and those beyond 55, making up 11.1% of the total. In terms of education, the majority of respondents held a master's degree (80.6%), while the remaining 19.4% had a doctorate.

B. Measurement Model

Validity test

TABLE II. Loading Factors

	CI	LPI	PEO	PU
CI1	0.946			
CI2	0.962			
CI3	0.926			
LPI1		0.895		
LPI2		0.893		
LPI3		0.889		
LPI4		0.902		
LPI5		0.855		
PEO1			0.823	
PEO2			0.847	
PEO3			0.887	
PEO4			0.865	
PU1				0.765
PU2				0.892
PU3				0.920
PU4				0.916
PU5				0.893

Prior to completing path model analysis and hypothesis testing, each question indicator was tested for validity and reliability using Smart PLS 3.2.0. A reflexive measure is considered legitimate if its loading value ( $\lambda$ ) with the latent variable being measured is equal to or greater than 0.6. If any of the indicators have value ( $\lambda$ ) less than 0.6, that indicator must be disregarded. This suggests that the indicator is insufficient in accurately measuring latent variables. The Latent construct the PEO1-PEO5 indicators evaluated perceived ease of use; the PU1-PU4 indicators measured perceived usefulness; and the LPI1-LPI5 indicators reflected the lecturer's innovativeness in technology. The continuation Intention is measured using three indicators: CI1-CI3. According to the findings of the validity test, all indicators of variables had met the requirement. Therefore, the research could be continued in further analysis.

TABLE III. Cross Loading

	CI	LPI	PEO	PU
CI1	<b>0.946</b>	0.756	0.673	0.800
CI2	<b>0.962</b>	0.738	0.643	0.803
CI3	<b>0.926</b>	0.662	0.619	0.733
LPI1	0.657	<b>0.895</b>	0.682	0.748
LPI2	0.629	<b>0.893</b>	0.603	0.706
LPI3	0.572	<b>0.889</b>	0.570	0.666
LPI4	0.673	<b>0.902</b>	0.633	0.708
LPI5	0.824	<b>0.855</b>	0.617	0.732
PEO1	0.543	0.619	<b>0.823</b>	0.630
PEO2	0.545	0.579	<b>0.847</b>	0.659
PEO3	0.548	0.540	<b>0.887</b>	0.653
PEO4	0.680	0.654	<b>0.865</b>	0.811
PU1	0.578	0.628	0.797	<b>0.765</b>
PU2	0.762	0.668	0.668	<b>0.892</b>
PU3	0.748	0.716	0.699	<b>0.920</b>
PU4	0.742	0.714	0.685	<b>0.916</b>
PU5	0.782	0.801	0.727	<b>0.893</b>

Table 3 showed that the loading factor for CI indicators (CI1-CI3 ATT4) had a loading factor on CI construct was higher than the other constructs where the loading factor of CI1 on CI was 0.945 which was higher than the loading factor on LPI, PEO, and PU. The same thing could also be seen in other indicators. Therefore, the latent constructs were more accurate in predicting the indicators within their own block compared to the indicators in other blocks. Other indices exhibited a comparable trend. As a result, the latent construct accurately predicted indicators within its block compared to indications in other blocks.

TABLE IV. Fornell-Larcker Criterion

	CI	LPI	PEO	PU
CI	<b>0.945</b>			
LPI	0.762	<b>0.887</b>		
PEO	0.683	0.702	<b>0.856</b>	
PU	0.825	0.805	0.812	<b>0.879</b>

The Fornell-Larcker test revealed that the square root of the AVE in the PEOU variable was 0.862, which was higher than the construct correlation value in the other hidden variables. The square root of AVE in the LPI data was 0.886, whereas the square root of AVE in the PU variable was 0.868. Both of these values exceeded the correlation values found in other latent variables. This suggested that all variables possessed discriminant validity.

Reliability Test

TABLE V. Reliability Testing

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
CI	0.940	0.943	0.962	0.893
LPI	0.932	0.934	0.949	0.787
PEO	0.878	0.884	0.916	0.732
PU	0.925	0.929	0.944	0.773

The reliability analysis indicated that the composite reliability of LPI, PEOU, PU, and Continuance Intention, was higher than 0.7, and Cronbach's alpha was higher than 0.6. This implied that the indicators utilized in each variable were dependable and proficient in assessing the design.

C. Structural Model Testing (Inner Model)  
The goodness of fit model

TABLE VI. R Square

Variable	R Square	Q <sup>2</sup> (=1-SSE/SSO)
CI	0.708	0.621
PEO	0.493	0.351
PU	0.768	0.584

Table 5 showed that the CI variable had affected PU, PEOU and the Lecturer's innovativeness accounted for 70.8% of CI variations, while other factors not accounted for made up the remaining portion. For the PEO variable, the R-squared value was 0.493. This meant that variables outside of the study model affected the remaining variables, while the LPI variable accounted for 49.3% of the PEO variable. Meanwhile, the PEO variable explained the perceived usefulness variable by 76.8%. The evaluation of the first and second inner models was very good in explaining continuity intention (CI). The study's Q square Predictive Relevance values of 0.621, 0.584, and 0.351 showed that the model was highly predictive.

The Hypothesis testing

The path parameter coefficient  $\beta=0.279$ , with a p-value of 0.004, reflected the effect of the LPI variable on continuance intention (CI). This proves that LPI significantly and positively affected the intention to continue. The parameter coefficient value of 0.279 indicated that the more inventive a lecturer is, the more likely he or she is to continue using e-learning. The influence of the LPI variable on PEO resulted in the path parameter coefficients of  $\beta=0.702$ ; p-value=0.0000 and  $\beta=0.464$ ; p-value=0.0000. These findings suggested that LPI had a significant influence on PU and PEO. The parameter coefficient's value of 0.702 indicated that the more personal innovativeness, the easier it was for lecturers to use e-learning. The parameter coefficient ( $\beta=0.464$ ) indicated that a lecturer's personal innovativeness correlated with the perceived benefits of e-learning.

The path parameter coefficient for the impact of the PEOU and PU On CI was  $\beta = -0.001; 0.602$ , P-value 0.984; 0.0000. This demonstrated that PEO had no significant effect on CI directly, whereas PU did. The more useful e-learning was the more likely the lecturers intended to use it again. The path parameter coefficient for the influence of the PEO variable on PU was  $\beta = 0.486$ , with a P-value of 0.000. This confirmed that PEO had a substantial effect on PU.

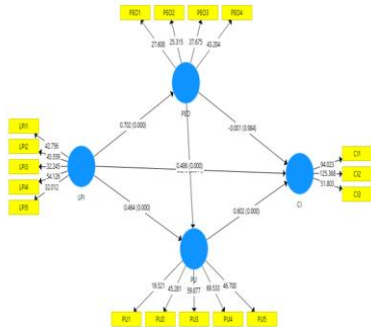


Fig 2. Path Diagram Output

TABLE VII. Direct Hypothesis Testing

	Parameter coefficient	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
LPI -> CI	0.279	0.113	2.462	0.014
LPI -> PEO	0.702	0.044	15.887	0.000
LPI -> PU	0.464	0.059	7.890	0.000
PEO -> CI	-0.001	0.076	0.020	0.984
PEO -> PU	0.486	0.055	8.759	0.000
PU -> CI	0.602	0.133	4.521	0.000

TABLE VIII. Indirect Hypothesis Testing

	Coefficient parameter	STDEV	T -Stat	P-values
LPI -> PEO -> CI	-0.001	0.054	0.019	0.984
LPI -> PU -> CI	0.279	0.054	5.170	0.000
PEO -> PU -> CI	0.292	0.084	3.487	0.001
LPI -> PEO -> PU -> CI	0.205	0.058	3.542	0.000
LPI -> PEO -> PU	0.341	0.040	8.482	0.000

The mediation hypothesis test revealed that PU acted as a mediator in both the relationship between LPI and PEO with CI ( $t=5.170, p=0.000; t=3.487, p=0.001$ ). The PEO has shown a comparable level of effectiveness in facilitating the connection between LPI and PU ( $t=8.482, p=0.000$ ). However, it did not have the same effect on the association between LPI and CI ( $t=0.019, p=0.984$ ). PEO did not have a direct impact on CI. However, it did have a significant effect on CI when mediated through the PU variable.

Based on the path parameter coefficients acquired and the explanation above, the structural equation model generated can be explained in a path diagram, similar to the model given in this research:

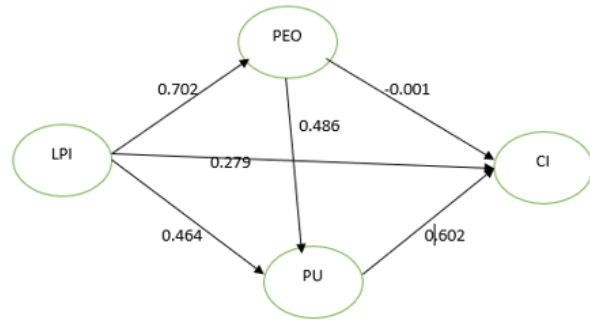


Fig 3. Research Path Diagram Model

D. Discussion

This research validated the TAM model within the setting of e-learning in higher education. The innovativeness of lecturers had a substantial positive impact on PU, PEOU, and intention to continue using e-learning ( $\beta=0.464, 0.702, 0.279; p=0.000, 0.000, \text{ and } 0.014$ , respectively). This meant that the higher the level of personal creativity in lecturers' technology, The more convenient and beneficial e-learning is judged to be, the more lecturers are to continue using it. The findings were in line with prior investigations (A.S. Al-Adwan et al., 2023; An & Eck, 2023; Baji et al., 2022; Chang, 2016; Wang et al., 2020). The PEOU variable was the most influenced by LPI ( $\beta = 0.702$ ). Out of the two TAM constructs that were considered, PU was the only one to show a significant impact on CI ( $\beta=0.602; p=0.000$ ), whereas PEOU made no difference ( $\beta=-0.001, p=0.020$ ). The findings indicated that the larger the perceived benefits, the more likely lecturers were to continue adopting e-learning. This was consistent with previous findings (Alassafi, 2022; Mohammadi, 2015; Sagnier et al., 2020; Wang et al., 2020). This analysis also discovered that PEO had a direct effect on PU. This meant that the more comfortable lecturers felt with e-learning, the more they perceived its benefits. The findings of this study confirmed prior research (An & Eck, 2023; Chang, 2016; Fagan et al., 2012; Mailizar et al., 2021; Natasia et al., 2021).

The mediation test revealed that PU could operate as a mediator in the correlation between PEO, LPI, and CI ( $\beta=0.292, \beta=0.279; p=0.000, 0.001$ ). The PEO variable could only moderate the link between LPI and PU ( $\beta=0.341; p=0.000$ ), not between LPI and CI ( $\beta=-0.001; p=0.984$ ). This suggested that the PU variable could only increase the link between LPI, PEO, and CI. The study's findings were in line with prior investigations (A.S. Al-Adwan et al., 2023; Fagan et al., 2012). Overall, the analysis revealed that the TAM model of technology acceptance adjusted with Lecturers' personal innovativeness had high explanatory power, as the model explains roughly 70.8 percent of the variance in endogenous variables. The model accounts for approximately 70.8 percent of the variation in endogenous variables.

#### IV. CONCLUSION

This study theoretically expanded on the existing online learning literature in Indonesia. The findings contributed to our comprehension of the variables that influence lecturers' intentions to continue using e-learning. The Lecturers' innovativeness (LPI) had a substantial effect on all TAM components PU, PEO, and CI. Thus, higher education administrators should consider continuing to build lecturers' innovativeness in addition to attractive e-learning platforms. It is imperative for lecturers to acquire technical literacy in order to keep pace with their students' technological proficiency and avoid being left behind.

From the two TAM constructs (PU and PEOU) tested, only the PU variable significantly influenced the intention to persist in utilizing continue e-learning, while the PEOU variable did not, and PU could mediate the interaction between PEOU, LPI, and CI. Higher education management should also consider perceived usefulness because if lecturers see the benefits of the online learning system, they will cultivate a positive disposition towards the system, which will therefore foster their inclination to persist in its usage. The combination of the TAM model with the variable of Lecturers' innovativeness demonstrated a strong predictive ability and effectively described the intention to persist in adopting e-learning. Consequently, higher education institutions may utilize this research model to integrate the traits revealed in this study into their policies.

This study did not specifically cover psychological aspects that may influence lecturers' acceptance of online learning; consequently, more research should be conducted with more psychology factors and larger data sets.

#### REFERENCES

- [1] F. D. Davis, "User acceptance of information technology: system characteristics, user perceptions and behavioral impacts," *International Journal of Man-Machine Studies*, vol. 38, no. 3, pp. 475–487, 1993, doi: 10.1006/imms.1993.1022.
- [2] F. D. Davis, "Perceived Usefulness, perceived Ease of Use and User Acceptance of Information Technology," *MIS Q.*, vol. 13, no. 3, pp. 319–340, 1989, doi: 10.1016/S0305-0483(98)00028-0.
- [3] D. Gefen, "Reflections on the dimensions of trust and trustworthiness among online consumers," *ACM SIGMIS Database*, vol. 33, no. 3, pp. 38–53, 2002, doi: 10.1145/569905.569910.
- [4] E. M. van Raaij and J. J. L. Schepers, "The acceptance and use of a virtual learning environment in China," *Comput. Educ.*, vol. 50, no. 3, pp. 838–852, 2008, doi: 10.1016/j.compedu.2006.09.001.
- [5] R. Agarwal and J. Prasad, "Are individual differences germane to the acceptance of new information technologies?," *Decis. Sci.*, vol. 30, no. 2, pp. 361–391, 1999, doi: 10.1111/j.1540-5915.1999.tb01614.x.
- [6] E. M. Rogers, *Diffusion of Innovations*, 2nd ed. New York: The free press, 1983.
- [7] Y. J. Joo, H. W. Lee, and Y. Ham, "Integrating user interface and personal innovativeness into the TAM for mobile learning in Cyber University," *J. Comput. High. Educ.*, vol. 26, no. 2, pp. 143–158, 2014, doi: 10.1007/s12528-014-9081-2.
- [8] A. Amid and R. Din, "Acceptance and use of massive open online courses: extending UTAUT 2 with personal innovativeness," *J. Pers. Learn.*, vol. 4, no. 1, pp. 57–66, 2021.
- [9] E. J. Kim, J. J. Kim, and S. H. Han, "Understanding student acceptance of online learning systems in higher education: Application of social psychology theories with consideration of user innovativeness," *Sustain.*, vol. 13, no. 2, pp. 1–14, 2021, doi: 10.3390/su13020896.
- [10] V. Singh and A. Thurman, "How Many Ways Can We Define Online Learning? A Systematic Literature Review of Definitions of Online Learning (1988-2018)," *Am. J. Distance Educ.*, vol. 33, no. 4, pp. 289–306, 2019, doi: 10.1080/08923647.2019.1663082.
- [11] P. J. Smith, "Learning preferences and readiness for online learning," *Educ. Psychol.*, vol. 25, no. 1, pp. 3–12, 2005, doi: 10.1080/0144341042000294868.
- [12] V. Chang, "Review and discussion: E-learning for academia and industry," *Int. J. Inf. Manage.*, vol. 36, no. 3, pp. 476–485, 2016, doi: 10.1016/j.ijinfomgt.2015.12.007.
- [13] S. Mohammadyari and H. Singh, "Understanding the effect of e-learning on individual performance: The role of digital literacy," *Comput. Educ.*, vol. 82, pp. 11–25, 2015, doi: 10.1016/j.compedu.2014.10.025.
- [14] R. Chandwani, R. De, and Y. K. Dwivedi, "Telemedicine for low resource settings: Exploring the generative mechanisms," *Technol. Forecast. Soc. Change*, vol. 127, no. June, pp. 177–187, 2018, doi: 10.1016/j.techfore.2017.06.014.
- [15] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models," *Manage. Sci.*, vol. 35, no. 8, pp. 982–1003, 1989, doi: 10.1287/mnsc.35.8.982.
- [16] V. Venkatesh and C. Speier, "Computer Technology Training in the Workplace: A Longitudinal Investigation of the Effect of Mood-Organizational Behavior and Human Decision Processes," *Organ. Behav. Hum. Decis. Process.*, vol. 79, no. 1, pp. 1–28, 1999.
- [17] E. K. and D. W. S. David Gefen, "TRUST AND TAM IN ONLINE SHOPPING: AN INTEGRATED MODEL," *MIS Q.*, vol. 27, no. 1, pp. 51–90, 2003, doi: 10.1017/CBO9781107415324.004.
- [18] M. J. Alsamyda, "Adaptation of the Technology Acceptance Model (TAM) to the Use of Mobile Banking Services," *Int. Rev. Manag. Bus. Res.*, vol. 3, no. 4, pp. 2016–2028, 2014.
- [19] P. Legris, J. Ingham, and P. Collette, "Why do people use information technology? A critical review of the technology acceptance model," *Inf. Manag.*, vol. 40, no. 3, pp. 191–204, 2003, doi: 10.1016/S0378-7206(01)00143-4.
- [20] T. Teo, M. Zhou, A. C. W. Fan, and F. Huang, "Factors that influence university students' intention to use Moodle: a study in Macau," *Educ. Technol. Res. Dev.*, vol. 67, no. 3, pp. 749–766, 2019, doi: 10.1007/s11423-019-09650-x.
- [21] S. A. Nikou and A. A. Economides, "Mobile-based assessment: Investigating the factors that influence behavioral intention to use," *Comput. Educ.*, vol. 109, pp. 56–73, 2017, doi: 10.1016/j.compedu.2017.02.005.
- [22] C. Ching-Ter, J. Hajiyev, and C. R. Su, "Examining the students' behavioral intention to use e-learning in Azerbaijan? The General Extended Technology Acceptance Model for E-learning approach," *Comput. Educ.*, vol. 111, pp. 128–143, 2017, doi: 10.1016/j.compedu.2017.04.010.
- [23] A. Azam, "Continuance intention model for mobile banking," *Int. J. Electron. Financ.*, vol. 8, no. 2–4, pp. 169–188, 2015, doi: 10.1504/IJEF.2015.070534.
- [24] V. Venkatesh and F. Davis, "A Theoretical extension of the technology acceptance model: four longitudinal field studies," *Manag. Res. Rev.*, vol. 46, no. 2, pp. 186–204, 2000, doi: 10.1287/mnsc.46.2.186.11926.
- [25] T. C. Lin and C. J. Chen, "Validating the satisfaction and continuance intention of e-learning systems: Combining tam and is success models," *Int. J. Distance Educ. Technol.*, vol. 10, no. 1, pp. 44–54, 2012, doi: 10.4018/jdet.2012010103.
- [26] M. G. M. and F. D. D. Viswanath Venkatesh, Gordon B. Davis, "USER ACCEPTANCE OF INFORMATION TECHNOLOGY: TOWARD A UNIFIED VIEW," *MISL*, vol. 3, pp. 425–478, 2003, doi: 10.1006/mvre.1994.1019.
- [27] Y. Wang, S. Wang, J. Wang, J. Wei, and C. Wang, "An empirical study of consumers' intention to use ride-sharing services: using an extended technology acceptance model," *Transportation (Amst.)*, vol. 47, no. 1, pp. 397–415, 2020, doi: 10.1007/s11116-018-9893-4.
- [28] A. S. Al-Adwan, N. Li, A. Al-Adwan, G. A. Abbasi, N. A. Albelbisi, and A. Habibi, "Extending the Technology Acceptance Model (TAM) to Predict University Students' Intentions to Use Metaverse-Based Learning Platforms," *Educ. Inf. Technol.*, vol. 28, no. 11, pp. 15381–15413, 2023, doi: 10.1007/s10639-023-11816-3.
- [29] S. An and T. Eck, "Understanding Consumers' Acceptance Intention to



- Use Mobile Food Delivery Applications through an Extended Technology Acceptance Model," 2023.
- [30] C. Sagnier, E. Loup-Escande, D. Lourdeaux, I. Thouvenin, and G. Valléry, "User Acceptance of Virtual Reality: An Extended Technology Acceptance Model," *Int. J. Hum. Comput. Interact.*, vol. 36, no. 11, pp. 993–1007, 2020, doi: 10.1080/10447318.2019.1708612.
- [31] A. Ashrafi, A. Zareravasan, S. Rabiee Savoji, and M. Amani, "Exploring factors influencing students' continuance intention to use the learning management system (LMS): a multi-perspective framework," *Interact. Learn. Environ.*, vol. 0, no. 0, pp. 1–23, 2020, doi: 10.1080/10494820.2020.1734028.
- [32] W. M. Al-Rahmi *et al.*, "Use of E-Learning by University Students in Malaysian Higher Educational Institutions: A Case in Universiti Teknologi Malaysia," *IEEE Access*, vol. 6, pp. 14268–14276, 2018, doi: 10.1109/ACCESS.2018.2802325.
- [33] M. M. Yazdani and M. Mohammadi, "The explicit instruction of reading strategies: Directed reading thinking activity vs. guided reading strategies," *Int. J. Appl. Linguist. English Lit.*, vol. 4, no. 3, pp. 53–60, 2015, doi: 10.7575/aiac.ijalel.v.4n.3p.53.
- [34] H. Mohammadi, "Investigating users' perspectives on e-learning: An integration of TAM and IS success model," *Comput. Human Behav.*, vol. 45, pp. 359–374, 2015, doi: 10.1016/j.chb.2014.07.044.
- [35] M. I. Alkhawaja, M. S. A. Halim, M. S. S. Abumandil, and A. S. Al-Adwan, "System Quality and Student's Acceptance of the E-learning System: The Serial Mediation of Perceived Usefulness and Intention to Use," *Contemp. Educ. Technol.*, vol. 14, no. 2, 2022, doi: 10.30935/CEDTECH/11525.
- [36] T. Pikkarainen, K. Pikkarainen, H. Karjaluoto, and S. Pahnla, "Consumer acceptance of online banking: An extension of the technology acceptance model," *Internet Res.*, vol. 14, no. 3, pp. 224–235, 2004, doi: 10.1108/10662240410542652.
- [37] P. Hanafizadeh, M. Behboudi, A. Abedini, M. Jalilvand, and S. Tabar, "Telematics and Informatics Mobile-banking adoption by Iranian bank clients," *Telemat. Informatics*, vol. 31, no. 1, pp. 62–78, 2014, doi: 10.1016/j.tele.2012.11.001.
- [38] Y. H. S. Al-Mamary, "Why do students adopt and use Learning Management Systems?: Insights from Saudi Arabia," *Int. J. Inf. Manag. Data Insights*, vol. 2, no. 2, p. 100088, 2022, doi: 10.1016/j.jjime.2022.100088.
- [39] M. Mailizar, D. Burg, and S. Maulina, "Examining university students' behavioural intention to use e-learning during the COVID-19 pandemic: An extended TAM model," *Educ. Inf. Technol.*, vol. 26, no. 6, pp. 7057–7077, 2021, doi: 10.1007/s10639-021-10557-5.
- [40] S.R. Natasia, Y. T. Wiranti, and A. Parastika, "Acceptance analysis of NUADU as e-learning platform using the Technology Acceptance Model (TAM) approach," *Procedia Comput. Sci.*, vol. 197, no. 2021, pp. 512–520, 2021, doi: 10.1016/j.procs.2021.12.168.
- [41] STaylor and P. A. Todd, "Understanding information technology usage: A test of competing models," *Inf. Syst. Res.*, vol. 6, no. 2, pp. 144–176, 1995, doi: 10.1287/isre.6.2.144.