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Exploring M-Learning User Information Systems through the Development of a Comprehensive Technology Acceptance Model

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***Abstract*—Digital technology brings a paradigm shift to the education quality ecosystem. Mobile learning provides an innovative space and motivation for information system users. The purpose of the research is to identify users who are adopting technology and support effective and efficient digital-based learning processes so that they can be improved in the future. It will also support an effective and efficient digital-based learning process, thereby increasing its usefulness in the future. The Technology Acceptance Model employs a method to evaluate technology acceptance based on the behavioral perception of information system users. Completion and data analysis using structural equation modeling validate the system that integrates satisfaction and academic performance values. Research materials were distributed through participant questionnaires targeting Mobile learning users via online forms. The study was conducted through a survey of students distributed through a questionnaire. A total of 510 participants were obtained. Based on a demographic survey, it was found that 54.24% used smartphones. The results showed that satisfaction and user behavior attitudes impact the intention to continue using mobile technology. The ease of the system has a positive impact on improving academic performance. The influencing factors are user satisfaction, continuation intention, and user behavioral attitude. So, it can be concluded that system usability and subjective norms influence the continuation intention of M-learning implementation. Future research implications can expand the variables from the perspective of motivation and economic factors in using mobile to improve online learning.**

***Keywords*—Information system; m-learning; technology; behavior.**

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I. INTRODUCTION

The dynamics of digital transformation pose challenges to improving practical learning goals. Sustainable Development Goals explain the development of science and technology through the Internet of Things to support the achievement of high-quality learning. Online class features are collaborative, interactive, innovative content, flexible, affordable, accessible, and easy-to-deliver material [1]. Mobile learning has a positive impact on independence and encourages academic achievement [2]. The findings show the importance of using information and communication technology to influence the perception of trust, security, and electronic information in the education sector [3]. The relationship between technology and information systems is closely interrelated. Technology includes hardware, software, networks, and infrastructure used to process and store data. The system is a combination to manage and distribute information. By combining both frameworks, organizations, humans, and technological compatibility can manage more effectively, increase productivity, and make more accurate and timely decisions [4]. Academic improvement is an indicator of the acceptance of technology and information systems [5], which has an impact on motivation, facility conditions, expectations, and efforts [6], [7].

The problems often faced are complex in integrating user experience, socio-cultural context, and technical aspects in one comprehensive model. Difficulties in collecting accurate and representative data on M-learning vary. System changes must be flexible and easy to adapt to, in order to remain relevant, alongside the development of supporting devices. Measurement of mobile usage is declared successful if it can meet needs quickly, and improve performance and stakeholders [8]. The transformation of the education quality system that was formed motivated students. However, resource limitations are greatly influenced by a lack of mastery and anxiety about new technology [9]. Communication, knowledge, and satisfaction have a significant influence on user intentions [10]. This push is primarily driven by the availability of infrastructure [11]. Students' interest in adopting technology is also influenced by the cost and the display of the application [12]. Based on these factors, it is necessary to study more deeply how to identify student behavior in using M-learning and explore information systems from the perspective of technology acceptance.

This study prioritizes mobile devices for accessing material content. The purpose of this study is to identify user behavior and external factors that influence the adoption of technology acceptance in support of mobile learning. The research's contribution has an impact on user motivation and digital literacy. This exploration aims to understand how the information system used by M-Learning users supports effective and efficient learning processes and how the system can be improved in the future.

II. Materials and Method

The research study discusses online tutorials, content, personal websites, diffusion of creativity, and social cognition. Another theory explains that the value of benefits is based on the willingness to use the system, which varies according to needs. Review the achievement of an information system by categorizing evaluation factors, elements, and the suitability of human tasks, organizations, and technology.

A. Information System and M-Learning

Mobile learning has the potential to revolutionize the higher education environment as innovative and effective technologies develop. This strategy contributes to the understanding of digitalization in M-learning [13]. New methods to empower self-learning processes [14]. Institutions and teachers can improve tutorial design to be more effective and suit students' preferences [15]. Exploring the system, conducting inspections, analysis, and reviews of users in the context of M-Learning [16]. The main priorities that need to be considered include the user Interface from the display side when interacting with the M-Learning application, the experience of how it feels, and satisfaction [17] in finding content, ease of navigation, and how effective the system is in helping learning; Data is collected, stored, and analyzed to improve data privacy and security; Functionality evaluates features, accessing materials, social interactions and quizzes; System performance checks the speed, reliability, and capacity functions in handling many users; Feedback as feedback to understand locations that need improvement. DeLone and McLean's theory explains six success variables, namely the quality of information, systems, services, use, intention, satisfaction, and benefits [18]. A system is said to be good if it is tested and constantly improved by the organizer [19] and effectiveness pays attention to social values and the role of technology for its users [20].

Although many theories have been proposed, there remains a lack of evidence to support their application in the context of mobile learning. Technology has not been able to keep pace with the rapid developments in digitalization, which are capable of exploring information systems. This basis becomes a reference to the proposed research.

B. Technology Acceptance Model

TAM is preferred to evaluate modern technologies based on the perception of usefulness, ease of use, attitude, interest, and behavior. The study's results stated that the two primary constructs come from psychological factors and user perceptions of the use of M-learning directly or indirectly [21]. Acceptance is more on the availability of facility conditions. Success is measured by the increase in users, the cost needs, and the user's interest in accepting the information system. So, there needs to be an improvement to support the performance of continuing education [22]. The role of leadership in developing service quality in supporting infrastructure facilities in higher education [23]. The research studies have shown the impact of enjoyment on intentions towards specific cases of technology adoption, such as system fidelity, significantly affecting performance expectations and effort [24]. Willingness to acquire skills using mobile technology. This pleasure will provide satisfaction in the learning experience when using a mobile [25].

The advantages of TAM have two primary constructs, namely perception and ease of use. TAM is a behavioral model that is useful for answering the question of why many technologies and information systems fail to be implemented. This is because users often do not intend to use them effectively. The research results state that psychological factors will determine the user's intention to use technology directly and indirectly [26]. Meanwhile, the weakness of the TAM model is that it only provides very general information about intentions and behavior in using information systems. And have not paid attention to attitude factors supporting the value of usefulness and convenience. Therefore, there is still a need for further research to develop elements of attitude towards behavior. So, TAM is more flexible while still prioritizing the primary, central construct.

C. Research Design

This type of research employs a quantitative approach with a descriptive methodology. The study aims to identify user behavior and external factors that influence the adoption of technology to support mobile learning. The survey method is used to collect information from a representative sample of a population. Data sampling was conducted at universities in Central Java, Indonesia. Data collection was carried out between June and December 2023

D. Participant

The target focuses on mobile learning users. Data were collected from 643 participants. Furthermore, filtering was carried out with standard deviation and heterotrait-monotrait, resulting in 510 that met the criteria. The students were from six faculties. From the total data distributed, there was one faculty that did not have participants. Table I provides information about respondent characteristics.

TABLE I
CHARACTERISTICS OF RESPONDENTS

Profile	Frequency	Percentage (%)
Gender		
Male	259	50.78%
Female	251	49.22%
Age (years)		
< 25	502	98.43%
26-35	8	1.57%
Level of Education		
Bachelor	510	100%
Long time using the Internet		
< 1 year	115	22.55%
1-2 year	202	39.61%
>2 years	193	37.84%
Faculty of		
Economics and Business	62	12.16%
Science and Teaching	107	20.98%
Law	13	2.55%
Engineering	326	63.92%
Agriculture	2	0.39%
Psychology	0	0%
Type of digital technology used for learning		
Blackboard	178	35%
Mobile	332	65%

E. Instrument

The survey approach is carried out by paying attention to the conditions being observed. Data distribution is via online questionnaires. The questionnaire is compiled based on a Likert scale [27]. For data processing purposes, the answers are given a score of 1-5, which is defined as follows: strongly disagree (1), disagree (2), undecided (3), agree (4), and strongly agree (5). Validity refers to the construct obtained without and/or with improvements, as well as rearrangement. In contrast, reliability can be trusted as a data collection tool. Three parts must be answered by respondents in the questionnaire, namely: (1) Demographic data; (2) Statement of experience using the internet, smartphones, and computers; (3) Assessment questions that represent each indicator and variable.

F. Data Analysis

Testing using SEM based on variance for the compilation of models oriented to the concept of theory, while the PLS approach predicts dependent variables by involving independent. The proposed research on the development of a technology acceptance model is comprehensive, involving two dimensions: quality and social, as independent constructs, and acceptance as the dependent construct. The results of the literature review state that the selection of variables is based on looking at the level of significance and adjusting to the conditions of the research needs [28]. Researchers use three independent variables, namely service quality dimensions, which have five elements: measurability, reliability, responsiveness, empathy, and guarantee of empathy. The intervening variables, namely, continuous intention to use [29] and attitude toward behavior are derived from the TAM model. Furthermore, to develop the research model, this study identifies three external variables that modify novelty, including self-directed learning system enjoyment and use satisfaction. These three external constructs serve as indicators of user sustainability in the use of M-Learning. To answer the research objectives, several questions were prepared, as follows:

- Identify user behavioral characteristics.
- External factors that influence the acceptance of technology to support mobile learning.

Hypothesis testing is based on the following questions:

- H1: System enjoyment influences technology acceptance.
- H2: Use satisfaction influences continuous intention to use M-learning.
- H3: Continuous intention to use impacts perceived academic performance in using M-learning.

III. RESULTS AND DISCUSSION

In the discussion, the results of the data analysis are used to answer two research questions. Statements of experience using technological devices to support M-Learning are explained in Table II.

TABLE II
EXPERIENCE USING TECHNOLOGY DEVICES

Name	Frequency	Percentage (%)
ICT devices that you have		
Computer PC	20	3.94%
Notebook	208	41.03%
Smart Phone	275	54.24%
Tablet	2	0.39%
Others	2	0.39%
Internet connection type		
Mobile data	268	52.55%
Broadband/ Wifi	236	46.27%
Others	6	1.18%
Digital devices can help users		
Yes	509	99.80%
No	1	1.18%
Frequency of using M-learning		
Everyday	436	85.49%
Once every 2 weeks	64	12.55%
Once a month	10	1.96%
Duration of time to access (hour)		
<=1	330	64.71%
2-3	146	28.63%
>= 4	34	6.6%
* N = 510		

This research employs PLS-SEM version 4 to identify factors that can measure the satisfaction of M-learning users about technology acceptance. The main factors in developing the Technology Acceptance Model construct are: (1) Exogenous constructs or independent variables are often referred to as independent, as these variables have an influence but are not influenced by other variables. The dimensions involved are the service quality dimension (SVQ), self-directed learning (SDL) and system enjoyment (SE); (2) Endogenous intervening constructs can be influenced and affect other variables, including use satisfaction (USAT), continuous intention use (CIU), and attitude toward behavior (ATB); (3) Endogenous dependent constructs are also called dependent variables, namely those that are influenced but do not affect other variables, including perceived academic performance (APC) and actual system use (AS).

The design model (see Fig. 1) describes the PLS-SEM results divided into two stages. In the first stage, external model analysis is conducted to verify the accuracy and consistency of the data before proceeding with internal model analysis. Average variance extracted (AVE), composite reliability, discriminant validity, convergent validity, and the second stage of Cronbach's alpha variable include the procedures used.

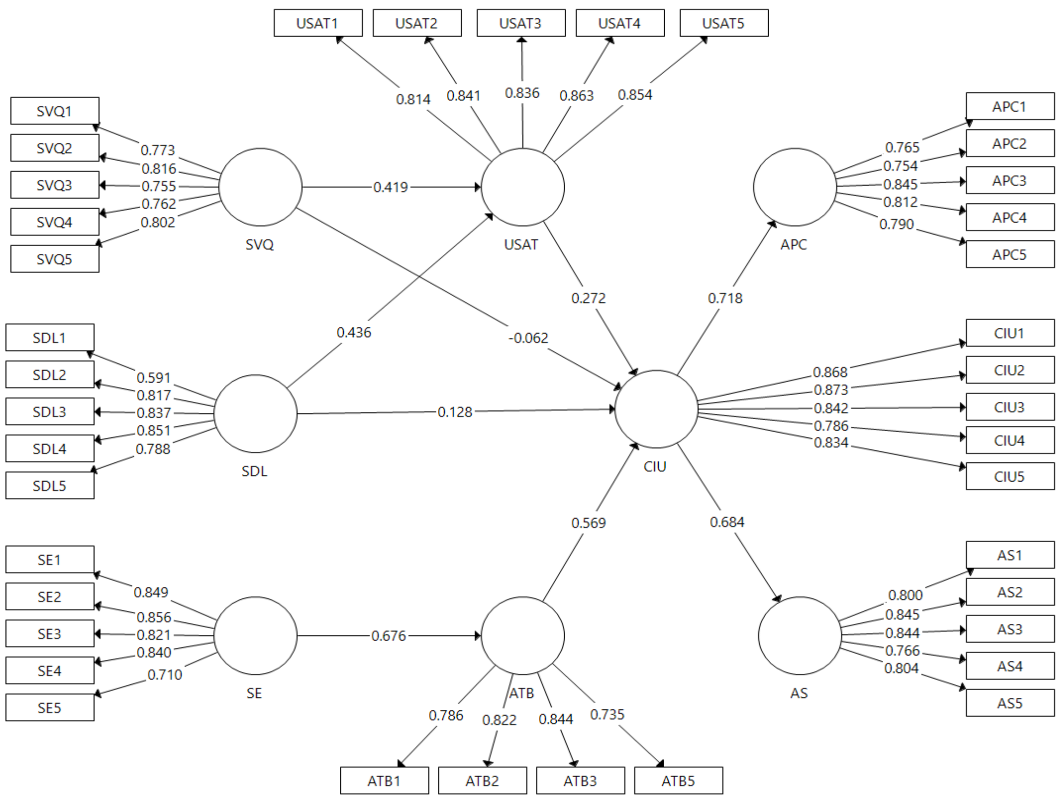

Fig. 1 Design Model

Criteria testing based on the evaluation of model measurements includes Factor loadings, which measure the correlation between the original variable and the construct. This research contributes to identifying key dimensions, including user satisfaction, independent learning, and continuous intention to use mobile technology. The loading factor correlates from -1 to +1, and values above 0.7 are considered higher, while those below 0.4 are considered weak. In the ATB4 test, the value is very low at 0.367, so cleaning is carried out. If the loading factor is below the limit, it indicates that the variable contributes weakly, so it needs to be filtered because it affects other constructs. Construct reliability to measure Cronbach's alpha and composite reliability. The range value is 0.808-0.897, and CR is 0.875-924. Construct validity was used to determine the convergent and Average Variance Extracted, which obtained a value of 0.611-0.708. The overall results of the analysis are shown in Table III.

TABLE III
FACTOR LOADING, VALIDITY AND RELIABILITY

	Factor loadings	Cronbach's Alpha	Composite Reliability	AVE	VIF
APC1	0.765	0.853	0.895	0.630	1.623
APC2	0.754				1.749
APC3	0.845				2.215
APC4	0.812				1.931
APC5	0.790	0.853	0.895	0.630	1.837

	Factor loadings	Cronbach's Alpha	Composite Reliability	AVE	VIF
AS1	0.800	0.871	0.906	0.660	1.932
AS2	0.8645				2.385
AS3	0.844				2.374
AS4	0.766				1.920
AS5	0.804				1.907
ATB1	0.786	0.808	0.875	0.636	1.707
ATB2	0.822				1.862
ATB3	0.844				1.880
ATB5	0.735				1.448
CUI1	0.868	0.896	0.924	0.707	3.515
CUI2	0.873				3.636
CUI3	0.842				2.309
CUI4	0.768				1.850
CUI5	0.834				2.217
SDL1	0.591	0.838	0.886	0.613	1.297
SDL2	0.817				1.907
SDL3	0.837				2.173
SDL4	0.851				2.223
SDL5	0.788				1.801
SE1	0.849	0.874	0.909	0.668	2.375
SE2	0.856				2.368
SE3	0.821				2.057
SE4	0.840				2.223
SE5	0.710				1.504
SVQ1	0.773	0.841	0.887	0.611	1.713
SVQ2	0.816				2.052
SVQ3	0.755				1.760
SVQ4	0.762				1.637
SVQ5	0.802				1.789
USAT1	0.814	0.897	0.924	0.708	2.161
USAT2	0.841				2.442

	Factor loadings	Cronbach's Alpha	Composite Reliability	AVE	VIF
USAT3	0.836				2.381
USAT4	0.863				2.814
USAT5	0.854				2.808

A. Heterotrait-Monotrait Ratio

In HTMT, there is a ratio between the average correlation of indicators for two different constructs (heterotrait) and the same construct (monotrait). Furthermore, the calculation is carried out to obtain a lower value for the same variable. A good HTMT recommendation has a confidence interval value of less than 1. Next, a multiple linear regression test was conducted to determine the relationship between variables, with a lower limit interval coefficient of 2.50% and an upper limit of 97.50%, at a 95% confidence level. The results are presented in Table IV.

TABLE IV
HETEROTRAIT MONOTRAIT RASIO RESULTS

	Original Sample (O)	Sample Mean (M)	2.50%	97.50%
SVQ → CIU	0.615	0.614	0.524	0.696
SVQ → ATB	0.681	0.680	0.595	0.756
SVQ → APC	0.707	0.707	0.628	0.773
SDL → CIU	0.741	0.741	0.669	0.805
SVQ → AS	0.747	0.748	0.678	0.806
SDL → AS	0.759	0.759	0.690	0.819
CIU → AS	0.769	0.769	0.698	0.826
USAT → CIU	0.771	0.771	0.706	0.826
SE →CIU	0.773	0.773	0.706	0.832
SVQ →SDL	0.783	0.784	0.719	0.833
SDL →APC	0.786	0.786	0.727	0.837
USAT → ATB	0.775	0.775	0.699	0.839
USAT → SDL	0.795	0.794	0.726	0.852
SDL →ATB	0.801	0.802	0.732	0.858
USAT → SVQ	0.810	0.809	0.747	0.862
SVQ →SE	0.814	0.814	0.754	0.864
SE →ATB	0.815	0.815	0.757	0.864
USAT → APC	0.813	0.814	0.746	0.869
CIU → APC	0.818	0.819	0.737	0.877
SE →AS	0.830	0.830	0.770	0.881
USAT ->AS	0.839	0.840	0.787	0.883
SE → APC	0.846	0.846	0.789	0.892
ATB → AS	0.852	0.853	0.793	0.901
SE → SDL	0.883	0.883	0.827	0.927
USAT → SE	0.920	0.920	0.885	0.950
CIU → ATB	0.915	0.915	0.830	0.979
ATB → APC	0.942	0.942	0.897	0.980
AS →APC	0.965	0.966	0.934	0.997

B. Structural Model

After the measurement model assessment, the next step is to evaluate the structural path to evaluate the coefficients and their significance. Model structure for testing hypotheses and evaluating construct relationships. The significance value of the t-value used is 1.96 (5% significance level), and the p-value is <0.05. The overall results can be seen in Table V.

TABLE V
HYPOTHESIS TEST

Items	Original Sample	Sample Mean	Standard Deviation	t-Statistics	p Values	Description
SVQ→USAT	0.419	0.418	0.045	9.373	0	Accepted
SVQ→CIU	-0.062	-0.060	0.037	1.655	0.098	Not Accepted
SDL→USAT	0.436	0.437	0.043	10.159	0	Accepted
SDL→CIU	0.128	0.129	0.039	3.248	0	Accepted
SE→ATB	0.676	0.678	0.029	23.068	0	Accepted
USAT→CIU	0.272	0.270	0.046	5.909	0	Accepted
ATB→CIU	0.569	0.570	0.043	13.170	0	Accepted
CIU→APC	0.718	0.720	0.031	23.021	0	Accepted
CIU→AS	0.684	0.686	0.028	24.573	0	Accepted

The calculation results show that there are eight hypotheses with t-statistics more than the t-table (10.85 > 1.96), so they are accepted. Meanwhile, the t-statistic of less than 1.96 is declared rejected.

C. Discussion

This study validates the development of a technology acceptance model by adding a comprehensive subjective norm variable. The results explore the M-learning user experience information system as an effort to create a comprehensive framework for understanding and improving interactions. The system integration of technical, psychological, and pedagogical aspects ensures that technology is not only accepted by users but is also expected to provide a practical and satisfying learning experience [30]. The main components that need to be considered include:

- Device acceptance factors, consisting of ease of use, perceived usefulness, experience, and user context of the M-learning system that prioritizes interface design [31], navigation, and accessibility. As well as the usage environment to achieve learning goals [32].
- Social and cultural factors.
- Data protection, security, and privacy policies.
- Satisfaction and retention of user satisfaction levels with long-term M-learning.

Therefore, there needs to be an ongoing effort to maintain relevance through content updates, feature improvements, and regular communication. The hypothesis reveals a strong and significant relationship between the dimensions, suggesting that users can readily accept technology. This statement is supported by research [33] that research gaps can be identified.

IV. CONCLUSION

The research findings address the study's objectives, specifically analyzing external factors of mobile learning acceptance using the Technology Acceptance Model (TAM). External factors are widely used to identify constructs in the development of technology acceptance models. Second, validate the development of a new Technology Acceptance

Model (TAM) through the Structural Equation Modeling (SEM)- Partial Least Squares (PLS) approach. There are positive impacts of system quality, computer efficiency, and satisfaction with ease of use, as perceived by students, on the mobile learning system. In addition, information quality, enjoyment, and accessibility have a positive influence on the perception of ease of use and usefulness of the information system received.

This research has limitations that affect the accuracy of the findings, including factors in the acceptance of M-learning technology that have not been fully explored. Impact of dependency on mobile adoption. Apart from that, user finances from implementing M-learning have not been analyzed. Data collection was further expanded at different institutions. Weaknesses in exploring information systems are limited to a single factor from the user's perspective. Future research should focus on the success of information systems in specific applications, which can be investigated through longitudinal studies to yield more accurate measurements.

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