Migration Letters

Volume: 21, No: 1, pp. 292-304

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)
www.migrationletters.com

Cracking the Code: Understanding What Influences Online Learning Adoption Among Indonesian Students

Jonathan Gozal[1]

Abstract

This study examines factors affecting OL adoption among 191 Indonesian students post-COVID-19. It addresses limitations in established models like TRA, TPB, TAM, and UTAUT while introducing new variables. Key findings include: (1) The strong positive effect of FAC and SEF on PEU, suggests that investments in infrastructure and student training could significantly enhance the acceptance and efficacy of OL platforms, (2) The influence of ITR on PUS and, subsequently, INT implies that enhancing ITR capabilities can positively affect both PUS and INT, thereby potentially increasing student engagement and adoption rates, (3) Localized variables like FAC and SEF have a strong positive influence on PEU. These findings contribute to both the theoretical and practical arenas by enhancing existing models and offering context-specific implementation strategies for Indonesia's emerging edtech sector. This study argues for a more holistic, nuanced approach to understanding OL adoption, providing actionable insights for educators and policymakers.

Keywords: *Online Learning, Perceived Ease of Use, Perceived Usefulness, Student's Intention, Technology Acceptance Model.*

Introduction

COVID-19 greatly impacted education in Indonesia, pushing traditional schooling online (Andries & Lengkoan, 2023), and inadvertently catalyzed the growth of educational technology (EdTech) companies. Market data showed substantial growth, with annual revenue reaching $467 million for vocational training, $690 million for formal education, and $24 million for professional certification by July 2023 (Statista, 2023). According to Anindhita et al. (2022), online learning (OL) platforms, offer flexibility and accessibility that meet modern educational needs. However, the effectiveness of OL compared to face-to-face (F2F) learning remains a topic of discussion, posing challenges for stakeholders (Andries & Lengkoan, 2023). This highlights the need to understand the effectiveness of these platforms in comparison to traditional F2F educational settings.

Numerous conceptual models exist for analyzing how people adopt and use technology, such as the theory of reasoned action (TRA), theory of planned behavior (TPB), technology acceptance model (TAM), and unified theory of acceptance and use of technology (UTAUT), each with advantages and limitations. For instance, the TRA and TPB are excellent at explaining behavioral intentions but are less focused on technological aspects. Conversely, the TAM and UTAUT offer great insights into technological acceptance but disregard other external or situational factors (Malatji, 2020). Christensen (2015) highlighted the need for a new model with factors that evaluate

[1]

not only just the system's degree of acceptance but also the perceived acceptance level of the entity concerned. Recognizing these gaps and the lack of comprehensive models capturing both technological and contextual elements, the objective of this study is to address the existing research gap by enhancing current models. Specifically, this study tailored these models to the Indonesian context during post-COVID-19. Notably, despite the widespread use of these models, no prior research has comprehensively examined this study's interrelated variables within the specific circumstances of Indonesia amidst COVID-19 crisis. This investigation seeks to bridge that gap in research.

This study aims to offer actionable insights into Indonesia’s rapidly expanding EdTech sector by enriching existing theoretical frameworks on technology adoption. In particular, the introduction of unique variables, which were uniquely relevant to the Indonesian context during the pandemic, provides a more comprehensive understanding of OL adoption. These variables serve as localized extensions to traditional technology adoption frameworks, such as the TAM and UTAUT. The aim of this study is to contribute to the design and implementation of OL platforms that are both technically sound and pertinent to the context. Ultimately, this study seeks to increase user engagement and adoption rates while contributing to the theoretical underpinnings of technology adoption in a context-specific manner.

Literature Review

2. 1 Student’s OL Intention (INT)

Behavioral intention is essential for system adoption, and this study focuses on INT as defined by Baber (2021) within the TRA and TPB frameworks, where INT precedes actual behavior. In consumer research, Black (1983) sees it as ongoing commitment, whereas Park (1998) as a tool for product diffusion. In organizational settings, Morwitz et al. (2007) highlight its role in testing new system viability. These perspectives align with TRA and TPB, emphasizing intention's role in action. Venkatesh et al. (2003) describe it as deliberate intent, while Montaño and Kasprzyk (2015) stress its importance in predicting behavior across contexts. In context of OL, Baber (2021) reflects a student's effort in planning OL engagement, aligning with TRA and TPB's principles where intentions are influenced by attitudes and social norms. In this study, INT is the focal variable, explained through these determinants.

2.1.1 Student’s OL Interaction (ITR)

Not part of the traditional TAM or UTAUT, ITR is now recognized as an influential factor in OL. Moore (2014) viewed ITR as behavior fostering closeness and reducing perceived distance. In OL domain, ITR involves knowledge, ideas, and feedback exchange using both asynchronous and synchronous tools (Alamri & Tyler-Wood, 2017), aiding intellectual knowledge acquisition. This study conceptualizes ITR as students' subjective assessments of online interactions' impact on their learning experiences (Choi et al., 2021). Actively engaging with peers, instructors, or the OL system makes students more likely to perceive OL's usefulness, influencing INT. Notably, extant research by Baber (2021) supports a direct positive ITR-INT relationship, but this study examines other potential relationships, specifically ITR's direct impact on PUS and its indirect effects on INT.

2.1.2 Student’s Facilitating Condition (FAC)

FAC, inspired by Venkatesh et al.'s (2003) is a vital consideration in this study on technology adoption. It assesses a person's belief in the presence of organizational and technical support for system usage, which is not always guaranteed (Zhou et al., 2010). FAC is typically evaluated by individuals' perceptions of essential resources and support (Tarhini et al., 2016). This study defines FAC as the perceived system's capacity to meet students' OL needs without modifications (Billanes & Enevoldsen, 2021). Empirical evidence supports FAC's importance in OL. Students perceiving adequate technical support and resources find the system user-friendly, boosting PEU and PUS, ultimately affecting INT. Silva-Contreras et al. (2019) confirmed FAC's direct positive effect on PEU and its indirect positive impact on PUS and INT.

2.1.3 Student’s Self-efficacy (SEF)

SEF is a crucial in OL, shaping students' perceptions of their abilities to use online platforms and their willingness to engage. Initially introduced by Venkatesh et al. (2003), SEF refers to a person's belief in their capability to accomplish tasks through system utilization. SEF's adaptability is evident in various contexts, such as remote work and online shopping (Silva-Contreras et al., 2019). In this study, SEF reflects students' self-assessments of their OL engagement skills (Billanes & Enevoldsen, 2021). Empirical evidence supports SEF's influence on PEU and its indirect effects on PUS and INT, highlighting its importance (Billanes & Enevoldsen, 2021; Silva-Contreras et al., 2019).

2.1.4 Student’s Perceived Ease of Use (PEU)

PEU remains a cornerstone in technology adoption, significantly influences user experience and intention. Stemming from Venkatesh et al. (2003), it revolves around an individual's belief in the ease of operating a system. This concept extends to domains like remote work, assessing how a system simplifies tasks (Silva-Contreras et al., 2019). In OL context, this study defines PEU as the cognitive effort students need to effectively use an online platform (Baber, 2021; Ng et al., 2023). Empirical study consistently shows that PEU positively influences PUS and INT (Ferri et al., 2021).

2.1.5 Student’s Perceived Usefulness (PUS)

PUS, crucial in explaining technology acceptance (Ng et al., 2023), represents the belief that using a system enhances job performance (Venkatesh et al., 2003). Refined in various contexts, like remote work, it concerns tangible benefits from a new system (Silva-Contreras et al., 2019). In this study, PUS focuses on the cognitive effort students believe is needed to gain OL benefits (Baber, 2021). Simply put, students are more likely to embrace OL if they find it beneficial. Empirical studies consistently support PUS as a significant precursor of INT, typically with a positive impact (Baber, 2021).

2.1.6 Student's Perceived F2F Risk (RSK)

RSK does not originate from established acceptance models and is generally conceptualized as user's subjective expectation of loss when pursuing an outcome. Billanes and Enevoldsen (2021) define it as the probability of an event and its consequences. RSK in this study measures students' evaluation of contracting COVID-19 and its consequences in F2F instruction (Baber, 2021). When the RSK exceeds their tolerance, students favor OL. Empirical studies confirm a positive RSK-INT relationship in F2F instruction, in line with Ferri et al. (2021) and Billanes and Enevoldsen (2021), which found a negative RSK-INT relationship in OL compared to F2F.

In light of this characterization and to address the research questions, the current study put forth a set of hypotheses that act as the conceptual underpinning of the research framework and aim to scrutinize the connections among the previously mentioned variables. Specifically, the following hypotheses were formulated:

H1 : ITR positively affects PUS.

H2a : FAC positively affects PEU.

H2b : SEF positively affects PEU.

H3 : PEU positively affects PUS.

H4a : PUS positively affects INT.

H4b : RSK positively affects INT.

H4c : PEU positively affects INT.

H5a : PUS positively mediates ITR and INT.

H5b : PUS positively mediates PEU and INT.

H6a : PEU positively mediates FAC and PUS.

H6b : PEU positively mediates SEF and PUS.

H6c : PEU positively mediates FAC and INT.

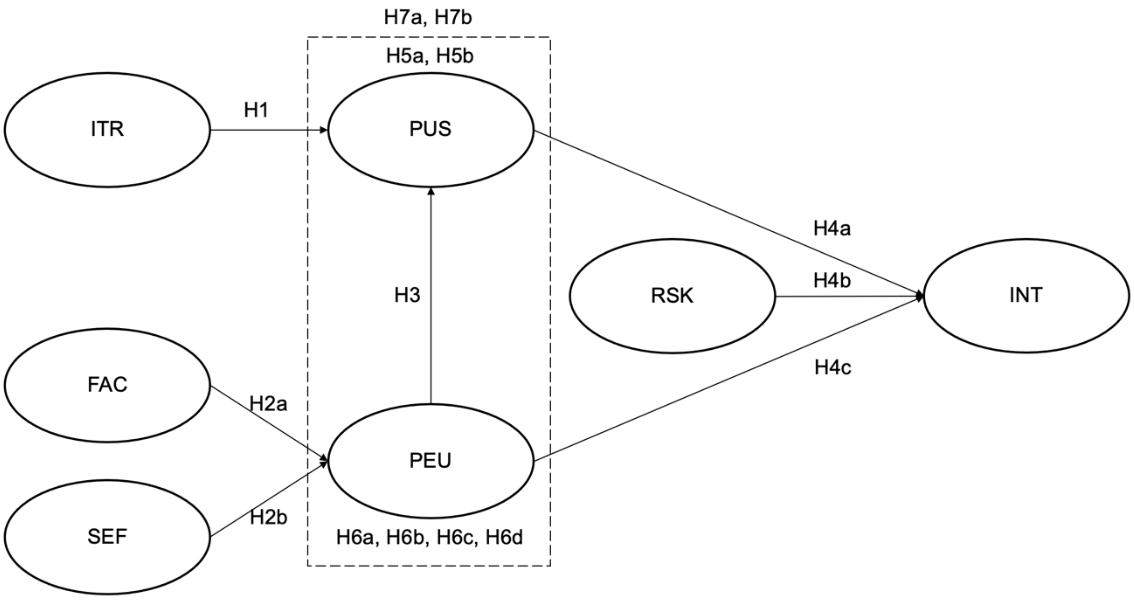
H6d : PEU positively mediates SEF and INT.

H7a : PUS and PEU collectively positively mediate FAC and INT.

H7b : PUS and PEU collectively positively mediate SEF and INT.

With these hypotheses as the research foundation, the author synthesized them into a proposed research model. This model serves as a conceptual framework for guiding the empirical analysis as follows:

Figure 1. Proposed Research Model



Research Method

This study used a quantitative descriptive research method to investigate characteristics, conditions, and events through a one-time cross-sectional data collection approach (Malhotra, 2019). Primary data was obtained through surveys with structured questionnaires to assess the impact of independent variables on the dependent variable. Data collection employed purposive sampling, a non-probability method based on research objectives and population characteristics, as suggested by Greener and Martelli (2018). To determine the sample size, the traditional indicator-based method was replaced with the more reliable inverse square root method (Kock and Hadaya, 2018). This approach resulted in a target sample of 191 participants with calculations based on a 2.75% significance level and a minimum path coefficient of 0.2

$$.a_{.0275}: n_{min} > \left(\frac{z_{.9725}+z_{.8}}{|p_{min}|}\right)^2$$

$$a_{.0275}: n_{min} > \left(\frac{1.915 + 0.842}{|0.2|}\right)^2$$

$$a_{.0275}: n_{min} > 190.17$$

Subsequently, the questionnaire was administered to respondents fitting the inclusion criteria, namely Jakarta students who engaged in OL during COVID-19. The minimum age for participation was set at 13 based on Conijn et al.’s (2020) study, ensuring reliable self-reporting. This study employed partial least squares structural equation modeling (PLS-SEM), chosen due to the research's complexity involving numerous constructs and latent variables. PLS-SEM enables the exploration of cause-and-effect dynamics, particularly suitable for exploratory research, theoretical development, and analyses introducing new dimensions to the field (Hair, et al., 2021).

Results

Based on the collected data, the majority of the 191 respondents were females, accounting for 74.87% of the total. Most respondents (66.49%) fell within the 13–20 age range, with 21–28-year-olds comprising 26.71%, while those aged ≥ 29 were less than 3%. In terms of educational background, the majority (62.30%) were pursuing or had completed an undergraduate degree, while high school attendees made up 28.27%, and those with postgraduate education were just over 6%.

Table 1. Descriptive Statistics of Respondents

Characteristic	Class	Frequency	%
Sex	Male	48	25.13
	Female	143	74.87
Age Range	13–20	127	66.49
	21–28	51	26.71
	29–36	5	2.62
	37–44	3	1.57
	45–52	4	2.09
	53 or above	1	0.52
Education Level	High School	54	28.27
	Associate Degree	6	3.14
	Bachelor’s Degree	119	62.30
	Master’s Degree	10	5.24
	Doctoral Degree	2	1.05

The mean scores for most variables ranged from 2.8-4.4, indicating moderate to high agreement among the respondents. FAC had the highest mean (4.369), signifying strong agreement. ITR had the lowest mean (2.848), indicating lower agreement levels. Standard deviations varied from 0.889-1.359, suggesting different degrees of variation around the mean for each variable. Skewness and kurtosis values indicated that FAC was negatively skewed and leptokurtic, with most responses clustering toward the higher end. Other variables showed more symmetrical distributions.

Table 2. Descriptive Statistics of Constructs

Construct	Mean	Std. Dev.	Skew.	Kurt.
ITR	2.848	1.161	0.218	-0.624
FAC	4.369	0.889	-1.674	2.931
SEF	3.606	1.078	-0.426	-0.505
PUS	3.162	1.255	-0.045	-1.040
PEU	3.417	1.198	-0.376	-0.753
RSK	3.306	1.359	-0.291	-1.065
INT	3.275	1.164	-0.208	-0.842

Convergent validity was confirmed by assessing whether diverse instruments measuring the same construct yielded highly correlated results. Hair et al. (2019) recommended eliminating indicators with loading factors below 0.7 as long ensuring average variance extracted (AVE) value above 0.5, it may be retained if its loading factor remains above 0.6. Based on Table 3, convergent validity is considered to have been met.

Table 3. AVE and Loading Factor

	AVE	ITR	FAC	SEF	PUS	PEU	RSK	INT
ITR	0.879							
ITR-2		0.941						
ITR-3		0.934						
FAC	0.802							
FAC-1			0.855					
FAC-3			0.934					
SEF	0.670							
SEF-1				0.731				
SEF-2				0.905				
SEF-3				0.810				
PUS	0.868							
PUS-1					0.931			
PUS-3					0.932			
PEU	0.649							
PEU-2						0.838		
PEU-3						0.815		
PEU-4						0.762		
RSK	0.781							
RSK-1							0.972	
RSK-2							0.785	

INT	0.899							
INT-3								0.943
INT-4								0.953

Discriminant validity was established through the heterotrait-monotrait (HTMT) ratio, following Hair et al. (2021). All HTMT values were below 0.9, except for one at 0.921, still below 1.0, which is acceptable, citing Gaskin et al. (2018). Therefore, discriminant validity can be considered robustly established.

Table 4. HTMT Matrix

	1	2	3	4	5	6	7
1. ITR							
2. FAC	0.287						
3. SEF	0.705	0.465					
4. PUS	0.783	0.230	0.669				
5. PEU	0.773	0.444	0.712	0.837			
6. RSK	0.356	0.102	0.350	0.287	0.329		
7. INT	0.734	0.337	0.589	0.921	0.829	0.366	

Reliability analysis using Cronbach's Alpha (CA) and Composite Reliability (CR) met the standard of 0.7 as cited from Hair et al. (2021), confirming reliability.

Table 5. Reliability Test

Construct	CA	CR
ITR	0.863	0.936
FAC	0.762	0.890
SEF	0.757	0.858
PUS	0.847	0.929
PEU	0.729	0.847
RSK	0.764	0.876
INT	0.888	0.947

In this research, multiple goodness-of-fit assessments, including SRMR, d_ULS, d_G, chi-square, and NFI, were employed to evaluate the model. SRMR, measuring the difference between observed and expected correlations, met the acceptable threshold of below 0.08 according to Hu and Bentler (1998), indicating a good fit. Both d_ULS and d_G values, assessing empirical-model covariance differences, were statistically significant, confirming model suitability as per Dijkstra and Henseler (2015). The chi-square reflected model complexity, and the NFI at 0.7 suggested marginal acceptability. Overall, these tests collectively validate the suitability and complexity of the models in this study.

Table 6. Goodness-of-Fit Test

	Saturated Model	Estimated Model
SRMR	0.079	0.101
d_ULS	0.850	1.382

d_G	0.444	0.447
Chi-Square	536.854	484.195
NFI	0.702	0.731

Hair et al. (2021) state that the inner or structural model examines variable interrelations. Validity and reliability are crucial. Tests conducted include assessing direct and indirect effects, effect size, predictive relevance, and coefficient of determination, ensuring a comprehensive evaluation of the model's structural integrity.

Table 7. Significance Test for Direct Effects and Effect Size Test

	β	x̄	s	t-stat.	p-value	Decision	f^2
H1	0.423	0.427	0.071	5.928	0.000	Supported	0.244
H2a	0.176	0.172	0.081	2.185	0.015	Supported	0.041
H2b	0.494	0.507	0.079	6.235	0.000	Supported	0.354
H3	0.398	0.395	0.074	5.410	0.000	Supported	0.215
H4a	0.613	0.610	0.058	10.484	0.000	Supported	0.676
H4b	0.114	0.116	0.044	2.584	0.005	Supported	0.038
H4c	0.237	0.239	0.054	4.418	0.000	Supported	0.101

Table 8. Significance Test for Indirect Effects

	β	x̄	s	t-stat.	p-value	Decision	Type
H5a	0.259	0.261	0.054	4.808	0.000	Supported	Partial
H5b	0.244	0.240	0.046	5.270	0.000	Supported	Partial
H6a	0.070	0.068	0.035	1.997	0.023	Supported	Partial
H6b	0.197	0.200	0.048	4.085	0.000	Supported	Partial
H6c	0.042	0.041	0.021	1.980	0.024	Supported	Partial
H6d	0.117	0.121	0.035	3.323	0.000	Supported	Partial
H7a	0.043	0.041	0.022	1.972	0.024	Supported	Partial
H7b	0.120	0.121	0.029	4.201	0.000	Supported	Partial

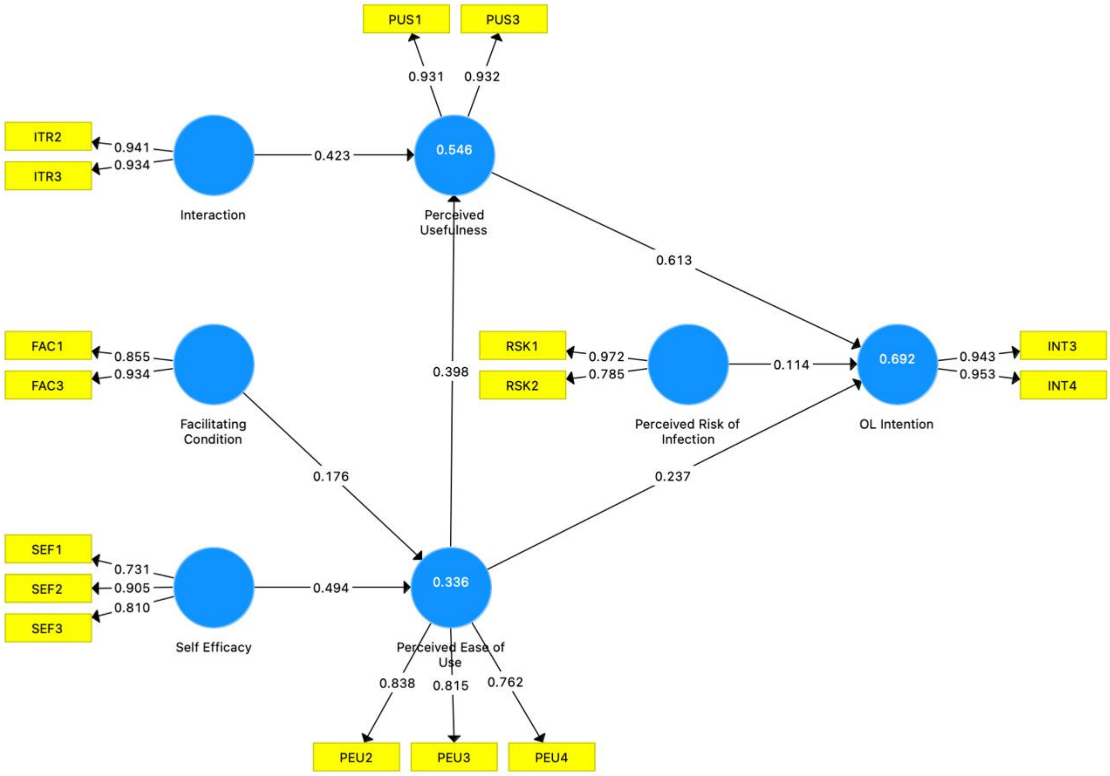
Significance tests for both direct and indirect effects utilized bootstrapping to measure p-values. T-statistics values in Tables 5 and 6, exceeding the critical t-value of 1.960 and featuring p-values below 0.0275 as recommended by Hair et al. (2019), lead to the acceptance of all research hypotheses. This study can be summarized in three key equations:

$$PUS = 0.42*ITR + 0.07*FAC + 0.20*SEF + 0.40*PEU + \varepsilon$$

$$PEU = 0.18*FAC + 0.49*SEF + \varepsilon$$

$$INT = 0.26*ITR + 0.09*FAC + 0.24*SEF + 0.48*PEU + 0.61*PUS + 0.11*RSK + \varepsilon$$

Figure 2. Structural Model Measurement



F^2 measures effect size, categorized as small (0.02), moderate (0.15), or large (0.35), as suggested by Hair et al. (2021). Table 7 shows large effects for H2b and H4a, moderate for H1, H3, and H4c, and small for H2a and H4b. For predictive relevance, Q^2 values greater than 0.0 confirms its fulfillment (Hair et al., 2021). Based on Hair et al. (2019), categories are 0.02 for low predictive relevance, 0.15 for moderate, and 0.35 for high. Table 9's Q^2 values show moderate predictive relevance for PEU, while high for PUS and INT.

Table 9. Predictive Relevance and Coefficient of Determination Tests

ELV	SSO	SSE	Q^2	R^2	Adj. R^2
PUS	382.000	202.612	0.470	0.546	0.541
PEU	573.000	457.364	0.202	0.336	0.329
INT	382.000	147.919	0.613	0.692	0.687

The coefficient of determination assesses dependent variables' influence on independent ones. As per Hair et al. (2019; 2021), the R^2 values typically range from 0.25 (minimal explanatory power) to 0.75 (maximum explanatory power). In social sciences with endogenous latent variables, a value of 0.65 suffices to indicate substantial explanatory power (Chin, 1998). From the R^2 values presented in Table 9, reveal that the independent variables in this research account for 69% of the variance in INT.

Discussion

This study provides an in-depth examination of Indonesia's EdTech ecosystem, accentuating the influence of specific factors on INT, namely ITR, FAC, SEF, PEU, PUS, and RSK. The dataset, augmented by demographic variables, yielded insights with both scholarly and pragmatic ramifications.

Regarding demographics, the investigation delineated a cohort that was predominantly youthful and female, with a noteworthy proportion holding a bachelor's degree. To elaborate, 67% of the respondents were within the 13–20 age range, 75% were females, and 62% had reached a bachelor's degree level of education. These demographic attributes serve as foundational elements for understanding the potential student base for EdTech solutions in Indonesia, thereby acting as pivotal variables to explicate this study's core focus areas.

This research provides a salient addition to the prevailing corpus of theories on technology adoption, encompassing the TRA, TPB, TAM, and UTAUT. While the TRA and TPB efficaciously elucidate behavioral intentions, they customarily neglect technological intricacies. Conversely, the TAM and UTAUT, although rigorous in their scrutiny of technological acceptance, often omit external and situational determinants.

This study advances understanding of indigenous OL adoption in Indonesia's post-pandemic context by introducing FAC and RSK as localized enhancements to traditional adoption models, such as TAM and UTAUT. Aligned with Christensen et al.'s (2015) comprehensive framework, it tailors the analytical model to Indonesia's unique post-pandemic landscape.

This research highlights the significant impact of FAC and SEF on PEU in EdTech. It underscores the need for user-centered designs, strong tech support, and partnerships between EdTech companies, local government, and internet service providers to improve digital infrastructure in low-connectivity areas. SEF's influence on PEU suggests the importance of EdTech programs for enhancing students' digital literacy.

Moreover, this study ascertained that enhancements in ITR facilities are positively correlated with both PUS and INT. From a pragmatic standpoint, it is necessary for EdTech platforms to prioritize functionalities that facilitate superior interactions between students and educators; imperatives such as robust video conferencing, interactive quizzes, and vibrant discussion forums warrant precedence in the developmental life cycle.

Since global society is currently transitioning into the post-pandemic phase, this study underscores the fact that RSK persists as a determinant in educational choices especially in EdTech. This creates an opportunity to market online learning as a safer option, ensuring educational continuity with lower risk compared to traditional in-person learning. Such messaging can alleviate concerns and boost adoption, particularly among risk-averse prospective students.

Conclusion

This study advances OL adoption within the unique socio-cultural and post-pandemic context of Indonesia, incorporating of localized variables, such FAC and RSK. These newly introduced factors offer a dual lens that captures both technological and situational nuances specific to the Indonesian context. In post-COVID-19, Indonesia's EdTech sector witnessed an unprecedented surge in both interest and adoption. This study's findings offer invaluable insights into this dynamic environment. It not only underscores the imperative for user-friendly interfaces, robust technological infrastructure, and real-time tech support but also emphasizes the quintessential role of focused training programs to enhance SEF. This study elucidates clear and actionable pathways by systematically addressing the delineated necessities and challenges, most notably concerning FAC, SEF, and ITR. These routes are designed to enhance both user acceptance and the operational efficacy of OL platforms, thereby fostering a more resilient and adaptable educational ecosystem. Moreover, this study highlights the lingering influence of RSK on educational choices. This often-overlooked variable continues to shape perceptions and decisions, providing an opportunity for educational platforms to emphasize the inherent safety benefits of OL, compared to traditional F2F settings. In a more expansive context, the conclusions of this study have the potential to substantially improve the quality of education in Indonesia. They serve as a multidimensional guide with broad implications affecting both the theoretical foundations of technology adoption and practical implementations that can drive the industry forward. By aligning technological, behavioral, and situational variables in a comprehensive model, this study contributes a new layer of complexity and understanding that is deeply rooted in the unique challenges and opportunities presented in a post-pandemic global context.

Limitations

This study presents a novel framework for understanding OL adoption in Jakarta, with a focus on local factors like FAC and RSK. However, it has limitations, including a narrow scope of variables, a limited sample of Jakarta students, and a focus on behavioral intention rather than actual usage behavior due to time constraints. Future research should consider broader factors like system acceptance, student/teacher attributes, governmental policies, and global comparative studies in different countries. Longitudinal studies would provide a deeper understanding of changes over time and reduce common method bias. The study also suggests that exploring demographic attributes as moderating variables could provide further insights. In summary, this study lays a strong foundation for understanding OL adoption in Indonesia but calls for future research to address these limitations by expanding the framework to diverse regions and cultures, offering a more comprehensive and global perspective on OL adoption.

Acknowledgment

The author expresses gratitude to AIBPM for hosting ICPM 2023 in Tokyo and Editage (www.editage.com) for editing and reviewing this manuscript for English language.

Declaration Of Conflicting Interests

The author reports that there are no competing interests to declare.

References

Alamri, A., & Tyler-Wood, T. (2017). Factors affecting learners with disabilities: Instructor interaction in online learning. Journal of Special Education Technology, 32(2), 59–69. doi:10.1177/0162643416681497

Andries, F., & Lengkoan, F. (2023). The importance of students' perception of online learning during pandemic. International Journal of Applied Business and International Management, 8(2), 142-152. doi:10.32535/ijabim.v8i2.2475

Anindhita, W., Nugrahaeni, E., Rahmawati, D., & Viendyasari, M. (2022). The role of podcast as a distance learning media during Covid-19 in higher education. Asia Pacific Journal of Management and Education, 5(2), 74-86. doi:10.32535/apjme.v5i2.1562

Baber, H. (2021). Modelling the acceptance of E-Learning during the pandemic of COVID-19: A study of South Korea. The International Journal of Management Education, 19(2): 1–15. doi:10.1016/J.IJME.2021.100503

Billanes, J., & Enevoldsen, P. (2021). A critical analysis of ten influential factors to energy technology acceptance and adoption. Energy Reports, 7, 6899–6907. doi:10.1016/j.egyr.2021.09.118

Black, W. (1983). Discontinuance and Diffusion: Examination of the post adoption decision process. Advances in Consumer Research, 10, 356-361.

Chin, W. W. (1998). The Partial Least Squares Approach to Structural Equation Modeling. Advances in Hospitality and Leisure, 8(2).

Choi, J.-J., Robb, C. A., Mifli, M., & Zainuddin, Z. (2021). University Students' Perception to Online Class Delivery Methods During The COVID-19 Pandemic: A focus on hospitality education in Korea and Malaysia. Journal of Hospitality, Leisure, Sport & Tourism Education, 29, 1–12. doi:10.1016/J.JHLSTE.2021.100336

Christensen, C. M., Raynor, M. E., & McDonald, R. (2015). What is Disruptive Innovation?. Retrieved from https://hbr.org/2015/12/what-is-disruptive-innovation.

Conijn, J. M., Smits, N., & Hartman, E. E. (2020). Determining at what age children provide sound self-reports: An illustration of the validity-index approach. Assessment, 27(7), 1604–1618. doi:10.1177/1073191119832655

Dijkstra, T. K., & Henseler, J. (2015). Consistent and asymptotically normal PLS estimators for linear structural equations. Computational Statistics & Data Analysis, 81, 10–23. doi:10.1016/j.csda.2014.07.008

Ferri, L., Spanò, R., Maffei, M., & Fiondella, C. (2021). How risk perception influences CEOs' technological decisions: Extending the Technology Acceptance Model to small and medium-sized enterprises' technology decision makers. European Journal of Innovation Management, 24(3), 777–798. doi:10.1108/ejim-09-2019-0253

Gaskin, J., Godfrey, S., & Vance, A. (2018). Successful system use: It's not just who you are, but what you do. AIS Transactions on Human-Computer Interaction, 10(2), 57–81. doi:10.17705/1thci.00104

Greener, S., & Martelli, J. (2018). An Introduction to Business Research Method. Retrieved from https://bookboon.com/en/an-introduction-to-business-research-methods-ebook?mediaType=ebook

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks: Sage Publication.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019) When to Use and How to Report the Results of PLS-SEM. European Business Review, 31(1), 2–24. doi:10.1108/EBR-11-2018-0203

Hu, L., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. Psychological Methods, 3(4), 424–453. doi:10.1037/1082-989x.3.4.424

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and Gamma-Exponential methods. Information Systems Journal, 28(1), 227–261. doi:10.1111/ISJ.12131

Malatji, W. R., Van Eck, R., & Zuva, T. (2020). Understanding the usage, modifications, limitations and criticisms of Technology Acceptance Model. Advances in Science, Technology and Engineering Systems Journal, 5(6), 113–117. doi:10.25046/AJ050612

Malhotra, N. K. (2019). Marketing Research: An Applied Orientation (7th ed.). Bingley: Pearson Education.

Montaño, D., & Kasprzyk, D. (2015). Theory of reasoned action, theory of planned behavior, and the integrated behavioral model. In K. Glanz, B. K. Rimer, & K. Viswanath (Eds.), Health behavior and health education: Theory, research, and practice (4th ed., pp. 67–96). New York: John Wiley & Sons.

Moore, J. (2014). Effects of online interaction and instructor presence on students' satisfaction and success with online undergraduate public relations courses. Journalism & Mass Communication Educator, 69(3), 271–288. doi:10.1177/1077695814536398

Morwitz, V. G., Steckel, J. H., & Gupta, A. (2007). When do purchase intentions predict sales?. International Journal of Forecasting, 23(3), 347–364. doi:10.1016/J.IJFORECAST.2007.05.015

Ng, H. S., Kuek, T. Y., Chen, K. H., Chang, J. H., Chee, Y. P., Chen, L. J., …, & Zirape, S. (2023). Factors influencing online academic performance among university students. Asia Pacific Journal of Management and Education, 6(2), 27-36. doi:10.32535/apjme.v6i2.22213

Park, K. (1998). Innovative product usage behavior in the post-adoption process. In K. Hung & K. B. Monroe (Eds.), Asia Pacific Advances in Consumer Research, 3 (pp. 107–112).

Silva-Contreras, A., Montoya, I. A., & Valencia, J. A. (2019). The attitude of managers toward telework, why is it so difficult to adopt it in organizations?. Technology in Society, 59, 1–10. doi:10.1016/j.techsoc.2019.04.009

Statista. (2023). Online Education - Indonesia. Retrieved from https://www.statista.com/outlook/dmo/eservices/online-education/indonesia

Tarhini, A., El-Masri, M., Ali, M., & Serrano, A. (2016). Extending the UTAUT Model to understand the customers' acceptance and use of internet banking in Lebanon: A Structural equation modeling approach. Information Technology & People, 29(4), 830–849. doi:10.1108/ITP-02-2014-0034

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. Management Information Systems Quarterly, 27(3): 425–478. doi:10.2307/30036540

Zhou, T., Lu, T., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. Computers in Human Behavior, 26(4), 760–767. doi:10.1016/J.CHB.2010.01.013