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Examining mobile learning adoption: The role of ease of use, usefulness, and intention

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ABSTRACT

The proliferation of mobile-based learning apps on the Google Play Store has been facilitated by the advancement of information technology. However, the level of optimal use is still a challenge with several problems related to: 1) Perceived Ease of Use (PEU), 2) Perceived Usefulness (PU), 3) Behavioral Intention (BI), 4) Use Behavior (UB). Therefore, this study aims to analyze the factors that influence the acceptance (UB) of mobile-based learning applications using the Technology Acceptance Model (TAM). This model uses the variables PEU, PU, BI, and UB. Data were collected through an online questionnaire with 107 respondents and analyzed using SEM-PLS. The results showed that PEU had a significant effect on PU (62.8%), but did not directly affect BI and UB. PU had a significant effect on BI (50.3%) and did not directly affect UB. While BI had a significant effect on UB (44.9%). This finding confirms that ease of use of an application (PEU) must go through usefulness (PU) to be able to influence user intention (BI), then BI influences UB or in other words BI mediation plays a very important role in bridging the influence of initial perceptions on actual use. The implications of this study can help developers of mobile-based learning applications to increase user engagement so that the application can be accepted and used by users.

Keyword: Technology acceptance model; mobile learning; perceived usefulness; behavioral intention; SEM-PLS

1. INTRODUCTION

Nowadays, various aspects of life are affected by the rapid development of information technology [1], including the domain of education. The application of information technology in the field of education, one of which is the existence of mobile-based learning applications available on the Google Play Store platform. Mobile-based learning applications serve as an effective medium for delivering educational content through mobile devices such as smartphones and tablets [2] [3]. Learning applications available on the Google Play Store platform include Ruang Guru, Khan Academy, Duolingo, Google Classroom and so on. The rating of learning applications on Google Play Store ranges from 3.8 to 4.8 out of 5. These applications offer flexibility for users to access learning materials anytime and anywhere [4]. While there are many learning apps available on the Google Play Store, optimal adoption and usage rates are still a challenge. Some of the problems that can be identified in this context include: 1) Perceived Ease of Use, where many users are reluctant to use apps because they find the interface trouble to use or unintuitive [5]. If the application is considered difficult to use, then users tend to be reluctant to try or use it on an ongoing basis, 2) Perceived Usefulness, namely users have not seen the direct benefits of the application in helping them achieve learning goals [6], Behavioral Intention to use, namely users have not considered the application useful and with features that are easy to use, so

they will use the application actively [7], Actual Use (UB): not all users who intend to use the application will actually use it in the long term [8][9]. External factors such as habit, social support, or other learning alternatives can influence the final decision to use a learning app [10]. This shows that there is a gap between users' expectation and real experience in using the learning app [11]. Thus, the goal of this research is to examine the variables that affect the adoption and utilization of programs for mob-based learning

2. METHOD

This research starts from problem identification, namely what factors influence the acceptance and use of mobile-based learning applications using the TAM model. Based on the problem, the researcher looks for literature reviews in the form of journals and books related to the research. Followed by making a conceptual framework and hypothesis testing and determining indicators and statements from each variable for making questionnaires. After that, to calculate the sample and collect data, questionnaires were distributed. Data from the distribution of questionnaires will be processed and analyzed with descriptive and SEM Pls analysis. The results of the analysis will be discussed and concluded. Figure 1 illustrates the research method's flow.

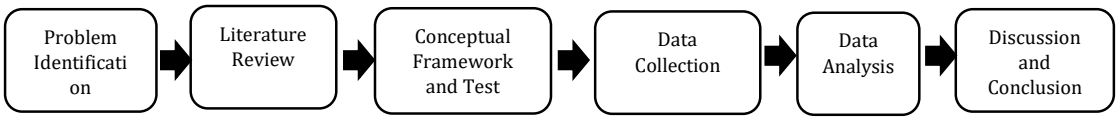

Figure 1. Flow of research

Conceptual Framework

The conceptual framework in this study was built with 4 variables, namely:

a. *Perceived Ease of Use* (PEU) is the extent to which someone thinks a system or technology will be simple to use or require little effort [12], [13].
   Hypothesis 1 (H1)*:* PEU significantly and favorably affects PU
   Hypothesis 2 **(**H2): PEU significantly and favorably affects BI
   Hypothesis 3 **(**H3): PEU significantly and favorably affects UB
b. Perceived Usefulness (PU) is the level of a person's belief that using a system or technology will improve their performance or productivity [14], [15]
   Hypothesis 4 **(**H4): PU significantly and favorably affects BI.
   Hypothesis 5 **(**H5): PU significantly and favorably affects UB
c. Behavioral Intention (BI) is the desire or intention of an individual to utilize a system or technology in the future [16], [17]
   Hypothesis 6 **(**H6): BI significantly and favorably affects UB.
d. *Use Behavior* (UB) is the degree to which a person actually uses a system or technology in their daily lives [18]. The conceptual framework is shown in *Figure 2*.

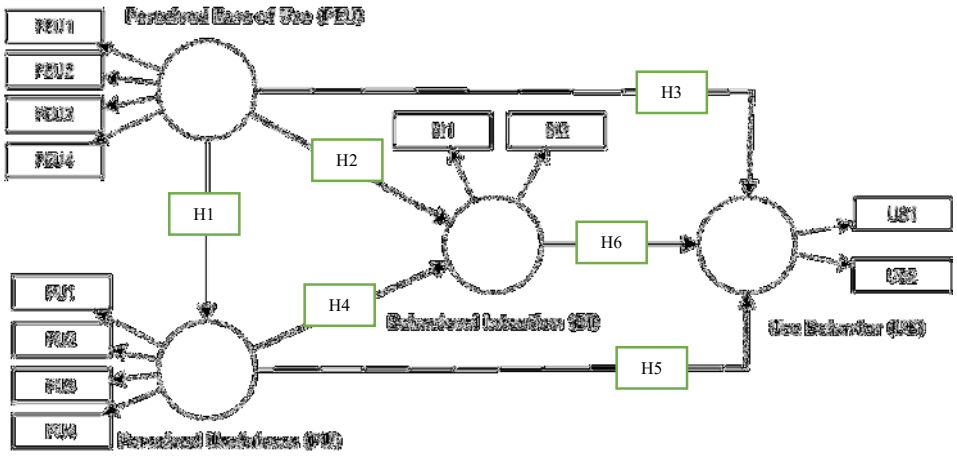

Figure 2. Research conceptual framework

Data collection

A Google Form was used to distribute surveys with 5-point Likert scale response options to samples in order to collect data (1 = Don't Agree, 2 = Less Agree, 3 = Moderately Agree, 4 = Agree, and 5 = Strongly Agree). Users of Surabaya-based mobile learning applications make up the study's population. Five to ten times as many samples are needed to determine the number of indications [19]. The study requires a minimum sample size of 60 respondents with a total of 12 indicators. In this research, the sample size was 107 respondents.

Data Analysis

Based on the outcomes of data processing using the Smart Pls 4 program, validity and reliability tests are now conducted. The validity test is carried out to test whether the indicator or statement represents the variable or not. Meanwhile, reliability testing serves to determine whether the respondent's answer can be trusted or not. Furthermore, descriptive analysis and SEM Pls analysis were carried out. Validity Test Formula with Heterotrait-Monotrait Ratio (HTMT):

$$HTMT = \frac{\sum_{i=1}^{n}\sum_{j=i+1}^{m}|Cor(X_i,Y_j)|}{\sum_{i=1}^{n}\sum_{i+1}^{m}|Cor(X_i,Y_j)|} \quad (1)$$

Where:
Xi,Yj : indicators of two different constructs
Cor (Xi,Yj) : indicators of two different constructs
Cor (Xi,Xj) : correlation between indicators of the same construct

Reliability Test Formula
1) Cronbach's Alpha (CA)

$$CA = \frac{k}{k-1}\left(1 - \frac{\sum Var(X_1)}{Var\,(\sum X_i)}\right) \quad (2)$$

Where:
k : number of indicators in one construct
∑Var(Xi): varians masing-masing indikator
Var(∑Xi): total variance of the construct

2) Composite Reliability (CR)

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum Var(\varepsilon_i)} \quad (3)$$

Where:
λi = factor loading dari setiap indikator
εi=1−λ_i^2 (error variance)

3) Average Variance Extracted (AVE)

$$AVE = \frac{\sum \lambda_i^2}{n} \quad (4)$$

Where:
λi : loading factor of the indicator to its construct
∑λ_i^2: variance extracted by the indicator
n : number of indicators in the construct

4) Goodness of Fit (GoF)

Utilized to validate the combined performance of the structural model (inner model) and the measurement model (outer model), with values ranging from 0 to 1. A little GoF is between 0-0.25, a moderate GoF is between 0.25 and 0.36, and a big GoF is above 0.36 [20].

$$GoF = \sqrt{\overline{Com}\ x\ \overline{R^2}} \quad (5)$$

Where:
$\overline{Com}$ = Communality average
$\overline{R^2}$ = R square average

3. RESULTS AND DISCUSSION

Respondents information

Respondents in this study were 80 men (74.8%) and 27 women (25.2%), with ages < 20 years as many as 9 (8.4%), ages 20-25 years as many as 94 (87.9%), ages> 25 years as many as 4 (3.7%). While the education of respondents is SMA/SMK equivalent as many as 58 people (54%), Diploma/Bachelor as many as 39 people (37%), and Postgraduate as many as 10 people (9%).

Results of the measurement model

The loading factor values in Table 1 are all more than 0.7. This shows the measurement items are valid and can reflect the measurement of the variables, CA is at 0.800 - 0.918, and CR is close to the value of 0.900 - 0.964. This indicates strong dependability. AVE is at 0.600 - 0.807 [21], this indicates convergent validity is good. Table 2 displays the discriminant validity results. A good HTMT value is <0.90 [22]. A HTMT of less than 0.90 in this study denotes high discriminant validity.

Table 1. Results of the measurement model

Construct	Items	Loading	CA	CR	AVE
PEU			0.875	0.878	0.727
	PEU1 : I find it easy to use this learning app	0.859			
	PEU2 : I can understand how this learning app works quickly	0.835			
	PEU3: The appearance of this learning application feels simple and easy to understand	0.883			
	PEU3: I rarely experience errors when using this learning app	0.833			
PU			0.815	0.845	0.642
	PU1: I understand the subject matter better with this learning app	0.748			
	PU2 : This learning app helps me in doing assignments	0.842			
	PU3 : This learning app makes my learning process more effective	0.882			
	PU4: This learning application is useful to support my learning activities	0.721			
BI			0.876	0.925	0.888
	BI1: I plan to keep using this app to further my education.	0.926			
	BI2 : I will recommend this app to my friends	0.958			
UB			0.918	0.924	0.924
	UB1: I use this app regularly to study	0.965			
	UB2 : I use this app to study for a long time.	0.957			

Table 2. Discriminant validity based on heterotrait-monotrait ratio (HTMT)

Construct	BI	PEU	PU	UB
BI				
PEU	0.413			
PU	0.616	0.719		
UB	0.653	0.451	0.564	

Table 3. Findings from the analysis of research hypotheses

Hypothesis	Relationship	Path coefficient	Mean	Standard deviation	t-value	p-value	Decision	f2	Inner VIF
H1	PEU → PU	0.628	0.639	0.063	10.041	0.000	Supported	0.651	1.000
H2	PEU → BI	0.055	0.055	0.050	0.141	0.387	Not Supported	0.003	1.651
H3	PEU → UB	0.126	0.117	0.106	1.196	0.232	Not Supported	0.016	1.655
H4	PU → BI	0.503	0.513	0.136	3.708	0.000	Supported	0.216	1.651
H5	PU → UB	0.186	0.205	0.096	1.940	0.052	Not Supported	0.030	2.007
H6	BI → UB	0.449	0.436	0.118	3.815	0.000	Supported	0.244	1.409

Table 4. The model's strength

Construct	Cross redundancy measure (Q2)			Coefficient of determination (R2)	
	SSO	SSE	Q^2 (=1-SSE/SSO)	R2	Adj. R2
PEU	428.000	428.000			
PU	428.000	331.313	0.226	0.394	0.389
BI	214.000	163.900	0.234	0.290	0.277

Construct	Cross redundancy measure (Q2)			Coefficient of determination (R2)	
	SSO	SSE	Q² (=1-SSE/SSO)	R2	Adj. R2
UB	214.000	140.296	0.344	0.414	0.397

If Q2 >0.05 then a construct model is obtained that is relevant. In Table 4, all Q2 values >0.05 mean that the exogenous variables used to predict the endogenous variables are correct.

Table 5. Index of goodness of fit

Communality average	R square average	GoF index
0.268	0,366	0.313

In Table 5, the GoF index value is obtained from Root (0.268 x 0.366) which is 0.313. The level of fit of the measurement model and the general structural model is included in the moderate category.

Correlation Analysis Discussion

Relationship between Perceived Ease of Use (PEU) and Perceived Usefulness (PU)

The results of the analysis from Table 3 show that Perceived Ease of Use (PEU) has a significant effect on Perceived Usefulness (PU) with a path coefficient value of 0.628, a t-value of 10.041, and a p-value <0.001. This effect is also supported by the effect size ($f^2 = 0.651$) which shows a large influence. This finding is consistent with the Technology Acceptance Model (TAM) framework where the perception of ease of using online learning applications significantly increases the perception of its benefits [23], [24].

Relationship between Perceived Ease of Use (PEU) and Behavioral Intention (BI)

Although TAM theoretically states that PEU also has a direct effect on Behavioral Intention (BI), in this study (Table 3) the hypothesis was not empirically supported (coefficient = 0.055, p = 0.387). The very small effect size value ($f^2 = 0.003$) indicates that PEU contributes almost nothing to the variance in BI. This can be explained by the possibility that users prioritize benefits (PU) over ease of use in determining their intention to use online learning applications.

Relationship between Perceived Usefulness (PU) and Behavioral Intention (BI)

The relationship between PU and BI in Table 3 is proven to be significant (coefficient = 0.503, p < 0.001), with a medium effect size ($f^2 = 0.216$). This confirms the important role of PU in shaping user behavioral intentions. This finding is consistent with previous studies stating that when users see the system as something that increases the effectiveness or efficiency of their work [25], [26]**.**

Relationship between Perceived Usefulness (PU) and Use Behavior (UB)

Based on Table 3, the coefficient value = 0.186 and p = 0.052, this shows that PU does not directly affect usage behavior, but rather through BI mediation. This strengthens the role of mediation of intention as an important intervening variable.

Relationship between Behavioral Intention (BI) and Use Behavior (UB)

In Table 3, the relationship between Behavioral Intention and Use Behavior is proven to be significant and strong (coefficient = 0.449, p < 0.001), with the second largest effect size ($f^2 = 0.244$). This finding confirms the basic assumption of TAM that intention acts as the main predictor of actual behavior. This means that users who have a high intention to use the system will tend to realize it in the form of real behavior. This is also relevant in the development of information systems, where encouraging user intention can be a major strategy in increasing adoption. This is in line with the results of previous studies that stated that BI has a significant effect on UB [27].

4. CONCLUSION

This study was conducted to analyze the factors that influence the acceptance and use of mobile-based learning applications, especially through the Technology Acceptance Model (TAM) approach. The results showed that Perceived Ease of Use (PEU) has a significant effect on Perceived Usefulness (PU), but has no direct effect on Behavioral Intention (BI) or Use Behavior (UB). Meanwhile, PU is proven to significantly affect BI, and BI acts as the main predictor of the actual use behavior of learning

applications (UB). In contrast, the direct effect of PU on UB is not significant. These findings indicate that the ease of use of the application will increase the perception of usefulness, and the perception of usefulness is what drives the intention to use. However, not all users who find the application easy to use and useful will immediately use it actively. The intention to use (BI) factor is proven to be a critical bridge connecting perception with actual behavior.

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