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Technology acceptance in statistics education: Implications for human capital and community capacity development

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ABSTRACT

This study evaluates the performance of a proposed model based on the Technology Acceptance Model (TAM) to forecast students' opinions of statistics education improved by advanced technology. Using a sample of 379 undergraduate students from Malaysia's East Coast, chosen by simple random sampling, this study examined six main constructs: social influence, self-efficacy, perceived usefulness, perceived ease of use, attitude toward using, and behavioral intention. The measurement model was validated using confirmatory factor analysis (CFA), which found that each construct satisfied the necessary thresholds for model fit, dependability, and validity. Students' attitudes toward using technology were found to be influenced by perceived usefulness, social influence, self-efficacy, and perceived ease of use, according to a structural model examined using Covariance-Based Structural Equation Modeling (CB-SEM). Attitude, perceived ease of use, social influence, and self-efficacy significantly affected behavioral intention; the direct path from perceived usefulness to behavioral intention was not statistically significant. Four major mediation effects were also found, which emphasizes the importance of attitude in connecting the antecedent variables to behavioral intention. Thus, by using the digital education for statistics course, the model under test is also sufficient to match the present development and will be helpful for future studies.

Keywords: technology acceptance model, statistics education, structural equation modeling, undergraduate students.

1. INTRODUCTION

Educational technology (ET) has become a fundamental component across all levels of education and has changed pedagogical practices. Particularly in higher education, universities are under increasing pressure to include ET in their curricula to match graduate characteristics with industry expectations. This covers the need to develop digital competencies, including computer literacy, mastery of specialized software, and the ability to negotiate technologically mediated environments—skills that are judged necessary for workplace readiness.

The adoption of ET brings a unique set of pedagogical and cognitive challenges in the field of statistics education for social science students. Although many students struggle to develop competencies in data analysis, computational procedures, and evidence-based interpretation, statistical literacy is generally agreed to be a basic graduate ability. For students in non-technical fields, these difficulties are compounded by a general lack of confidence and past knowledge regarding quantitative approaches. The sudden change to remote learning during the COVID-19 pandemic magnified these problems, which called for both teachers and students to quickly adjust to digital learning platforms and the remote use of analytical tools without sufficient supporting data.

Although earlier studies have examined teachers' opinions on technology adoption in the classroom, especially in relation to applied statistics, little is known about how students develop attitudes and intentions toward the use of educational technologies. Applying the Technology Acceptance Model (TAM) to investigate user acceptance across different educational environments, existing studies have often shown its robustness in spotting important elements, including perceived usefulness, perceived ease of use, attitude toward use, self-efficacy, and social influence. Few studies have concentrated on statistics education in developing nations, where further contextual limitations arise from technological access, curriculum design, and student preparedness.

This study aims to assess the applicability of TAM in explaining students' acceptance of educational technology in statistics education, considering this discrepancy. Specifically, this study intends to build and validate a measurement model that captures the interrelationships among important TAM constructs, offering empirical insights into the underlying factors influencing students' behavioral intentions toward technology use in a quantitative learning environment. This study aims to add to the larger conversation on digital pedagogies and guide institutional policies aimed at improving student interaction with technological instruments in higher education.

2. LITERATURE REVIEW

TAM has been utilized extensively in educational research to predict and explain users' attitudes toward the acceptance of educational technologies. According to Natasia et al. (2022), the premise that users' perceptions of the value and ease of technology define their behavioral intention to use it is at the core of TAM. Musa et al. (2024) stated that The TAM has been demonstrated to be an effective instrument in educational settings for identifying the factors that influence the acceptance of technology in teaching and learning contexts. According to Mailizar et al. (2021), TAM is widely recognized as a key paradigm for evaluating the use of technology in education. This study provides insights into how students interact with digital tools and incorporate them into their academic practices. According to Tahar et al. (2020), the model highlights the following factors as the primary determinants of technology adoption: behavioral intention, attitude toward usage, perceived usefulness, and perceived ease of use. Over the past few years, researchers have expanded this model by incorporating additional components such as perceived enjoyment, self-efficacy, subjective norms, and facilitating conditions. This has resulted in a more intricate depiction of technology acceptance, particularly in specialized fields such as statistics education (Leong et al., 2024).

2.1. Perceived Ease of Use

It has long been known that one of the most important factors influencing technology adoption is perceived ease of use (PEOU). PEOU was first conceptualized by Davis et al. (2024), who described it as "the degree to which a person believes that using a particular system would be free of effort." Numerous disciplines continue to provide substantial empirical evidence for this idea. According to Almaiah et al. (2022), PEOU has a major impact on users' decisions to adopt digital technologies, especially in educational settings. The significance of usability in influencing user behavior was also highlighted by Alsyouf et al. (2023), who found that people are more likely to adopt technologies when they believe that they are easy to use and can simplify their tasks.

Yulianto et al. (2022) discovered that healthcare professionals were more inclined to use information systems (IS) in the healthcare industry if they thought the systems would reduce their workload. On the other hand, users are less likely to intend to adopt a system if they believe it to be complicated or requires a lot of work (Rohani & Yusof, 2023). Rey-Moreno et al. (2022) also underlined that even when a technology has obvious operational advantages, resistance may result from perceived difficulties in learning or using it. To foster favorable user attitudes and enable routine integration, Veikkolainen et al. (2023) emphasized that companies should prioritize ease of use when designing their systems.

PEOU has a profound effect on users' attitudes and intentions in the field of education, going beyond simple system adoption. Several studies have demonstrated that PEOU influences behavioral intention both directly and indirectly through attitudes toward using the technology (Venkatesh & Davis, 2024; Mohammadi, 2015). Students are more likely to adopt a favorable attitude toward using a learning platform or tool when they believe it to be simple and intuitive, which in turn increases their intention to use it frequently. The strategic development of educational technologies that prioritize usability and user experience is supported by this dual influence, which strengthens the fundamental role of PEOU in technology acceptance models. The hypotheses are as follows:

H1: Perceived Ease of Use has significant impact on Attitude to Use
H1: Perceived Ease of Use has significant impact on Behaviral Intention

2.2. Perceived Usefulness

Technology adoption has been found to be significantly influenced by perceived usefulness (PU). PU, which Davis (1989) defined as "the degree to which a person believes that using a particular system would enhance his or her job performance," is crucial in determining user attitudes and behavioral intentions. According to Almaiah et al. (2022), people are more likely to embrace and incorporate technology into their daily routines if they believe it will enhance their learning or productivity. This relationship is particularly noticeable in educational settings, where students frequently embrace systems that they believe have a significant impact on their academic performance.

This connection has been supported by empirical research in various fields. According to Alsyouf et al. (2023), users are more inclined to interact with technologies that show observable performance advantages. While Rohani and Yusof (2023) found that perceived lack of usefulness decreased acceptance, even when the systems were required, Yulianto et al. (2022) observed that practitioners preferred systems that they thought would improve operational efficiency in the healthcare setting. Similarly, Rey-Moreno et al. (2022) contended that, irrespective of organizational support, technologies that are viewed as having no functional value encounter greater resistance.

Moreover, a large body of research has demonstrated that PU affects Attitude Toward Technology Use, which in turn affects Behavioral Intention. Venkatesh and Davis (2024) assert that PU has a direct impact on both of the Technology Acceptance Model (TAM) constructs, emphasizing its dual function in influencing perception and usage intent. According to Mohammadi (2015) and Teo (2011), students' perceptions of the value of these platforms in assisting their academic performance had a significant impact on their attitudes and intentions to use e-learning platforms. These results imply that users' attitudes become more positive, and they are more likely to continue using technology if they believe it is relevant and improves performance. Therefore, highlighting the usefulness of educational technologies continues to be a crucial tactic for increasing user acceptance and engagement. Therefore, the hypotheses are as follows:

H1: Perceived Usefulness has significant impact on Attitude to Use
H1: Perceived Usefulness has significant impact on Behaviral Intention

2.3. Attitude towards Using

An individual's general opinion, whether favorable or unfavorable, of a person, thing, or circumstance is referred to as attitude. This opinion is influenced by various factors, including socialization, past experiences, and cognitive evaluations. Its three main constituents are affective (emotions), behavioral (actions), and cognitive (beliefs). Attitude is a key factor in determining how well teachers and students adjust to digital tools and environments when it comes to the adoption of educational technology, especially during disruptive events such as the COVID-19 pandemic. As lecturers' attitudes toward change have a direct impact on the caliber and efficacy of instruction provided, the sudden shift to online learning has forced them to reassess their methods.

According to research, a positive and cooperative attitude between instructors and students creates an atmosphere favorable for candid communication, understanding, and productive knowledge sharing (Yusoff et al., 2021). It has been demonstrated that instructors' positive attitudes, which are demonstrated by their responsiveness to students' needs and supportive communication, specifically enhance students' perceptions of the quality of their instruction and their own involvement in the learning process (Kebritchi, Lipschuetz, & Santiague, 2017). These peer-to-peer and teacher-student interactions boost self-esteem and confidence, encouraging motivation and continued engagement.

Importantly, many studies have shown that, according to the TAM, Attitude Toward Use and Behavioral Intention are strongly and directly related. A positive attitude toward utilizing a system greatly raises the possibility that users will plan to use it frequently, claim Davis and Granić (2024). Students who have favorable opinions of digital learning platforms are more likely to embrace and stick with them, according to research that has been supported in a number of educational settings (Teo, 2011; Mohammadi, 2015). Therefore, encouraging positive attitudes through user-friendly system design, clear communication, and encouraging learning environments is crucial for improving students' behavioral intentions and general use of educational technology. Thus, the hypothesis is as follows:

H1: Attitude to Using has significant impact on Behavioral Intention

2.4. Self – Efficacy

Self-efficacy was first defined by Bandura (1977) as a person's confidence in their ability to carry out particular actions to accomplish desired results. Self-efficacy has become a key psychological concept in the context of digital education, affecting how students interact with online platforms, especially when they are confronted with difficulties or new tasks. Self-efficacy is crucial in determining whether learning activities in technology-mediated environments are initiated or continued. Self-efficacy in online learning environments refers to the self-assurance and proficiency required to use educational technology, engage with course materials, and interact with peers and teachers.

By creating validated measures of self-efficacy in online learning environments, Shen et al. (2013) added to this conversation and showed how crucial it is to influence student interaction, engagement, and overall academic performance. Higher self-efficacy among students increases their likelihood of active participation, perseverance through challenges, and more efficient use of available resources, all of which improve the learning outcomes.

Crucially, earlier research has also shown that self-efficacy has a major impact on behavioral intention and attitudes toward technology use. Teo (2009) asserts that students who are confident in their ability to use educational technologies are more likely to have positive attitudes toward their use. According to Liaw (2008) and Mohammadi (2015), people with high levels of self-efficacy are also more likely to develop positive attitudes and, as a result, exhibit stronger behavioral intentions to embrace and stick with digital learning systems. This relationship demonstrates the motivational power of self-belief, as self-assured users are more willing, open, and ready to incorporate technology into their education processes. To boost adoption rates and encourage meaningful engagement with online educational tools, it is imperative to improve students' self-efficacy through training, scaffolding, and user-friendly platform design. Therefore, the hypotheses are as follows:

H1: Self-efficacy has significant impact on Attitude to Use
H1: Self-efficacy has significant impact on Behaviral Intention

2.5. Social Influence

People's decisions to use educational technologies are greatly influenced by social factors, especially in statistics education. It includes various social elements that collectively influence user attitudes and behavioral intentions, such as group identity, perceived norms, and the impact of important referents (Al Kurdi et al., 2020). According to Social Identity Theory, people frequently adopt technology in ways that are consistent with the norms and expectations of their social groups (Unal & Uzun, 2021). Students are more likely to adopt educational technologies and have a positive opinion of them when they believe that their teachers or peers value and actively use them (Natasia, Wiranti, & Parastika, 2022).

Peer and instructor influence can greatly increase students' willingness to use digital tools in the context of statistics education, where learning is frequently seen as difficult because of the intricacy of calculations and abstract concepts. Seeing classmates and teachers use technology effectively can boost self-esteem and create favorable attitudes toward it (Pitafi et al., 2020). Furthermore, it has been demonstrated that support from friends, family, and online learning communities fosters positive attitudes and raises the probability of long-term technology use (Sinaga et al., 2021). The idea that social influence has a positive impact on behavioral intention and attitude toward using technology is also supported by empirical evidence.

Davis and Granić (2024) assert that social factors significantly impact an individual's intention by affecting their views of appropriate and expected behavior. Al-rahmi et al. (2021) found that peer support and social interaction improve students' attitudes and intention to use e-learning platforms in educational settings. Therefore, to encourage digital integration in classrooms, educators and policymakers must have a thorough understanding of the effects of social influence. Learning outcomes and digital readiness can be enhanced by utilizing social dynamics, such as instructor endorsement and peer modeling, as potent tactics to promote acceptance and engagement with educational technologies. Therefore, the hypotheses should be stated as follows (also see Figure 1)

H1: Social Influence has significant impact on Attitude to Use
H1: Social Influence has significant impact on Behaviral Intention

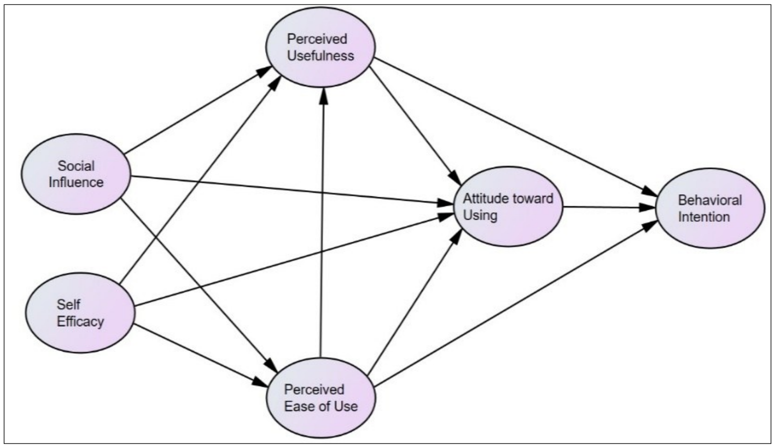

Figure 1 The Proposed Model

3. METHODOLOGY

3.1. Sample Size

Within the scope of this study, a technique known as simple random sampling was used to recruit participants. The computation approach proposed by Hair and Alamer (2022) and Hair et al. (2021) was utilized to determine the minimum required sample size. The authors proposed that there should be a minimum of ten participants for each measurement indication. Considering that the instrument comprised 30 items based on the Likert scale, the minimum sample size required was thirty times ten, which is equivalent to 300 individuals who responded to the survey. It is estimated that around 420 questionnaires were developed and distributed to handle the possibility of incomplete data or non-responses.

3.2. Research Design

This research utilized a quantitative methodology, and it was conducted through the use of an online questionnaire that was closed-ended. In Malaysia, five prominent public universities are distinguished for their emphasis on statistics education: Universiti Sultan Zainal Abidin (UniSZA), Universiti Malaysia Terengganu (UMT), Universiti Malaysia Pahang (UMP), Universiti Teknologi MARA (UiTM), and Universiti Sains Malaysia (USM). These educational institutions are gradually gaining recognition for their contributions to statistics education.

It was not possible to determine the overall number of the academic community because of the lack of comprehensive data regarding the academic community. This study aimed to collect the opinions of academic staff specializing in statistics. These individuals' ideas are vital for understanding the acceptance and integration of technological improvements into educational practices.

Data were collected using a random sample technique, and the online questionnaire was distributed through Google Forms to a selected group of lecturers from business and management faculties. In accordance with the social distancing regulations that are now in place, the installation of an online approach contributed to an increase in convenience and accessibility, while simultaneously lowering the health risks associated with face-to-face encounters.

3.3. Conventional Structural Equation Modeling (CSEM)

Confirmatory Factor Analysis (CFA), a component of the Conventional Structural Equation Modeling (CSEM) paradigm, was utilized in this study. CFA is a method that is widely recognized in a variety of fields, including education, social sciences, business, and information systems (Al-Hattami et. al., 2021; Henseler, Hubona, & Ray, 2016; Abdelrahman, 2020). It can evaluate the validity and fit of any construct inside a specified measurement model, which is one of its primary advantages.

The construct validity of the study was evaluated using model fit indices, which included absolute fit, incremental fit, and parsimonious fit. These indices show the degree of consistency between the observed data and the model posited regarding the data. Specifically, pertaining to CSEM, these indices contribute to the confirmation of the sufficiency of the measurement model, hence providing support for the validity of data derived from surveys (Rasheed et al., 2023).

Factor loading, often referred to as indicator loading, is a method that assists in determining the degree to which each observable item accurately reflects its corresponding latent component. The higher the loadings, the greater the alignment between the items and the construct (Mahmood et al., 2022). Furthermore, the addition of additional factor loadings results in improved Composite Reliability (CR) and Average Variance Extracted (AVE) values. These are two essential measures used to evaluate the internal consistency and convergent validity of a model. In light of this, Confirmatory Factor Analysis (CFA) serves as an essential instrument for verifying the measurement model before testing the hypothesis to study the structural connections between the components.

4. RESULT AND DISCUSSION

4.1. Result

This study applied CFA using Conventional Structural Equation Modeling (CSEM) via IBM-SPSS-AMOS software to examine factor loadings, evaluate the fit of the measurement model, verify construct correlations, and evaluate construct reliability and validity.

4.1.1. Descriptive Statistics

Five universities on the east coast were included in the online survey data. The universities were UniSZA, UMT, UiTM, UMPSA, and USM. The sample size involved 379 responses. Strategically, these universities were chosen because of the potential lure for participation that they offer, particularly in light of the fact that the Business Statistics course is available during this semester. The respondents' profiles were diverse, with significantly more women (58.31%) than men (41.68%). Regarding the distribution of ages, the age group of 21-23 years had the highest number of respondents (52.5%), followed by the age range–18-20 years, which had 25.59%). According to the data presented in Table 1, students enrolled in bachelor's degree programs made up the largest percentage of respondents, accounting for 56.72 percent of the total, with 215 individuals providing their responses. In terms of survey responses, UniSZA ranked highest (37.46%), followed by UMT (21.37%). This appears to be due to the fact that the poll was available during the short semester that UniSZA was held. There was a considerable preference for online courses over in-person programs, with a difference of over 30 percent between the two categories. This preference was most prevalent among the respondents. There were also differences in opinions regarding the level of difficulty associated with statistics; the majority of respondents (49.86%) believed that it was moderate, while 36.14 percent said that it was difficult. Because they highlight the demographic composition of the persons surveyed as well as their preferences, these results provide intriguing information that can be used for further study and analysis of the survey results. See Table 1

Table 1. Descriptive Statistics

Variable	Frequency	Percentage (%)
Gender		
Male	158	41.68
Female	221	58.31
Age		
18-20 years	97	25.59 52.5
21-23 years	199	16.88
24-26 years	64	5.01

More than 26 years	19	
Education Level		
Diploma	81	21.37
Bachelor	215	56.72
Master	83	21.89
University		
UniSZA	142	37.46
UMT	81	21.37
UiTM	75	19.78
UMPSA	53	13.98
USM	28	7.38
Class Preferable		
Online	243	64.11
Offline	136	35.88
Statistics Difficulty		
Easy	53	13.98
Moderate	189	49.86
Difficult	137	36.14

Source: Own Work

4.1.2 Inference Statistics

Initially, a CFA was conducted in this study for the purpose of inferential statistics. Over the course of the research, six primary constructs were investigated, each of which was modeled as a reflecting measurement model. Every component, including Social Influence, Self-Efficacy, Perceived Usefulness, Perceived Ease of Use, Attitude Towards Use, and Behavioral Intention, was evaluated using five different indicators. IBM SPSS AMOS 26 was used to conduct the CFA data analysis (Figure 2).

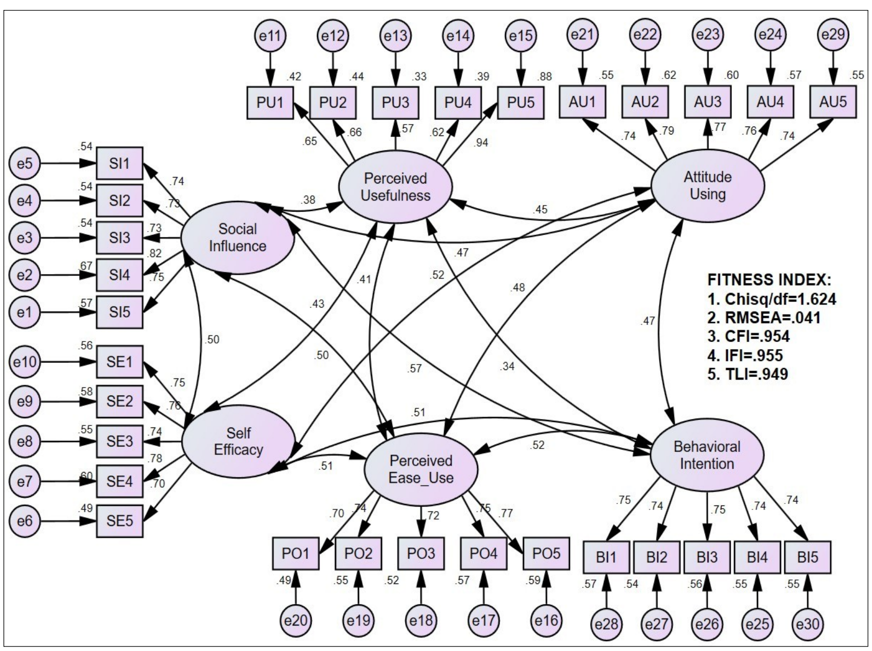

Figure 2. Confirmatory Factor Analysis

Source: Own Work

Table 2. Standardized Loading between SEM

ITEM	FACTOR LOADING
Social Influence (Unal & Uzun, 2021; Sinaga & Pustika, 2021)	
Online learning communities influence my adoption of educational technology.	.735
My family supports my use of technology for educational purposes.	.734
I use technology for learning statistics because my classmates do.	.735
My instructors expect me to use technology in my statistics coursework.	.816
My peers encourage me to use technology for learning statistics.	.753
Self-Efficacy (Natasia, Wiranti, & Parastika, 2022; Fauzi et al., 2021)	
I believe I can successfully complete statistical tasks using technology	.748
I feel competent in applying technology to solve statistical problems	.763
I can troubleshoot minor technical issues while using educational technology	.739
I can effectively use statistical software and online tools without help.	.776
I am confident in my ability to use technology for statistics learning.	.701
Perceived Usefulness (Kanwal, & Rehman, 2017; Daragmeh, Lentner, & Sagi, 2021)	
Using technology enhances my learning experience in statistics	.655
Educational technology improves my understanding of statistical concepts	.668
Technology makes completing statistics-related tasks more efficient.	.577
Learning statistics through technology increases my productivity	.629
I find technology useful in performing my statistical coursework	.947
Perceived Ease of Use (Prastiawan et al., 2021; Chen & Aklikokou, 2020; Filieri et al., 2021)	
I can use educational technology without assistance	.702
It is easy for me to become skillful at using technology for learning statistics	.742
I find educational technology to be flexible and easy to use	.721
Interacting with technology for learning statistics is simple and understandable	.753
I find it easy to learn how to use technology for statistics education	.766
Attitude Toward Using (Sinaga & Pustika, 2021; Al-Rahmi et al., 2021)	
I enjoy using technology for learning statistics.	.744
I believe that using technology makes learning statistics more engaging	.739
Using educational technology is a good idea for statistics learning	.789
I have a positive attitude towards integrating technology into my studies	.773
I feel comfortable using technology for statistics coursework	.755
Behavioral Intention (Sinaga & Pustika, 2021; Al-Rahmi et al., 2021)	
I intend to use technology-based tools (e.g., statistical software, online learning platforms) in my statistics courses regularly.	.754
I plan to continue using technology for learning statistics even after completing my current course.	.737
I am willing to recommend the use of technology to my peers for learning statistical concepts.	.748
I expect to rely on technology (e.g., e-learning, statistical software) to improve my understanding of statistics in the future.	.741
If I have access to technology-based learning tools, I will actively use them to enhance my statistical skills.	.740

Source: Own Work

Based on Table 2, all measurement items used to reflect the six constructs—Social Influence, Self-Efficacy, Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, and Behavioral Intention—showed acceptable to strong loadings, indicating good construct reliability and convergent validity. With just one item under Perceived Usefulness slightly below at 0.574, which is still considered acceptable in exploratory research, most items recorded standardized loadings above the commonly accepted threshold of 0.70 across the constructs. With 0.940, the highest loading noted reflects a strong indication of perceived value in completing statistical homework. Emphasizing the importance of both formal and informal networks in determining students' technology adoption behaviors, items related to social pressure—including expectations from teachers and peer encouragement—loaded strongly on Social Influence. In similarly high degrees of confidence among students in independently managing and using technology to solve statistical problems, self-efficacy items were included.

While Attitude Toward Using showed consistently strong indicators, confirming students' favorable attitude toward integrating technology in their learning processes, Perceived Ease of Use was consistently reflected through student responses stressing the simplicity and flexibility of using instructional technologies. Finally, consistent loading of Behavioral Intention items indicates students' obvious dedication to keep using and recommending technology in statistics education. These findings generally support the fact that the measurement items fairly reflect their intended construct and offer a strong basis for later structural model analysis.

The structural equation model's fitness indices showed a first-rate overall model fit. With a Chi-square to degrees of freedom ratio (φ^2/df) of 1.624, which is much below the generally accepted threshold of 3.0, the observed data and the hypothesized model seem to have minimal difference. The RMSEA is 0.041, suggesting a close and reasonable fit, since values below 0.05 show a quite good approximation of the population covariance structure. Both surpassing the 0.95 benchmark usually connected with outstanding fit, the Comparative Fit Index (CFI) is 0.954, and the Incremental Fit Index (IFI) is 0.955. The Tucker-Lewis Index (TLI) was also reported at 0.949, somewhat below the 0.95 cut-off but still within a range suggesting good model fit. These indices show that the model can be regarded as robust for structural analysis and further interpretation and fits the data rather well.

4.1.3. Reliability and Validity Assessment

Six constructs evaluated using Confirmatory Structural Equation Modeling (CSEM) have their average variance extracted (AVE) and composite reliability (CR) values shown in this table. Evaluating the convergent validity and internal consistency dependability of the measurement model depends mostly on these values. All constructions showed CR values above 0.80, which exceeds the generally accepted threshold of 0.70 (Hair et al., 2024), indicating that the items inside each construct are highly consistent and regularly measure the latent variables. This implies that the measuring scales used in the research were internally consistent.

An AVE value of 0.50 or above is usually regarded as reasonable for convergent validity, which is the degree to which a construct explains the variance of its indicators. Therefore, it can be concluded that each of the six constructs demonstrates appropriate convergent validity because they all meet or exceed the threshold of 0.50 for the AVE. This indicates that each construct captures a substantial part of the variance that is derived by its indicators (Table 3)

Table 3. AVE and CR

Construct	CSEM AVE	CSEM CR
Social Influence	.570	.869
Self-Efficacy	.556	.862
Perceived Usefulness	.500	.829
Perceived Ease of Use	.543	.856
Attitude toward Using	.578	.872
Behavioural Intention	.554	.861

This study omits the cross-loading results because the model utilizes first-order constructs for all elements within the research framework. The Fornell and Larcker criterion was employed to evaluate discriminant validity using conventional structural equation modeling (CSEM), as presented in Table 4. Notwithstanding this limitation, the study successfully performed a significant comparison of factor loadings, enabling the computation of the Average Variance Extracted (AVE) and Composite Reliability (CR). These metrics are crucial for assessing the reliability and validity of the constructs, thus ensuring the robustness of the model's theoretical foundations and the integrity of its findings. This approach emphasizes the methodological rigor of the study and highlights the specific analytical choices made regarding the structural specifications of the model. The results show that discriminant validity was achieved, as shown in Table 4.

Table 4. Discriminant Validity

	Attitude Using	Social Influence	Self Efficacy	Perceived Usefulness	Perceived Ease Use	Behavioral Intention
Attitude Using	0.760					
Social Influence	0.474	0.755				
Self Efficacy	0.521	0.500	0.746			
Perceived Usefulness	0.450	0.382	0.426	0.701		
Perceived Ease Use	0.479	0.496	0.508	0.406	0.737	
Behavioral Intention	0.471	0.566	0.515	0.341	0.521	0.744

Source: Own Work

4.1.4. Structural Model

Using AMOS, figure 1 shows the SEM analysis findings, highlighting both the structural components and measurement of the model. The fit indices showed an adequate degree of model adequacy (ChiSq/df = 1.624, RMSEA =.041, CFI =.954, IFI =.955, TLI =.949), and the general model fit was judged to be good. A set of observed indicators measured all constructions, and most factor loadings exceeded the advised threshold of 0.60, indicating that the indicators sufficiently reflected their respective latent constructions.

The coefficient of determination (R^2) revealed that the model accounted for 39% of the variation in "Attitude Toward Using" and 44% of the variance in "Behavioral Intention," indicating that the model had sufficient explanatory power. The proposed model is theoretically robust and experimentally validated, offering significant insights into the primary determinants of users' behavioral intentions regarding technology acceptance.

Table 5. Structural Results

			Estimate	S.E.	C.R.	P	Result
Attitude_Using	<---	Perceived_Usefulness	.222	.065	3.430	***	Significant
Attitude_Using	<---	Social_Influence	.179	.063	2.844	.004	Significant
Attitude_Using	<---	Self_Efficacy	.266	.071	3.768	***	Significant
Attitude_Using	<---	Perceived_Ease_Use	.160	.059	2.714	.007	Significant
Behavioral_Intention	<---	Attitude_Using	.135	.065	2.076	.038	Significant
Behavioral_Intention	<---	Perceived_Ease_Use	.190	.059	3.226	.001	Significant
Behavioral_Intention	<---	Perceived_Usefulness	.000	.063	.006	.996	Not Significant
Behavioral_Intention	<---	Social_Influence	.299	.065	4.637	***	Significant
Behavioral_Intention	<---	Self_Efficacy	.195	.071	2.766	.006	Significant

The structural model (Table 5) was evaluated to investigate the expected relationships among the constructs. Attitude Toward Using was influenced by all four antecedent factors, as shown in the table. Attitude (β =.222, CR = 3.430, p <.001) was specifically positively and significantly influenced by perceived usefulness, meaning that those who find the system useful are more likely to develop a favorable attitude toward using it. Attitude (β =.179, CR = 2.844, p =.004) was similarly highly predicted by Social Influence, implying that external social pressure or expectations help shape users' attitudes. Furthermore, Self-Efficacy had the strongest impact on attitude (β =.266, CR = 3.768, p =.001), which reflects that people's confidence in their capacity significantly influences their readiness to implement the system. Although with a somewhat smaller magnitude, PU also had a notable impact on attitude (β =.160, CR = 2.714, p =.007), improving user acceptance at the attitudinal level.

Five direct paths were investigated for predicting behavioral intention. With a significant and strong positive effect (β =.299, CR = 4.637, p <.001), Social Influence was the strongest predictor, underscoring the important role peer and society expectations play in determining intention. Significant predictors were self-efficacy (β =. 195, CR = 2.766, p =.006) and Perceived Ease of Use (β =.190, CR = 3.226, p =.001), indicating that both internal confidence and usability influence users' intent to use the system. Attitude Toward Using supports its mediating function in the technology acceptance process by a statistically significant, though smaller, effect on Behavioral Intention (β =.135, CR = 2.076, p =.038). Fascinatingly, Perceived Usefulness had no appreciable direct influence on Behavioral Intention (β =.000, CR =.006, p =.996), suggesting that attitude or another factor entirely mediates its impact or is overwhelmed by other factors, including Social Influence and Self-Efficacy.

Table 6. Indirect Effect Results

PATH	INDIRECT EFFECT (β)	DIRECT EFFECT (β)	RESULT
Perceived Ease Use → Attitude Using → Behavioral Intention	0.024 (Significant)	0.21 (Significant)	Hypothesis is supported. The type of mediation is partial.
Perceived Usefulness→ Attitude Using → Behavioral Intention	0.026 (Significant)	0.00 (Not Significant)	Hypothesis is supported. The type of mediation is full.
Social Influence→ Attitude Using → Behavioral Intention	0.024 (Significant)	0.31 (Significant)	Hypothesis is supported. The type of mediation is partial.
Self Efficacy→ Attitude Using → Behavioral Intention	0.033 (Significant)	0.19 (Significant)	Hypothesis is supported. The type of mediation is partial.

Based on Table 6, the mediation research examined whether Attitude Toward Using mediates the association between the exogenous factors and Behavioral Intention. Although its direct effect is substantial (β = 0.21, p < .05), the findings indicate that Perceived Ease of Use exerts a large indirect impact on Behavioral Intention via Attitude (β = 0.024, p This indicates a partial mediation in which ease of use directly influences users' intention to utilize the technology while also indirectly enhancing their attitude towards its utilization.

Similarly, Social Influence exhibited a robust and significant direct effect on Behavioral Intention (β = 0.31, p < .05), along with a notable indirect effect through Attitude (β = 0.024, p < .05), so demonstrating another instance of partial mediation. This conclusion indicates that cultivating a favorable disposition towards system utilization directly and indirectly affects users' susceptibility to social pressures.

Concerning self-efficacy, both the direct impact on behavioral intention (β = 0.19, p < .05) and the indirect effect through attitude (β = 0.33, p < .05) were significant, thereby confirming another instance of partial mediation. This outcome substantiates the idea that individuals' confidence in their ability to utilize the system influences their intentions both directly and indirectly through their attitudes.

In contrast, the direct impact of Perceived Usefulness on Behavioral Intention was negligible (β = 0.00, p = ns), but the indirect effect through Attitude was considerable (β = 0.026, p < .05). This indicates that Attitude Toward Using completely mediates the influence of Perceived Usefulness on Behavioral Intention. In other words, utility alone does not inherently motivate intention unless it fosters a favorable disposition.

4.2. Discussion

In order to find out how well a learning platform enhances students' experiences and acceptance of learning statistics, quantitative data was collected. Evaluating the platform's impact on learning outcomes and adoption was the primary objective. Strict statistical methods, such as Confirmatory Factor Analysis (CFA), were used to guarantee the validity and dependability of the research model. Each latent construct in the framework was validated using CFA. Convergent validity and internal consistency were confirmed by the findings, which showed that all constructs met or surpassed the suggested thresholds for Average Variance Extracted (AVE) and Composite Reliability (CR). The measurement model's soundness was supported, for example, by the fact that all six constructs—Social Influence, Self-Efficacy, Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, and Behavioral Intention—reported CR values above 0.80 and AVE values at or above 0.50. These results highlight CFA's capabilities as a strong methodological tool that allow researchers to precisely validate measurement models and investigate intricate relationships between latent variables (Afthanorhan, Awang, & Aimran, 2020). Strong model fit indices and noteworthy inter-construct correlations further reinforced the model's integrity and bolstered trust in the used structural framework.

Insightful conclusions about the predictive relationships within the Technology Acceptance Model (TAM) were obtained from the structural analysis after the measurement model was validated. The findings showed that Attitude Toward Using was significantly improved by Perceived Utility, Social Influence, Self-Efficacy, and Perceived Ease of Use. Behavioral Intention to use educational technology for statistics learning was then significantly influenced by Attitude Toward Using, Perceived Ease of Use, Social Influence, and Self-Efficacy. Interestingly, there was no statistically significant correlation between perceived usefulness and behavioral intention, indicating that its influence is mediated indirectly through students' attitudes. Additionally, four noteworthy mediating effects were validated, underscoring the pivotal function of Attitude Toward Using as a crucial mechanism connecting the antecedents to behavioral intention. These results support TAM's theoretical soundness and provide important insights into how social, cognitive, and attitudinal factors interact to influence students' adoption of educational technologies in higher education settings.

5. CONCLUSION

In summary, this study applies rigorous statistical procedures to validate the Technology Acceptance Model's (TAM) theoretical and empirical strength in the context of statistics education. All constructs exhibited satisfactory levels of reliability and convergent validity, according to Confirmatory Factor Analysis (CFA), with Composite Reliability (CR) values exceeding 0.80 and Average Variance Extracted (AVE) values meeting or exceeding the suggested 0.50 threshold. These results validate the measurement model's reliability and lend credence to its application in assessing students' adoption of educational technology.

The structural analysis also showed that Attitude Toward Using Educational Technology was significantly positively impacted by Perceived Usefulness, Social Influence, Self-Efficacy, and Perceived Ease of Use, while Behavioral Intention was significantly influenced by Attitude, Social Influence, Self-Efficacy, and Perceived Ease of Use. The impact of perceived usefulness may be better explained by attitudinal mediation, as evidenced by the fact that the only non-significant path was from perceived usefulness to behavioral intention. Four important mediating effects in all were found, highlighting the critical role that attitude plays in influencing students' intentions to use digital learning tools for statistics.

Despite statistics' historically formula-intensive and calculation-driven nature, it can be concluded that undergraduate students today are more likely to embrace digital learning methods for their statistics education, as evidenced by the fact that almost all hypothesized relationships were supported. This represents a clear departure from the traditional teaching methods that were popular before the COVID-19 pandemic. Digital education has become more commonplace in the pandemic era, and students now seem to favor it because of its accessibility and flexibility. Many students value the ability to review lectures at their own pace, particularly those who are self-motivated or who are having academic difficulties. Furthermore, students who participate in extracurricular activities or who hold leadership positions can better balance their academic obligations thanks to digital learning.

There is encouraging potential for the future development of micro-credential or MOOC-based statistics courses given the increasing acceptance of digital learning in a quantitative field like statistics. Such platforms were previously believed to be best suited for non-technical subjects, but recent trends show that students are technologically savvy and prepared to interact with complex material via digital platforms. The flexibility of asynchronous learning, which measures participation and progress through task completion rather than in-person attendance, is another advantage for part-time students.

This change is consistent with broader cultural changes in the way that technology is incorporated into day-to-day activities. Beyond classroom instruction, this shift also has implications for broader capacity development, as digital competencies acquired in higher education increasingly shape graduates' participation in the labor market and their engagement within professional and community contexts. Education is changing quickly, much like the world has moved toward electric cars, which were once thought to be an unthinkable alternative to fuel-based transportation. People must constantly improve their skills and adaptability to keep up with the rapid advancements in technology. This momentum is reflected in digital learning in statistics education, which urges educators, institutions, and policymakers to adopt innovative curriculum delivery methods that cater to the needs of modern students.

In order to preserve methodological rigor and relevance, future research should keep improving validation techniques. Predictive power and theoretical understanding could be enhanced by incorporating machine learning, Bayesian techniques, or mixed-method designs. The external validity of such findings will also be improved by broadening the scope to encompass more varied student demographics, geographic locations, and educational contexts. In the end, a better comprehension of behavioral intention and digital learning preferences will significantly advance the continuous transformation of higher education in the digital era.

Ethical Approval

Not Applicable

Informed Consent Statement

Not Applicable

Authors' Contributions

AA contributed to the conceptualization of the study, development of the research framework based on the Technology Acceptance Model, and overall coordination of the research process. He also led the data analysis using confirmatory factor analysis and covariance-based structural equation modeling, as well as contributed to the interpretation of the empirical results. NZM was involved in the research design, questionnaire development, and data collection process. She also contributed to the validation of the measurement model and assisted in drafting the methodology and results sections of the manuscript. NHF contributed to the theoretical review and refinement of the research constructs, particularly those related to behavioral intention, perceived usefulness, and perceived ease of use. She also supported the discussion of mediation effects and ensured theoretical consistency. MF contributed to the discussion of technological integration in statistics education and the practical implications of digital learning. He also assisted in interpreting the findings from the perspective of educational innovation and sustainability. ANA provided support in statistical modeling and methodological rigor, particularly in evaluating model fit, reliability, and validity. He also reviewed the analytical procedures to ensure accuracy and robustness of the findings. SAM contributed to the critical review of the manuscript, refinement of the discussion, and alignment of the findings with broader trends in technology-enhanced learning. He also participated in revising the manuscript to improve clarity, coherence, and academic quality.

Disclosure statement

Throughout the research process and writing of this journal article, the research team affirms that none of the researchers had any personal interest in the research, data collection, data analysis, or publication. This study was conducted to ensure that the journal article produced by the research team would have an impact, particularly on the management of sustainable tourism, with the goal of increasing local revenue from the tourism sector and improving the welfare of the surrounding community.

Data Availability Statement

The primary data in this study is sourced from the direct results of the research, while the secondary data is sourced from several research publications. If any researcher wishes to conduct further research on the same topic, the researcher is willing to share the data.

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