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Analyzing University Students' Attitude And Behavior Towards Jesi Program Using Technology Acceptance Model

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ABSTRACT

Purpose of the study: This study aimed to examine university students' attitudes and behavioral intentions toward the JESI Interactive Learning Module using the Technology Acceptance Model (TAM), focusing on perceived ease of use and perceived usefulness.

Methodology: A structured 5-point Likert scale questionnaire adapted from Davis (1989) was distributed via Google Forms. A total of 269 university students were selected using stratified random sampling. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS 4.0 and descriptive statistics via Jamovi software.

Main Findings: The findings revealed that PU ($\beta = 0.495$, $p < 0.000$) has significant direct effects toward attitude, while PEOU ($\beta = 0.117$, $p < 0.144$) has no significant direct effects toward attitude. Additionally, attitude ($\beta = 0.594$, $p < 0.00$) has also been found to have a significant direct effect toward behavioral intention to use. Additionally, the structural model demonstrated a good-fit in all PLS-SEM indices.

Novelty/Originality of this study: This study is the first to apply TAM to evaluate JESI, a context-specific ILM in Philippine higher education. It advances theoretical understanding of technology acceptance and offers practical insights for improving ILM design and adoption across similar digital platforms in higher education institutions.

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1. INTRODUCTION

The rapid advancement of technology has significantly transformed higher education, influencing how students access resources, engage in learning, and collaborate in academic environments [1]. The integration of educational technology, such as videos and interactive exercises, has been shown to enhance student engagement and academic performance [2]. Among the various digital tools implemented in higher education, Interactive Learning Modules (ILMs) have gained prominence due to their ability to foster active learning, critical thinking, and problem-solving skills [3]. ILMs are characterized by features such as learner support, contextualized content, situated activities, and technical adaptability, all of which impact student engagement and learning outcomes [4].

A notable example of an Interactive Learning Module (ILM) in higher education is the JESI interactive learning module, developed for students enrolled in the Purposive Communication course at the University of

Mindanao. JESI leverages technology to structure activities and challenges that strengthen students' communication skills [5]. Although ILMs have been shown to foster deeper educational engagement [6], the specific challenges students face in utilizing such platforms-particularly JESI-remain underexplored. Globally, the integration of ILMs is increasingly promoted through educational policies that support digital transformation in learning environments. Institutions worldwide are embedding ILMs into curricula to facilitate interactive, student-centered learning experiences [7], offering learners greater autonomy and promoting motivation and knowledge retention [8]. However, the effectiveness of ILMs ultimately depends on their alignment with students' expectations, learning preferences, and technological proficiencies.

Despite the advantages of ILMs, students may face significant challenges in their adoption. Two major barriers to the effective use of JESI include ease of use and concerns over data privacy. Previous studies suggest that students' perceptions of usability influence their willingness to adopt online learning modules [9], [10]. If an ILM's interface is perceived as complex or non-intuitive, students may hesitate to engage with the system. Similarly, concerns regarding data security may deter students from actively participating in digital learning environments [11], [12]. In the case of JESI, students' reluctance may stem from apprehensions about data privacy or difficulties in navigating the platform's interface, which ultimately affects engagement and learning outcomes.

While previous research has examined the impact of ILMs on student learning and engagement [13], [14], there remains a gap in literature regarding the specific factors influencing university students' acceptance and use of the JESI program. Studies have explored students' attitudes towards simulation-based learning and digital learning platforms [15], [16]. Further, TAM, developed by Davis [17], is a robust theoretical framework for understanding users' acceptance of new technologies, emphasizing the roles of perceived ease of use, perceived usefulness, and attitude in shaping behavioral intention. However, no prior study has systematically applied TAM to JESI or explored how its constructs manifest in a context-specific ILM embedded in a Philippine university.

This study fills that gap by utilizing TAM to assess university students' perceptions and behavioral intentions toward JESI. By doing so, it contributes theoretically by extending TAM's application to a novel context and practically by offering actionable insights into how JESI-and similar ILMs-can be improved to enhance student adoption and academic outcomes.

Moreover, this study is timely and relevant within the broader context of the global digital transformation in education. As universities worldwide shift toward hybrid and technology-enhanced learning environments, the development of effective ILMs has become a strategic priority. Findings from this study can inform institutional strategies not only for JESI but also for the design, implementation, and scaling of similar platforms in other higher education settings. In highlighting both user perceptions and structural design factors, this research offers a replicable model for integrating technology into instruction in a way that maximizes engagement, usability, and learning impact.

By bridging the existing research gap and addressing the barriers to ILM adoption, this study contributes to the limited but growing body of literature on context-specific ILMs and responds to the pressing need to evaluate technology acceptance in localized academic environments. By grounding the analysis in TAM and focusing on JESI, this research bridges theoretical constructs with practical innovations in higher education.

2. THEORETICAL FRAMEWORK

The increasing demand for e-learning resources and technological tools within higher education necessitates a comprehensive understanding of the factors influencing student acceptance and adoption of these innovations. The Technology Acceptance Model (TAM), proposed by Davis [17], remains one of the most widely used frameworks in examining technology adoption. TAM posits that user motivation is influenced by three primary components: perceived ease of use, perceived usefulness, and attitude toward using technology. This model has been extended through TAM2 [18] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [19], which incorporate situational factors such as self-efficacy, social norms, and cognitive instrumental processes.

TAM has been extensively applied in educational contexts, including blended e-learning systems, mobile learning, and learning management systems. Meta-analyses by Yousafzai et al. [20] confirm the model's validity, demonstrating a positive correlation between perceived ease of use, perceived usefulness, and behavioral intention to use technology. However, criticisms of TAM highlight methodological limitations, including its reliance on self-reported data and exclusion of external factors influencing technology adoption [21], [22]. Scholars have argued for the need to integrate additional theoretical perspectives to enhance TAM's explanatory power.

To address these limitations, this study extends the traditional TAM framework by incorporating qualitative data and contextual variables that influence student engagement with JESI. By considering both self-reported data and observational insights, this study aims to provide a more holistic understanding of how students interact with ILMs in real-world educational settings.

3. RESEARCH METHOD

This study adopts a quantitative research design, specifically utilizing a non-experimental correlational approach. As noted by Creswell and Creswell [23], quantitative research utilizes investigative methods, including surveys and experiments, that employ predetermined instruments to generate statistical measurements for data collection.

3.1. Research Design

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3.2. Research Subjects

The research participants consisted of university students from the University of Mindanao. To ensure equitable representation of the study variables, the researchers employed stratified random sampling to select participants.

3.3. Data Collection Instruments and Techniques

Data was collected using a survey questionnaire, adapted from Davis [17], employing a 5-point Likert Scale to gauge participant responses. The Google Forms platform was used to distribute the survey to randomly selected individuals. Before data collection, a power analysis was conducted using G*Power 3.1.9.6, indicating that a minimum sample size of $N = 89$ would be required to achieve 80% power for detecting a medium effect size ($f^2 = 0.15$) at a significance level of $\alpha = 0.05$. The 10-times rule proposed by Hair et al. [24] was also applied to determine the appropriate sample size for the study. However, the study included a total sample of two hundred sixty-nine surpassing the recommended samples based on the power analysis and 10-tems rule.

3.4. Data Analysis Techniques

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), which allows for the estimation of complex cause-effect relationships involving multiple constructs, indicator variables, and structural paths without the assumption of specific distributional relationships. This method explains causal effects and prediction in statistical modeling [25], [26]. PLS-SEM is particularly advantageous for small sample sizes; however, larger sample sizes are preferred to strengthen the extrapolation of results to the broader population [27]. Descriptive statistics were analyzed using Jamovi software, an open-source statistical tool with a user-friendly interface.

To evaluate the validity and reliability of the measurement model, Cronbach’s alpha was calculated. Convergent validity was assessed using the Average Variance Extracted (AVE), while discriminant validity was evaluated through the Heterotrait-Monotrait Ratio (HTMT). Multicollinearity was examined using the Variance Inflation Factor (VIF). Finally, the hypothesized structural model was assessed through the bootstrapping algorithm executed with SmartPLS 4.0 software to ensure robust statistical estimation.

3.5. Research Procedure Flowchart

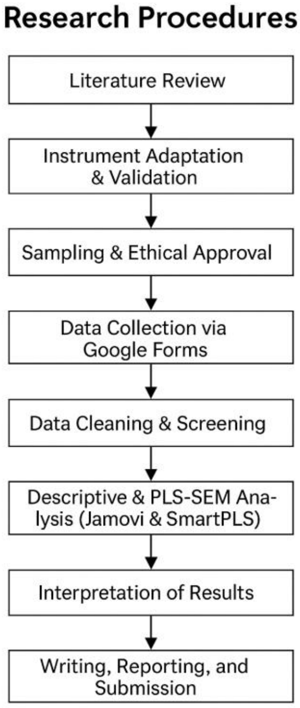

Figure 1. Research Flow Chart

4. RESULT AND DISCUSSION

4.1. Assessment of Measurement Model

The preliminary step in doing structural equation modeling is to ascertain the validity and reliability of the measurement model [28]. Cronbach's alpha and composite reliability are widely used metrics for assessing internal consistency. These measures evaluate reliability by examining the interrelationships among the variables represented by the items [29]. Table 1 presents the reliability of the instruments used in the study, with Cronbach's alpha identified as the most effective method for assessing the instruments. The Cronbach's alpha values for the questionnaires are as follows: 0.902 for the Affective Component (AC), 0.911 for the Behavioral Component (BC), 0.856 for the Behavioral Intention to Use (BIU), 0.942 for the Cognitive Component (CC), 0.903 for the Perceived Ease of Use (PEOU), 0.938 for the Perceived Usefulness (PU). These values indicate that the questionnaires have a high degree of internal consistency (SI). Composite reliability and Cronbach alpha values that fall within the range of 0.60 to 0.70 are considered acceptable; however, in the more advanced stage, the value absolutely must be greater than 0.70 [30].

The composite reliability test by Jöreskog [31] assesses the internal consistency of indicators for a latent construct, accounting for varying item contributions based on their factor loadings. It provides a more precise reliability measure compared to Cronbach's alpha, with values above 0.7 considered acceptable and above 0.8 ideal for established scales. AC (0.909), BC (0.943), BIU (0.861), CC (0.952), PEOU (0.917), and PU (0.938) have values of more than 0.7, which simply implies that all are acceptable. Generally, CR values above 0.7 are considered acceptable [32].

The instruments' convergent validity evaluation was conducted by calculating the Average Variance Extracted (AVE). Convergent validity is the degree of agreement regarding the correlation between multiple indicators of the same construct [29]. AC (0.836), BC (0.734), BIU (0.874), CC (0.812), PEOU (0.722), and PU (0.844) all constructs had AVE values exceeding the 0.5 threshold, which is considered acceptable. An AVE value of 0.50 or higher indicates that the construct explains at least 50% of the variance in the items that define it [30], [33]-[35].

Table 1. Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Average Variance Extracted (AVE)
Affective Component	0.902	0.909	0.836
Attitude	0.911	0.943	0.734
Behavioral Component	0.856	0.861	0.874
Behavioral Intention to Use	0.942	0.952	0.812
Cognitive Component	0.903	0.917	0.722
Perceived Usefulness	0.938	0.938	0.844

The HTMT values were the next test used. According to Hamid et al. [29], this test assessed the scales' discriminant validity, or how much the items empirically differ from one another. All constructs' HTMT values are less than 0.85, which is considered acceptable for discriminant validity. According to Henseler et al. [36], any ratio below the 0.85 threshold indicates good discriminant validity. They require theoretical justification for their conceptual overlap, ensuring the distinctness of constructs is maintained [24], [39], [36]. All ratios are less than the 0.85 threshold, indicating significant discriminant validity between the constructs [37]. In addition, Gold and Malhotra [38] recommended that the threshold be set at 0.90.

Table 2. Heterotrait-Monotrait Ratio (HTMT)

	AC	At	BC	BIU	CC	PEOU	PU
Affective Component							
Attitude	0.676						
Behavioral Component	0.858	0.886					
Behavioral Intention to Use	0.881	0.640	0.827				
Cognitive Component	0.828	0.608	0.883	0.746			
Perceived Ease of Use	0.802	0.497	0.719	0.724	0.782		
Perceived Usefulness	0.881	0.598	0.855	0.812	0.891	0.792	

4.2. Assessment of Structural Model

Variance Inflation Factor (VIF) is a test to determine multicollinearity issues [39]. VIF values of <3.5 to 5.0 are the ideal thresholds to ascertain that the constructs are free from multicollinearity issues [40], [41]. As shown in Table 3 all constructs are within the acceptable range. This indicates that the constructs do not exhibit significant multicollinearity issues, ensuring the reliability and validity of the regression analysis results. This supports the appropriateness of including these constructs in the model for further analysis and interpretation.

Table 3. Variance Inflation Factor (VIF)

	VIF
Attitude -> Affective Component	1.000
Attitude -> Behavioral Component	1.000
Attitude -> Behavioral Intention to Use	1.000
Attitude -> Cognitive Component	1.000
Perceive Ease of Use -> Attitude	2.156
Perceive Usefulness -> Attitude	2.156

The results of this study provide empirical support for the Technology Acceptance Model (TAM) by demonstrating the significant relationship between attitude and behavioral intention to use the JESI program ($\beta = 0.594$, $p < 0.001$, $f^2 = 0.544$). This finding aligns with prior research indicating that a positive attitude significantly enhances individuals' willingness to adopt a technology-driven system [42], [43]. The robust effect size suggests that fostering positive attitudes can substantially increase students' engagement with and intention to use the JESI program, reinforcing the fundamental premise of TAM that attitudes play a pivotal role in shaping behavioral intentions [20].

Contrary to several prior studies indicating a significant direct impact of perceived ease of use on attitude [44]-[47], the findings of this study suggest that perceived ease of use does not significantly influence attitude ($\beta = 0.117$, $p = 0.144$). This result is consistent with alternative research streams suggesting that perceived ease of use may primarily influence attitude indirectly, via perceived usefulness [48], [49]. The non-significant relationship observed in this study indicates that while ease of use is an important factor, its effect on attitude might be mediated by other variables such as perceived usefulness or external contextual factors.

The moderate yet significant relationship between perceived usefulness and attitude ($\beta = 0.495$, $p < 0.001$, $f^2 = 0.173$) underscores the critical role of perceived usefulness in shaping student attitudes toward adopting the JESI program. These findings corroborate prior studies highlighting that when users perceive a system as valuable, their attitudes toward its adoption become significantly more favorable [48]-[52]. Moreover, contextual variations suggest that additional factors, such as system compatibility and self-efficacy, might further moderate this relationship [53]. Therefore, designing interventions that enhance the perceived usefulness of online learning platforms is critical in fostering positive attitudes and increasing adoption rates.

The significant effect of attitude on behavioral intention observed in this study reinforces existing literature that identifies attitude as a primary determinant of individuals' willingness to adopt new technology [42], [43]. Research in both educational and commercial technology settings has consistently shown that attitude serves as a strong predictor of behavioral intention, often surpassing other determinants such as self-efficacy and subjective norms [54], [55]. The strong association between attitude and behavioral intention in this study aligns with these findings, further validating TAM's theoretical assumptions that attitude mediates the relationship between external variables and technology adoption.

From a practical standpoint, these results highlight the necessity of developing online learning platforms that emphasize perceived usefulness and cultivate positive attitudes among users. Given the non-significant direct relationship between perceived ease of use and attitude, platform developers should prioritize features that enhance the program's usefulness rather than focusing solely on ease of use. Previous research has demonstrated that the usability of an online education system significantly influences user engagement and satisfaction, thereby improving overall adoption rates [56]. Furthermore, designing interventions that reinforce the perceived value of the JESI program—such as demonstrating its effectiveness in improving learning outcomes—can significantly enhance students' attitudes and, consequently, their behavioral intention to use the system.

This study contributes to the existing literature by validating the Technology Acceptance Model in the context of the JESI program. The significant impact of attitude on behavioral intention underscores the importance of fostering positive perceptions toward the system. Additionally, the results suggest that perceived usefulness plays a more crucial role than perceived ease of use in shaping students' attitudes. These findings have important implications for the design and implementation of online learning platforms, emphasizing the need for interventions that enhance perceived usefulness and strengthen students' engagement with digital education tools.

Table 4. Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	f-square
Attitude -> Behavioral Intention to Use	0.594	0.594	0.048	12.478	0.000	0.544
Perceive Ease of Use -> Attitude	0.117	0.118	0.080	1.460	0.144	0.010
Perceive Usefulness -> Attitude	0.495	0.496	0.074	6.640	0.000	0.173

The R-squared (R^2) and Adjusted R^2 values represent the proportion of variance explained by the model. The variance presented for At-AI is 34.3%, which indicates a moderate effect size consistent with the Technology Acceptance Model (TAM) literature. Further, the variance presented for BIU is 35.2%, suggesting a strong relationship in the context of technology acceptance. The Predictive Relevance (Q^2) value demonstrates the model's predictive relevance. A Q^2 value greater than zero indicates that the model has predictive relevance for the construct. The Q^2 predictive values for Attitude (32.8%) and Behavioral Intention (38.8%) confirm the model's predictive relevance.

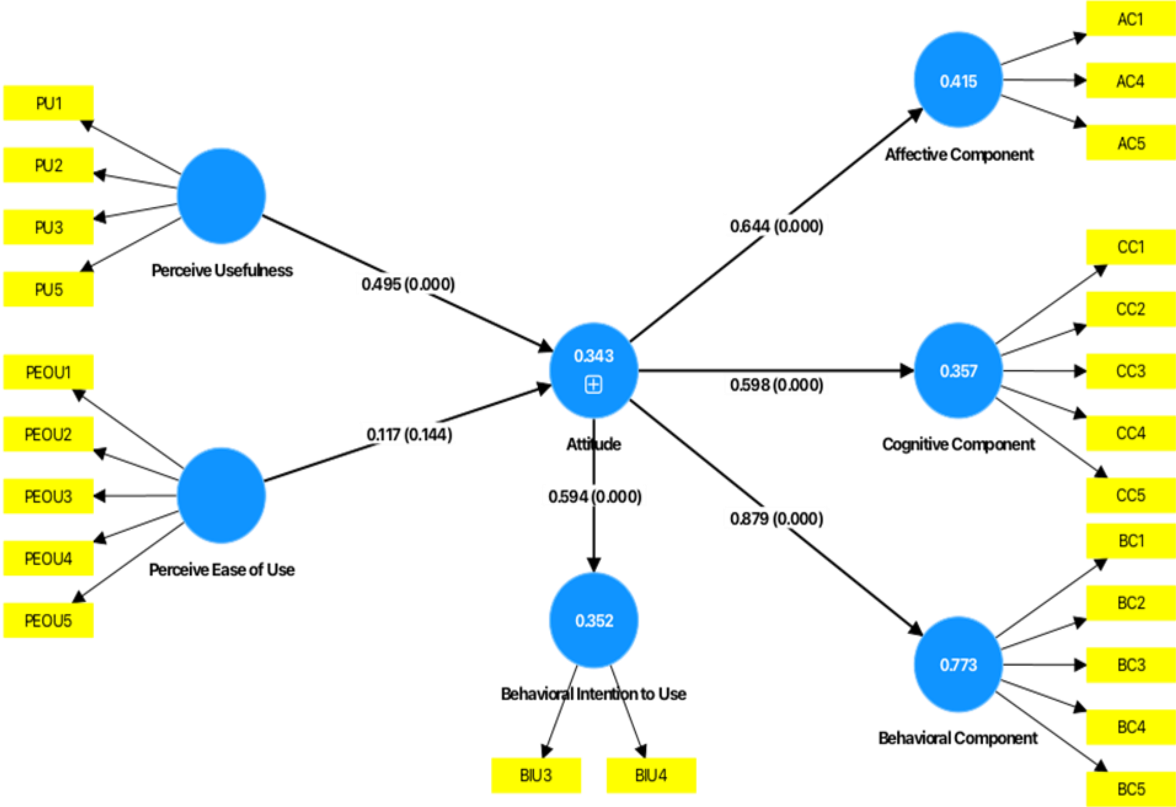

Figure 2. Partial least squares structural equation modeling (PLS-SEM) Results using Smart PLS 4.0

The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are measurements of the average error between the predicted and observed values. Lower values are preferable as they indicate that the model's predictions are relatively close to the observed values. Predictive metrics such as RMSE and MAE demonstrate acceptable prediction accuracy, underscoring the model's robustness for practical applications [57]. The Standardized Root Mean Square Residual (SRMR) is a measure of model fit used in structural equation models, where values below 0.08 are generally considered good. The SRMR value of 0.063 indicates that the model achieves a good fit.

Table 5. Model Fit

	R-square	R-square adjusted	Q^2predict	RMSE	MAE
Attitude	0.343	0.338	0.328	0.825	0.639
Behavioral Intention to Use	0.352	0.35	0.388	0.788	0.652
	Saturated model	Estimated model			
SRMR	0.063	0.240			
d_ULS	1.306	18.713			

The Unweighted Least Squares discrepancy (d_ULS) and Geodesic discrepancy (d_G) are discrepancy functions based on unweighted least squares and geodesic distances. The smaller these values, the better the model fits. Based on the value of the estimated model (18.713), which is relatively high, it indicates a greater discrepancy between the model's predictions and the data. On the other hand, the value of the saturated model (1.306), which is relatively low, suggests close alignment with the observed data. The difference between these values shows that the proposed model does not fit nearly as well as the saturated model. Moreover, the absence of d_G values further emphasizes the need to rely on other fit indices for a comprehensive assessment.

This study contributes significant insights into the adoption of the JESI program, yet it has several limitations. Primarily, the research is anchored in the Technology Acceptance Model (TAM), which may not encompass all factors affecting technology adoption. Future research could explore moderating or mediating variables such as institutional policies, security features, and social influences that may impact students' acceptance of JESI.

Moreover, the rapid pace of advancements in educational technology could render the study findings outdated, underscoring the need for continuous research to stay aligned with emerging trends. Longitudinal studies, in particular, would enhance our understanding of how student perspectives and intentions evolve over time as they gain familiarity with JESI.

Expanding the scope of future investigations to include a broader range of research subjects and integrating various constructs, theories, and methodologies could deepen our knowledge of students' attitudes and behaviors toward technology acceptance. Specifically, factors such as peer dynamics and collaborative learning interventions merit further exploration, as they appear to influence JESI engagement but have not been fully examined within existing frameworks like TAM.

Additionally, while the findings have important theoretical and practical implications, it is essential to recognize certain contextual limitations. The focus on the specific JESI program may restrict the generalizability of the results to other online learning platforms. The reliance on self-reported data also introduces risks of bias, including social desirability and self-perception biases.

To build on this foundation, future research should employ longitudinal designs to track shifting attitudes and perceptions over time and consider the impact of additional variables on behavioral intentions. Moreover, broadening the study to encompass diverse educational settings and incorporating qualitative insights could further illuminate the dynamics of technology acceptance in online learning environments. These suggested avenues for future inquiry will ultimately enhance our collective understanding of the facilitators that influence the adoption and effective use of interactive learning modules within educational contexts.

5. CONCLUSION

This study applied the Technology Acceptance Model (TAM) to analyze university students' attitudes and behavioral intentions toward the JESI Interactive Learning Module, focusing on perceived ease of use, perceived usefulness, and behavioral intentions. The findings indicate that while perceived ease of use has no significant effect, perceived usefulness and students' positive attitudes significantly influence their intention to adopt JESI. These results highlight the crucial role of demonstrating the practical value of JESI in enhancing learning experiences.

To improve the adoption and sustained use of the JESI module, several measures should be considered. Enhancing the interface and increasing the module's perceived usefulness can significantly boost student engagement and satisfaction. Additionally, mitigating external barriers, such as concerns regarding data privacy and complex user interfaces, will foster a more favorable reception of JESI. Ensuring that module tasks align with learners' needs and preferences can further reinforce engagement. A continuous feedback system should be integrated to evaluate and refine the module based on user experiences, thereby ensuring iterative improvements.

Moreover, promoting positive user experiences through clear demonstrations of benefits, success stories, and peer engagement strategies can strengthen students' attitudes and behavioral intentions toward JESI. Future research should explore the role of interaction and peer learning clusters in influencing technology adoption, as these factors, though not explicitly covered by TAM, appear to interact with user engagement in a meaningful way. By addressing these areas, educators and developers can enhance the effectiveness, adoption, and sustainability of digital learning tools in higher education settings.

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