The Impact of the Learning Mobile Application on Student Performance Using the Technology Acceptance Model

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***Abstract*—Technology is being increasingly used in education to develop various forms of media that effectively support instruction and learning. The purpose of this study is to determine the extent to which students majoring in electronics engineering education at Higher Education benefit from the use of different learning applications and how much influence they have on the overall level of student performance, by exploring the area of the correlation between the independent variable of Learning Strategy and student performance, with the consideration of the Technology Acceptance Model (TAM) as a possible mediator in this correlation. The current study utilized purposive sampling to collect a representative sample of 229 participants. The data was then analyzed using the Structural Equation Model (SEM), utilizing the Partial Least Square (PLS) method as the initial approach. The software used for this analysis was SmartPLS 4.0 and Network Analysis was conducted to determine the relationship between items in this study. Based on the results of this study, effective learning strategies and a high level of student acceptance of technology will have a positive impact on student performance or lead to improved student performance. Educational applications provide the potential to be streamlined and utilized by students through a pedagogical approach, as their user-friendly nature facilitates effective deployment.**

***Keywords*—performance, technology acceptance model, smartphone application, structural equation model, network analysis**

I. Introduction

Due to the rapid advancement of technology, educational institutions, education providers, and teachers now have access to the most modern teaching resources. Using digital platforms, multimedia presentations, and educational software, educational institutions can now provide students with stimulating and participatory lessons. while in periods of crises such as the COVID-19 pandemic, technology has played a significant role in facilitating distance and online learning [1]. Based on active learning technology, students' learning motivation is currently undergoing development, and to modernize education, not only the standard of education must change, but also the way students think. The quality of education and the tools available have a big impact on how motivated students are [2]. Thanks to learning management systems, video conferencing tools and online collaboration platforms, learners can now continue their education even when they are not physically present in the classroom.

This ensures that they receive consistent education and makes it easier for them to access it. The use of technology makes collaboration between learners and education providers and teachers easier [3]. Online discussion forums promote collaboration among learners, allowing them to collectively construct knowledge, share ideas, and actively participate. Video conferencing tools, and networking systems, collaborative tasks can be carried out despite participants' geographical dispersion. Students and education providers and wealth of information that was previously unavailable to teachers that is now inaccessible thanks to the internet. E-books, educational websites, and digital libraries are examples of online resources that provide access to a wide variety of educational materials [4]. As a result, traditional textbooks are no longer the only source of educational information.

Formal educational institutions that have the responsibility to produce the best graduates are required to be able to prepare their students to continue to adapt to the shifts that have taken place in order to acquire trustworthy abilities in the professional sphere [5]. It is important for electronics engineering education, industry and community stakeholders to work more closely together. Educators must modify course material to meet the changing demands of the workforce [6]. This is done in the belief that enhancing people's educational opportunities will help them become better informed and better equipped to handle the challenges they encounter on a daily basis. Development in an educational environment equipped with the competence of the desire to learn that exists in every student increases awareness of the importance of their innovation [7].

Smartphone technology is increasingly integrated into the educational experience of today's learners [8]. Learning remotely has emerged as a viable option thanks towards the strong advancement of technological devices through applications designed to provide lessons or learning materials that are always available on the application and can be accessed whenever the learner wants. The tendency of students to spend a lot of time using smartphones [9], can have a good impact on the design of smartphone-based applications. This is a support for students to be able to open the lessons they want wherever and whenever they want.

The use of innovative tools for teaching and training has the potential to improve not only overall learning outcomes for learners, but also the quality of their understanding,

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opportunities to access learning, learner capacity for skill development through the use of real-world experiences, and overall learning outcomes. However, if the learner is not interested in utilizing these expectations, then they will be pointless [10]. The usefulness of lessons that utilize readily available media is constantly being improved. The process of making learners understand the relevance of what they are learning should be considered. Therefore, it ought to be studied to comprehend the acceptance or rejection of online learning environments by potential students and to determine the factors that have an effect their adoption technologies [11].

In the technology acceptance paradigm described by Davis [12], perceived usefulness and perceived ease of use have an impact on the attitude of technology users. Mobile learning applications have been found to improve students' academic performance and capacity for learning. Lai *et al.* [13] found that students' perspectives on their coursework were significantly influenced by their use of technological tools. In this investigation, students' use of a smartphone app as a learning tool is being investigated. Mobile learning applications can boost students' happiness with their learning experience, as they often provide a more interesting and interactive learning environment. Educational institutions must develop innovative pedagogical methods to keep up with technological advances. Mobile media devices are becoming more popular because students need easy access to course materials [14]. Education providers can adapt to improve student learning.

There is a strong correlation between the ease of utilizing readily available resources and how well users realize the value of a resource [15]. Therefore, using a TAM-based model, the primary objective of our study is to determine whether or not the educational practices of students who participate in online learning environments, which may include virtual laboratories, interactive exercises, learning videos, and tools, are aligned with those of the online learning environments themselves [16], and the influence that can have on the educational performance of learners in electronics engineering education. University teachers and researchers studying how mobile apps affect engineering students can help students succeed. Engineering labs can be improved with mobile apps with real-time data, simulations, and other interactive learning tools. This study could determine if mobile learning in engineering labs and classrooms makes learning more engaging.

This study wanted to find out if students' ways of learning are compatible with the apps that can help them learn and what effect that has on their ability to learn. Evaluating how well technology is used in schools is one way to make sure that the learning setting stays high for the students. Several studies have found that bachelor's degree holders in engineering need to quickly learn how to use new technologies to get professional jobs in the digital age we live in now. Another important issue is that conducting system evaluations to keep a high-quality learning environment for students requires specific technology-related skills [17].

From the explanation above, the general research questions of the present work are, (1) does the adoption of mobile applications in learning have a significant impact on students' learning performance (2) Is an approach like mobile applications well received by students. (3) Can the easy access to media offered by mobile apps have a positive influence on students? By answering this question, considerations regarding the uses of technology for online learning will be explored.

II. Literature Review

A. Learning Strategies

Individuals will apply various methods to achieve learning-related goals, and these methods are referred to as learning strategies [18]. Recognizing techniques, also known as cognitive strategies, have been the subject of extensive study and are generally agreed upon for their benefits; however, a consensus has yet to be reached on how best to define and categorize those approaches [19]. Learning strategies, as defined by Weinstein and Mayer [20], are actions or ways of thinking that are meant to affect how one learns new information, stores it in memory, and retrieves it when it is needed. These behaviors or thoughts can be displayed by learners when they are in the process of learning. Thus, according to Mayer [21], learning strategies are behaviors that shape the way learners process knowledge. Mayer defines these behaviors as learning strategies. Based on these definitions, the term "learning strategies" most often refers to methods that learners use to find solutions to their problems or procedures that enable learners to learn on their own [21].

B. Technology Acceptance Model

As higher education demand for e-learning materials and technological learning tools rises, so does students' desire to use and adopt them [14]. Understanding the factors that influence their acceptance is crucial. Davis's [12] Technology Acceptance Model (TAM) is the most widely used model for studying how people accept and implement new technology, information systems, and innovations. TAM says people use technology because of its utility, user-friendliness, and outlook on technology. TAM was used to analyze learner behavior related to education's adoption of cloud computing [22]. Faculty and student satisfaction with learning management systems has been measured using TAM [23, 24].

1) Perceived ease of use

Davis [15], defines perceived efficacy as the extent to which individuals anticipate that employing a given system will result in improved outcomes. Users' perceptions of the utility and usability of the technology are often cited as predictors of adoption; however, the effects of these perceptions can feel different for each technology and its users, depending on the context in which the technology is used [25]. The perceived usefulness and perceived ease of use of educational apps are predictive of participants' intended to continue using educational apps, as found by Cheon *et al.* [25]. Researchers Lai *et al.* [26] discovered that students' expectations for the use of technology were strongly correlated with their actual use of technology in the classroom. According to Park *et al.* [27], students' opinions of the value of mobile education are strongly influenced by their own estimations of its practicality.

Davis [15] argues that due to the apparent simplicity of technological advancement, the implementation of technology for educational purposes has developed into a fundamental component of every-day existence, and the variety of learning technology has increased across all fields of study. The views that students hold regarding the usefulness and accessibility of the instructional support system that they make use of have an impact on their attitudes toward participating in the learning process, which then in turn affects their interest to maintain experiencing by utilizing digital devices or in another setting with the utilization of equipment [28].

2) Perceived usefulness

In the technology acceptance model proposed by Davis [21], perceived usefulness and perceived ease of use have an impact on the attitude of technology users. In research conducted by Weng *et al.* [29], discovered that how learners make use of modern tools has a significant effect on their attitudes towards the lessons they are undergoing. In this study, the learning technology used is a smartphone-based application that has been used by students in undergoing their learning. User value is realized when resources are easily accessible. Our study uses a TAM model to determine whether students' educational practices in online learning environments, such as virtual laboratories, interactive exercises, learning videos, and tools, match the environments [12] and how that affects electronics engineering students' academic performance. We wanted to determine if students' learning styles fit learning applications and how that affects performance.

3) Attitude toward using application

Evaluation of educational technology maintains student learning standards. According to multiple studies, engineering graduates must swiftly adapt to new technologies to find work in the digital age. Technology skills are needed to provide high-quality education [13]. Innovative teaching and training technologies can increase students' learning, understanding, ease of learning, skill development through real-life situations, and overall learning. These instructions are less useful without the student's compliance [10]. Easy-to-use media lessons improve constantly. Consider helping learners understand why what they're studying matters. Thus, it should be investigated why certain students are amenable to online learning and others are not [11]. The utilization of smartphones among contemporary students within educational settings has witnessed a notable rise [8]. The ability to engage in remote learning has become feasible as a result of the swift progress in technology. Students have constant access to mobile applications that offer educational lessons and supplementary learning resources. The extensive utilization of mobile phones by students [9] proves advantageous for developers of phone applications. This feature enables students to participate in lessons at their convenience and from any location. Mobile applications can affect students' academic performance and happiness depending on the type of app, the setting in which it is used, and their backgrounds.

C. Performance

Learner performance can be defined and measured in numerous methods that are not limited to course completion, grade point average, and skill development [30]. Online education has been found to have detrimental effects on both high-achieving and low-achieving students, with a particular emphasis on the negative impact it has on the latter group [31–33]. The aforementioned figures provide evidence in favor of the assertion that online instruction has negative implications for instructors' professional trajectories. Based on empirical studies [34–37], it has been found that virtual classes present more rigorous challenges for students with lower academic performance. According to the findings of Johnson and Palmer [36], there is a higher propensity for students with worse academic performance to enroll in online courses. Pursuing a Bachelor's Degree in higher education has the potential to assist policymakers in creating an optimal educational setting for students. Senior students, who are on the verge of entering the volatile labor market, require a robust set of abilities. The present study offers an opportunity for practicum students to fulfill their obligations remotely, as opposed to being physically present in practicum classes, by engaging in simulations or practicums as required by their courses.

According to Driscoll *et al.* [38] and Lombardi and Oblinger [39] education institutions as well as educators may not always accurately capture learners' real learning capacities through the use of a variety of evaluations such as assessments, assignments, and final grades. The use of such assessments to gauge student progress is widespread, and they are generally accepted as valid measures of whether or not a course's stated goals have been met [40]. This study employs a technology-based learning strategy, in this case android-based applications (Fig. 1), to demonstrate that the learning of students enrolled in electronic engineering education programs affects student performance, with the Technology Acceptance Model (TAM) serving as a mediating connection among each of them.

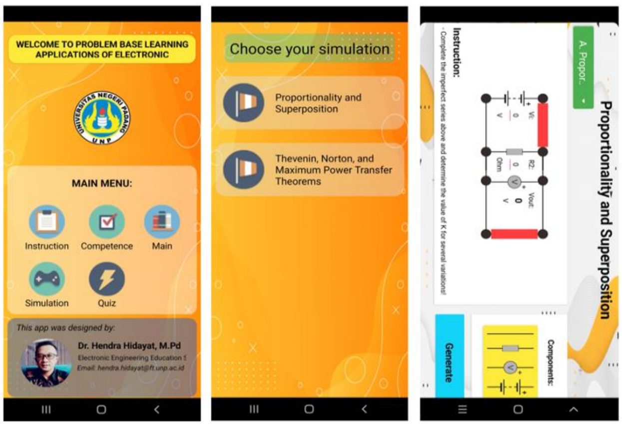

Fig. 1. The mobile android learning application.

III. Method

A. Data Collection

Based on the compiled findings of Burns and Grove [41], a comprehensive research recording procedure encompasses various elements such as research settings, component members and populations, limitations in studying trust, as well as methods for accumulating and investigating data in research endeavors. The sampling methodology employed in this study was purposive sampling, which was utilized to acquire a sample that effectively represents the research objectives and fulfills the criteria for obtaining reasonably accurate information from students. The study consisted of a sample size of 229 participants who were enrolled as students in the Electronics Engineering Education program at Padang State University. The participants possessed prior experience in utilizing educational applications based on the Android platform, which was specifically developed to facilitate the process of learning. The participants for this study were obtained through online channels, and they completed a questionnaire using a web-based platform that had been prearranged.

B. Measures

To assess the learning strategies variable, this study utilized four items from a previous study conducted by Stark [14], which were hypothesized to effectively represent the variable under investigation. Students' provision of responses to questions related to "Repeating subject matter" and "remembering keywords of important concepts" serves as a means to assess the degree to which they are employing effective learning strategies.

To assess the construct of Perceived Usefulness, a key component of the Technology Acceptance Model (TAM), this research employed three items that were selected based on prior findings by Weng *et al.* [29], which suggested their suitability in capturing the essence of the construct under investigation. The variable being discussed here pertains to the measurement of students' perception of the usefulness of the learning applications they utilize, in response to assertions such as "Technology enhances interest in learning" and "Technology is beneficial for students." The aforementioned statements pertain to the utilization of learning applications based on the Android platform, which have been specifically designed to facilitate the process of acquiring knowledge.

To assess the construct of Perceived Ease of Use, a key component of the Technology Acceptance Model (TAM), this study employed four items that were selected based on prior research conducted by Weng *et al.* [29], which suggested that these items were likely to accurately capture the essence of the construct. These statements pertain to the accessibility of options provided by the Android-based educational application. The application offers multiple choices to assist students in their learning process. This variable assesses the degree to which students perceive the application as user-friendly, as indicated by their responses to statements such as "This technology is characterized by ease of use" and "The application is easily accessible and simple to learn".

This study incorporated three items, as suggested by Weng *et al.* [29], to assess the Attitude Toward Using Application variable, which is a key component of the Technology Acceptance Model (TAM). These items were selected based on prior research and are expected to effectively capture the essence of this variable. The three components under consideration are as follows: (1) an individual's attitude toward utilizing an application; (2) An individual's view of the usefulness of the application; and (3) An individual's view of the ease of using the application. This variable assesses the degree to which students' attitudes are inclined towards utilizing the Android-based learning application that has been made available, as indicated by their responses to statements such as "Attitude towards granting permission for use" and "the level of enthusiasm exhibited by users towards the application". This pertains to the attitudes exhibited by students in their utilization of Android-based educational applications.

This study aims to assess the performance variable, which quantifies the degree of success of the learner's strategy when utilizing the provided learning application, with the assistance of the Technology Acceptance Model (TAM). To measure this variable, three items have been selected, which are anticipated to accurately represent this variable. These items have been chosen based on prior research conducted by Sharma *et al.* [42]. This variable quantifies the proficiency of the learner in effectively utilizing pre-existing learning applications. This process involves the learner's response to statements such as "Perceived increase in skills" and "Association of value with the achieved learning outcomes."

C. Data Analysis

The data was analyzed using the Partial Least Squares (PLS) method in conjunction with SmartPLS version 4 to generate a Structural Equation Model (SEM). This decision was made due to the fact that Partial Least Squares (PLS) serve as an alternative methodology to the conventional Structural Equation Modeling (SEM) technique. The reliability of both the data and the underlying structural model was assessed. The present study was carried out following the two-stage data analysis approach suggested by Anderson and Gerbing [43], the initial phase involved an examination of the soundness and consistency of the research constructs in relation to the measurement model. The study examined the convergent validity of the items through the utilization of item loading and Average Variance Extracted (AVE). Additionally, the discriminant validity of the items was assessed using the Heterotrait-Monotrait Correlation Ratio (HTMT). Furthermore, the researchers employed Composite Reliability (CR) and Cronbach's alpha to examine the interdependence and internal consistency of the research constructs. During the second phase, we conducted an analysis to assess the statistical significance of the structural relationships among the various components of the research. In order to accomplish this, a total of 5,000 bootstrap samples were generated.

D. Network Analysis

The practice of representing system-related data and information in the form of a network is commonly known as network analysis. This approach is a viable method that can be employed for this purpose. The system is comprised of component parts known as "nodes" and "edges" [44]. Nodes in this context refer to distinct psychological elements such as mood states, symptoms, or attitudes, which possess the property of differentiability. On the other hand, edges represent statistical connections that lack certainty and require estimation [45]. Edges in a network are commonly known as links as they establish a connection between two nodes. Links, in the context being discussed, can be referred to as edges. The application of statistical modeling in network analysis reveals the importance of the interactions among multiple variables. Hence, the utilization of network analysis holds the capacity to elucidate the enigmatic data patterns generated by the latent variable model.

The study employed a visual network analysis approach to examine data collected from participants who completed a structured questionnaire. The analysis was conducted using Jeffreys' Amazing Statistics Program (JASP) software. The utilization of JASP was necessary for conducting this particular analysis. The process was conducted using the JASP platform. The EBICglasso model was employed during the network assembly process. The model in question is based on the Extended Bayesian Information Criterion (EBIC) [46], which is a regularization technique derived from the graphically least absolute shrinkage and selection operator [47]. The aforementioned blueprint was employed as the foundational framework for the establishment of the network, and it was effectively utilized in the pursuit of this undertaking. By setting the tuning parameter to 0.5, the resulting network will exhibit a higher level of condensation and enhanced comprehensibility. This phenomenon can be attributed to the network possessing a reduced number of constraints and an increased level of specificity and sensitivity, the network comprises nodes that establish connections between two fundamental factors, and the nodes that serve as bridges are characterized by their symptomatic nature. Nodes are fundamental elements within a network that serve to symbolize and encapsulate crucial characteristics of the variables under investigation [48]. Although edges represent the linkage between nodes, the thickness of an edge is inversely related to the extent of correlation between the two nodes. The different directions of correlation are denoted by the distinct colors of the edges. Specifically, the blue and red edges correspond to positive and negative correlations, respectively. The central region of the graph exhibits several correlations among the variables.

The researchers conducted calculations and analyses of centrality indices to determine the relative importance of each node within the network. Several centrality indices that are closely interconnected include betweenness, closeness, and strength [47, 49]. There exists a strong correlation between betweenness and closeness measures. Based on the findings of prior studies, it was determined that the strength index exhibited the highest level of reliability compared to other indices. The index for determining the degree of direct relation between a given node and other nodes in the network can be obtained by calculating the sum of the absolute weights of all edges connecting the given node to the directly connected nodes in the network [50]. The index quantifies the extent to which a specific node is directly connected to other nodes within the network. Previous research findings have consistently demonstrated that the strength index exhibits the highest level of reliability compared to other indices. Furthermore, the concept of Expected Influence (EI), which refers to the anticipated impact, was employed to consider potential conflicting connections.

IV. Result and Discussion

A. Descriptive Results

Among the 229 data points collected the respondent profile presented in Table 1, 170 individuals identified as male, accounting for 74.24% of the total sample. Conversely, 59 respondents identified as female, representing 25.76% of the overall population. In the age group ranging from twenty-three to twenty-four years old, there were a total of nine participants, accounting for 3.39% of the overall respondents. Similarly, the age group spanning from twenty-one to twenty-two years old consisted of 81 participants, representing 35.37% of the total respondents. Furthermore, the age range between nineteen and twenty years old included 102 individuals, comprising 44.54% of the total respondents. Lastly, the age group of seventeen to eighteen years old had 37 participants, making up 16% of the total respondents. Among the individuals who utilize smartphones for more than ten hours per day, a total of 74 individuals or 32.31% fall into this category. Similarly, within the group that uses smartphones for a duration of seven to nine hours, there are 82 individuals or 35.81%. The group consisted of 55 individuals who engaged in work for a duration ranging from four to six hours per day, constituting approximately 24.02% of the overall population. Additionally, there were 18 individuals who worked for a duration ranging from one to three hours per day, accounting for approximately 7.86% of the total population.

Table 1. Respondent profile

Demographics	Variable	Frequency	Percentage
Gender	Man	170	74.24%
	Woman	59	25.76%
	Total	229	100.00%
Age	17–18	37	16.16%
	19–20	102	44.54%
	21–22	81	35.37%
	23–24	9	3.39%
	>24	0	0%
	Total (years old)	229	100.00%
Duration of Using Smartphone a Day	1–3	18	7.86%
	4–6	55	24.02%
	7–9	82	35.81%
	>10	74	32.31%
	Total (hours)	229	100.00%

B. Measurement Model

The study employed the internal Variance Inflation Factor (VIF) statistical technique and the Partial Least Squares Structural Equation Modeling (PLS-SEM) method to determine the existence of a shared bias [51]. Based on the data presented in Table 2, it can be observed that all values pertaining to Composite Reliability and Cronbach's alpha exceed the threshold of 0.70 [52]. The data successfully passed the convergent validity test, as evidenced by the results presented in Table 2. This is indicated by the fact that all of the factor loadings for each indicator on their respective latent constructs exceed the established threshold of 0.60. The VIF values observed in this study ranged from 1.503 to 2.834, which falls below the established criterion of 3.30 [53] for ensuring that significance tests are not affected by a common method bias. Additionally, the Average Variance Extracted (AVE) for each construct surpasses the benchmark value of 0.50, as referenced in a previous study [52].

The Heterotrait-Monotrait Ratio (HTMT) method was employed to assess the discriminant validity between two reflective constructs is presented in Table 3. In order to determine validity, a criterion called HTMT value, which was required to be less than 0.9, was used. The obtained results of the discriminant validity test exhibited a range from 0.667 to 0.876, which falls below the recommended threshold of 0.9 suggested by esteemed scholars and practitioners in the relevant field.

Table 2. Variance Inflation Factor (VIF), Cronbach's Alpha, Composite Reliability, Average Variance Extracted (AVE)

Indication	VIF	Cronbach's alpha	CR	AVE
ATUA1	1.941	0.821	0.821	0.736
ATUA2	1.790			
ATUA3	1.805			
ATUA4	1.832			
LS1	1.813	0.866	0.872	0.714
LS2	2.295			
LS3	2.394			
LS4	2.031			
PEU1	2.300	0.891	0.892	0.753
PEU2	2.253			
PEU3	2.834			
PEU4	2.455			
PU1	1.670	0.778	0.783	0.692
PU2	1.689			
PU3	1.503			
PU4	1.534			
Pr1	1.920	0.831	0.849	0.746
Pr2	2.139			
Pr3	1.777			

Note: ATUA: Attitude Toward Using Application; LS: Learning Strategies; PEU: Perceived Ease of Use; PU: Perceived Usefulness; Pr: Performance

Table 3. Heterotrait-Monotrait Ratio of Correlations (HTMT)

Indication	ATUA	LS	PEU	PU
LS	0.825			
PEU	0.803	0.841		
PU	0.876	0.828	0.868	
Pr	0.771	0.675	0.652	0.667

C. *Structural Model and Hypothesis Testing*

The outcomes of the data collected from participants and analyzed using SmartPLS are presented in Fig. 2 and Table 4. These visual and tabular representations illustrate the relationships between the proposed hypotheses in this study. The results of this study demonstrate that Hypothesis 1, which examines the impact of learning strategies on perceived usefulness, a key component of the Technology Acceptance Model (TAM), shows a statistically significant positive effect (β = 0.338, p < 0.001). Additionally, Hypothesis 2, which explores the relationship between learning strategies and attitude toward using the application, also indicates a significant association between these two variables (β = 0.197, p = 0.039). The relationship between learning strategies and perceived ease of use is found to be positive and significant (β = 0.742, p = 0.000), as hypothesized in Hypothesis 3.

The findings of this research study provide empirical support for Hypothesis 4, which posits that there is a positive and statistically significant relationship between perceived ease of use and perceived usefulness (β = 0.476, p < 0.001). According to Hypothesis 5, the impact of perceived usefulness on attitudes towards using an application is both positive and significant (β = 0.237, p = 0.019). Additionally, the effect of perceived ease of use on attitudes towards using an application is also significant and positive (β = 0.455, p = 0.000). The findings of the analysis conducted on Hypothesis 7 demonstrate a significant and positive effect of attitude towards using the application on performance (β = 0.646, p = 0.000).

Table 4. Direct effects hypothesis

Hypothesis	β	T	ρ	Results
H1: LS → PU	0.338	4.657	0.000	Supported
H2: LS → ATU	0.197	2.067	0.039	Supported
H3: LS → PEU	0.742	19.567	0.000	Supported
H4: PEU → PU	0.476	6.217	0.000	Supported
H5: PEU → ATU	0.455	5.785	0.000	Supported
H6: PU → ATU	0.237	2.354	0.019	Supported
H7: ATU → Pr	0.646	12.933	0.000	Supported

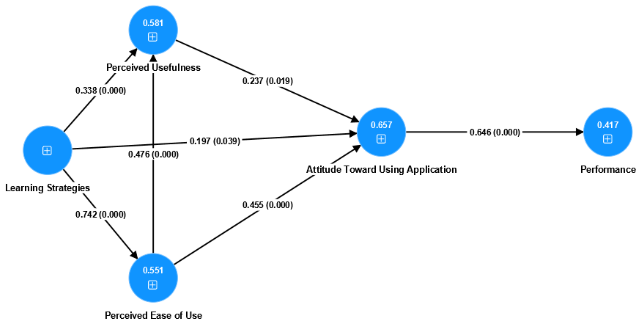

Fig. 2. Analysis result.

This study encompasses several variables that exhibit no direct correlation with each other, a subset of which are presented in Table 5. The study found that the Technology Acceptance Model (TAM) proposed in this research demonstrated a statistically significant positive impact (β = 0.451, p < 0.001). The impact of learning strategies on performance is mediated by this model. The study identifies two indirect relationships: the impact of learning strategies on perceived usefulness, which is mediated by perceived ease of use (β = 0.354, p = 0.000), and the influence of learning strategies on attitude toward using the application, mediated by perceived ease of use (β = 0.502, p = 0.000). These relationships are among several others investigated in this study. Furthermore, this study encompasses various direct relationships. The relationship between perceived ease of use and attitude towards using an application is mediated by perceived usefulness (β = 0.113, p = 0.037). Similarly, the relationship between perceived ease of use and performance is mediated by attitude towards using the application (β = 0.367, p = 0.000). Lastly, the relationship between perceived usefulness and performance is mediated by attitude towards using the application (β = 0.153, p = 0.022).

This study was using Structural Equation Modelling (SEM) which provides an explanation for how students come to accept and adopt learning applications that make use of utilizing technological tools to facilitate the learning process. Through the mediation of the technology acceptance model, this structural model is predicated on student performance-influencing learning strategies. This model is based on the user's attitude toward using the application, their expectations regarding its simplicity of use, and their perception of its utility. Our research results support the contention that Davis's [15] model is an important one with the potential to influence future technological advances in the field of education. Based on the results of several experiments designed to yield useful data for advancing the quality of the educational system, this conclusion has been reached.

Table 5. Indirect effects hypothesis

Indirect Effects	β	t	ρ	Results
LS → Pr	0.451	8.038	0.000	Supported
LS → PU	0.354	5.732	0.000	Supported
LS → ATUA	0.502	8.236	0.000	Supported
PEU → ATUA	0.113	2.083	0.037	Supported
PEU → Pr	0.367	7.134	0.000	Supported
PU → Pr	0.153	2.290	0.022	Supported

D. Network Analysis

The characteristics of nodes are presented in Table 6 and Fig. 3, specifically in relation to Betweenness. Among these characteristics, the highest Betweenness value is observed for learning strategies with item LS3, which has a value of 2.421, representing the highest value within this particular variable group. The highest variable in this network possesses the knowledge that it is an item of utmost significance and holds a favored position. Other items within the network rely on this particular item for their functioning. In alternative terms, the aforementioned variable possesses the comprehension that the aforementioned entity is an object of utmost worth. The aforementioned variable possesses the highest level of self-awareness within its respective group, and it is cognizant of this fact. The second betweenness value represents an individual's inclination to use the program ATUA2. With a value of 1.237, this indicates that it holds substantial importance and serves as a central node within the network. Furthermore, the second betweenness value signifies an individual's disposition towards utilizing the ATUA2 application.

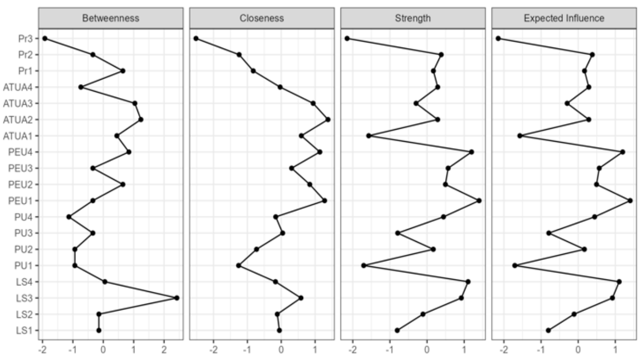

Fig. 3. Centrality plot.

Table 6. Centrality measures per variable

Variable	Network			
	Betweenness	Closeness	Strength	Expected influence
LS1	−0.145	−0.054	−0.803	−0.803
LS2	−0.145	−0.116	−0.110	−0.110
LS3	2.421	0.582	0.923	0.923
LS4	0.052	−0.170	1.106	1.106
PU1	−0.935	−1.260	−1.707	−1.707
PU2	−0.935	−0.730	0.168	0.168
PU3	−0.343	0.043	−0.791	−0.791
PU4	−1.133	−0.163	0.444	0.444
PEU1	−0.343	1.281	1.402	1.402
PEU2	0.644	0.842	0.495	0.495
PEU3	−0.343	0.307	0.568	0.568
PEU4	0.842	1.140	1.199	1.199
ATUA1	0.447	0.594	−1.571	−1.571
ATUA2	1.237	1.381	0.286	0.286
ATUA3	1.039	0.943	−0.296	−0.296
ATUA4	−0.738	−0.033	0.287	0.287
Pr1	0.644	−0.827	0.171	0.171
Pr2	−0.343	−1.243	0.381	0.381
Pr3	−1.923	−2.519	−2.154	−2.154

The determination of an item's closeness to its network group relies on the incloseness and outcloseness values of certain individuals [54]. The aforementioned values are employed for the purpose of quantifying the degree of proximity among certain individuals. In a role where it will serve as a resilient intermediary linking the other two elements of the network. The network exhibits a connector, referred to as ATUA2, which possesses the highest closeness value of 1.381, indicating its effectiveness in connecting various components within the network. The item with the second highest closeness value in the network is PU1, which is perceived to be useful. It has a closeness score of 1.281. This item serves multiple roles in connecting two other items in the network, thus contributing to its high closeness value.

The term "node strength" is used to describe the extent to which a specific node within a network is directly linked to other nodes in the same network. In order to achieve this objective, the cumulative weights of all the edges that are linked to the specific node are computed and subsequently aggregated [55]. All values have undergone standardization, wherein a higher value signifies a heightened level of network centrality. The network's item with the highest strength is PEU1, possessing a strength score of 1.402, thus making it the item with the utmost strength on the network. The strength score value ranked second highest is PEU4, which has a score of 1.199.

Visual network analysis is a method employed to investigate and analyze intricate networks. Nodes, also known as vertices, are the essential elements comprising a network. The additional constituent of a network is commonly known as edges, which are alternatively referred to as links due to their role in connecting the nodes [54]. The graph is composed of nodes, which represent the entities or elements, and edges, which depict the relationships or connections between the nodes. The concept of visual network analysis involves the creation of a graphical depiction of a network with the purpose of enhancing one's understanding of the network's structure, patterns, and characteristics [55, 56]. This approach aids researchers and analysts in elucidating valuable insights and correlations that may not be readily apparent solely from unprocessed data. These observations and associations may serve to illuminate a previously undisclosed phenomenon.

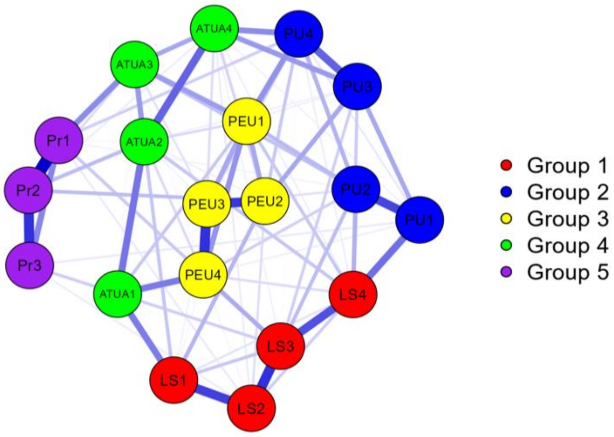

Fig. 4. Network analysis according to relationship.

The network analysis summary reveals that there are a total of 19 nodes and 89 out of 171 edges have non-zero values. The sparsity coefficient is 0.480, as seen in Fig. 4, indicating a significant correlation between learning strategies and perceived utility. The influence on an individual's utilization of the application is contingent upon their mentality, which subsequently affects the relationship between learning strategies and the individual's perception of the application's usefulness. Furthermore, the influence of perceived usefulness on this association exhibits a robust correlation with the linkage between attitudes towards utilizing an application and perceived ease of use. The reason for this is that there exists a robust correlation between the perception of usefulness and the perception of ease of use. This phenomenon can be attributed to the strong association between individuals' attitudes towards utilizing an application and their perception of its ease of use, which in turn significantly influences their perception of its usefulness. The perceived utility of the application is closely intertwined with this association, and the two factors are interconnected. These two relationships are inherently interconnected with each other. There exists a moderately positive correlation between performance and the attitude towards utilizing applications, and performance exerts a moderately significant impact on the three constituent variables that contribute to performance. The perception regarding the utilization of applications exerts a significant impact on the three constituent variables contributing to performance.

Educational institutions must work hard to create classroom instructional methods that can keep up with rapid technological change. Estriegana *et al.* [23] confirms that students need easy access to diverse study resources like course materials. The above tendency drives mobile media device popularity. Education providers and educators can make adjustments to help students access learning strategies. This element is crucial for learners. Educational apps like the ones mentioned help students by providing easy access to learning materials. Thus, educational apps like these help students.

Online media like android apps helps electronics engineering students understand the material. Students pay more attention to what they're learning. They can also virtually see and hear the components [57]. Students often think diverse learning strategies will boost their academic engagement. Their learning strategies allow students to apply theoretical concepts in real life. This emphasizes the information they're learning. In electronic engineering pedagogy, real-world applications and exemplifications can make the subject matter more relevant to students' daily lives. To ensure students understand the subject, they must have access to relevant information. When students see the practical applications of the material they are learning, they are more likely to prioritize it in their education.

The effectiveness of learners' existing learning strategies can be enhanced by recognizing the importance of having access to all available resources. Each individual learner possesses a distinct and personalized approach to the process of education. Meeting the diverse learning needs and preferences of individuals can be achieved by offering a range of instructional methods, including visual aids, group discussions, simulations, and online resources. Therefore, it is imperative to bear in mind that the correlation between diverse learning strategies and the degree to which an individual can derive advantages from employing those strategies is intricate and can differ among individuals. The perspectives of the learner are also influenced by various factors, including the learner's prior knowledge, level of motivation, and the instructional methodology employed. The establishment of synergistic relationships between education providers and learners can be facilitated by the implementation of effective learning strategies that promote active engagement, alongside the provision of accessible and user-friendly educational resources.

Individuals who hold the belief that a particular approach to utilizing an educational instrument is straightforward to navigate are likely to experience enhanced efficacy in their learning endeavors. Learners perceive online resources and software as more user-friendly and convenient when they possess qualities such as clarity, well-structured organization, and ease of navigation. The field of electronic engineering education frequently employs technological tools, software, and equipment as its primary instructional medium. The utilization of user-friendly and intuitive technology resources has the potential to enhance the learning experience for students. Simulation software with user-friendly interfaces or online platforms with explicit instructions can assist learners in utilizing these resources and optimizing their learning outcomes, thereby influencing their academic performance. Learners are more inclined to experience a sense of ease and engage with learning strategies and tools when they receive appropriate guidance, tutorials, or training. The level of the learner's familiarity with their own learning strategies and their ability to effectively apply these strategies will impact the usability of the resources.

Learners who possess prior familiarity with analogous learning strategies and tools may discover a heightened ease in incorporating said strategies and tools into their educational journey within the realm of electronics engineering. Due to variations in cognitive processing among individuals, specific instructional approaches will yield greater benefits for particular learners. Certain individuals may acquire knowledge more efficiently by utilizing visual aids or conceptual explanations rather than engaging in hands-on activities and practical demonstrations. The implementation of learning strategies can facilitate the utilization of educational applications, thereby enhancing the level of consciousness among individual learners. Moreover, enhancing the awareness of learners regarding the resources at their disposal and facilitating their utilization can potentially augment the maximum level of achievement attainable by each learner.

The usefulness and ease of use of applications affect Padang State University Electronics Engineering Education instructors' attitudes toward using them as instructional resources. Grani and Maranguni found that application ease affects product usefulness [58]. Integration of learning strategies, utility of supporting technology, and convenience influence student attitudes today. Students like technological tools like the learning app because of their functionality and features. The app's utility and convenience make users happy. The correlation between these variables supports including this factor as a key consideration for education decision-makers. The importance of students' attitudes in improving academic performance is well known [59–61]. Educational decision-makers may consider this. A positive and constructive mindset helps students learn new information, affecting their academic success.

V. Conclusion

Modern society is characterized by advanced technology, which affects daily tasks. These actions have many effects on humanity's future. In modern education, diverse individuals with extensive knowledge and expertise in educational technologies are common. Electronic technical education uses these technologies to share information. Thus, technology adoption in education and pedagogy is becoming a notable research area. Its significant impact on education is the main reason for this finding. Scholars worldwide trust the Technology Acceptance Model (TAM) for empirical education research. This study examines how diverse instructional approaches affect student academic achievement while learning new material. A downloadable program for portable electronic devices helped collect crucial data for the investigation. Technological advances have enabled assessment and feedback innovation. Advances in this field have aided technological progress. Students receive timely and useful feedback thanks to digital portfolios, online quizzes, and automated grading systems. This shows significant educational progress. This improves learning overall and helps students grow.

Online courses can help people improve their teaching skills, try new pedagogical methods, and stay current on education policy and practice. One way to find more opportunities is as follows. The increasing complexity of global issues has driven the adoption of advanced educational technologies worldwide. This happens globally. According to research, developing certain apps may benefit students, indicating their development. Network analysis shows that certain variables are advantageous. Educational decision-makers should consider this to improve student learning. This convenient instructional method may help students progress academically. Students may find this instructional method convenient. The above benefit is an example of how this strategy may benefit educational settings.

This research contributes to the advancement of knowledge regarding the determinants of students' academic achievement in higher education, specifically in bachelor's degree programs that incorporate mobile applications. However, it is crucial to acknowledge certain limitations and identify potential avenues for further research in order to fully understand the implications of this study. Firstly, it is important to note that the sample size utilized in this study is relatively small when considering the overall population of students enrolled in higher education. Additionally, it is crucial to acknowledge that the data was collected solely from one university, which may pose challenges in terms of generalizing the findings to a global context. In future investigations pertaining to this topic, it is recommended to incorporate larger sample sizes derived from an expanded array of universities and colleges situated in diverse nations. Furthermore, the utilization of self-reported data carries the inherent risk of introducing biases related to recall and other similar factors. The researchers face challenges in accurately evaluating the extent to which individuals' responses align with their real educational experiences. Although our analysis indicated that our study was not affected by general technique bias, it is advisable to conduct further research to replicate the study using data collected from two separate sources. Furthermore, it is recommended that future studies employ a longitudinal correlation-effect research methodology to enhance the precision and validity of findings pertaining to the widespread implementation of the aforementioned strategy.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Hendra Hidayat: Concept and design, Supervision, Drafting manuscript. Zamzami Zainuddin: Data acquisition, Critical revision of manuscript. Muhammad Anwar: Technical and material support, Supervision. Hadi Kurnia Saputra and Anggarda Paramita Muji: Drafting manuscript, Statistical analysis. Syukhri and Ilmiyati Rahmy Jasril: Collecting Data, Statistical analysis. All authors had approved the final version.

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