TAM as a Model to Understand the Intention of Using a Mobile-Based Cancer Early Detection Learning Application

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Abstract—Technology Acceptance Model (TAM) framework was utilized in this study. Its purpose was to determine the correlation between independent variables consisting of Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude toward Using (AU) with dependent variable Behavioral Intention to Use (BIU). Data collection techniques were carried out by distributing questionnaires through group discussion forums. Respondents consisted of medical workers and health cadres both in Jakarta and Yogyakarta. Data were analyzed using correlation test and t-test. The results of the correlation test state that the correlation between PEU and AU is 0.30, which shows a weak correlation. Meanwhile, the correlation of PU and AU is 0.56, PEU and BIU is 0.41, and PU and BIU is 0.47, which are considered as moderate correlations. Finally, a strong correlation exists between AU and BIU. T-test results show that the effect of PU on AU is statistically significant with CI = 95%. Likewise, the effects of PEU on AU, AU towards BIU, PU towards BIU, and PEU towards BIU are significant (p < 0.05).

Keywords—Mobile learning, TAM, cancer early detection

1 Introduction

The International Agency for Research on Cancer (IARC) estimates that one in five men and one in six women worldwide will suffer cancer during their lifetime. Even one in eight men and one in eleven women will die from the disease. Based on the 2018 International Agency for Research on Cancer (IARC) Globocan data, global cancer has risen to 18.1 million cases. Furthermore, 9.6 million have died from cancer worldwide (see figure 1).
The incidence of cancer in Indonesia (136.2/100,000 population) ranks 8th in Southeast Asia, while in Asia ranks 23. The number of new cancer cases in Indonesia is 348,809 cases, with the number of cancer deaths of 207,210 (see figure 2). The low level of knowledge and understanding is one of the factors that cause patients to delay early detection [1].

A series of efforts have been made by the Government of Indonesia to reduce the number of people living with cancer, including counseling and formal training. However, this effort requires a lot of money [2]. Also, the Government of Indonesia, through the Ministry of Health, created an early detection program for breast cancer and cervical cancer. Women aged 30-50 years can use clinical breast examination methods and visual inspection with acetic acid (IVA test) for the cervix. Another program is breast self-examination by examining her breasts by looking and feeling with fingers to detect whether there are lumps in her breasts [3], as well as developing early cancer discovery programs in children, cancer palliative services, early detection of lung cancer risk factors, and national cancer registration system.

The spread of early breast and cervical cancer detection programs can also be through community-based network organizations [4] by empowering health activists to help underserved individuals to get regular and quality health care [5]. The series of efforts turned out not to be able to reach remote areas optimally and requires a new step to provide broader services.
Online-based learning, or known as online learning to detect cancer, is the first step ever developed to answer the challenges above [6]. As technology advances, mobile-based cancer detection learning is developed, which is a continuation of this research.

Benchmarks used to determine, explain, and predict the level of acceptance of mobile learning applications by users is to use the Technology Acceptance Model (TAM) method [7]. This study aims to determine the correlation between independent variables, namely Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude toward Using (AU), and dependent variables, namely Behavioral Intention to Use (BIU), and also to find out how the influence of independent variables on the dependent variable.

2 Literature Review

2.1 Mobile learning

Mobile learning is the intersection of mobile computing and e-learning [8]. The spread of the use of mobile devices as the first learning process occurred in the mid-1990s [9], which was very helpful in accessing and disseminating information [10]. Mobile learning is utilizing educational technology devices such as laptops, digital personal assistants (PDAs) [16], tablets, cell phones, and e-book reader applications. The devices allow users to use mobile learning anytime and anywhere [11]. A study in Guangzhou showed that the students agreed to use mobile devices because they could study outside of school rather than having to be present in the classroom [14].

Many researchers agreed that mobile learning provides many benefits in enhancing creativity, collaboration, and communication in the teaching and learning process.
[12]. Furthermore, mobile learning also greatly helps teachers in distributing modules or materials to be taught every day. Mobile learning also helps teachers to interact in the process of teaching and learning online, so they do not always have to meet their students face to face [13]. Thus mobile learning can overcome the problem of distance in transferring knowledge between teacher and student.

Despite having many of these advantages, there are also disadvantages of using mobile learning. Among others is the dependence on the Internet and electricity network reliability. This dependency can hamper the usage of mobile learning because not everyone has an adequate Internet and electricity network [15]. Besides, the problem of social interaction is also minimal when using mobile learning due to the lack of direct meetings between instructors and students [17].

2.2 Technology acceptance model

TAM (Technology Acceptance Model) was first implemented by Davis in 1989 [7], which is a model for analyzing the acceptance factors of an information system and technology from users [18]. TAM can be used to analyze the habits of students in using e-learning [19].

The original TAM model includes 4 variables that measure an information system, namely Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavioral Intention to Use (BIU), and Attitude toward Using (AU). Perceived Ease of Use (PEU) is the main factor of the acceptance of an information system [20]. Perceived Usefulness (PU) is a factor used where the person believes that an information system can improve performance in work [21].

2.3 Effects of perceived usefulness (PU) on attitude toward using (AU)

Pro or contra attitude toward the application of information systems is influenced by the level of one's confidence in the utilization of the system [24]. The higher the usefulness felt by the user when using a system or technology, the more positive the user's attitude towards the use of the technology. A study of the factors that influence the intention to use Mobile Payment states that perceived usefulness is positively related and significantly influences attitude toward using [22]. Likewise, other research related to determinants of mobile learning adoption, states that perceived usefulness is positively related and significantly influences attitude toward using [23]. Therefore, the first research hypothesis is:

**H1:** Perceived Usefulness (PU) influences Attitude toward Using (AU)

2.4 Effect of perceived ease to use (PEU) on attitude toward using (AU)

The ease of use influence the pros or cons attitude towards the information systems [24]. Perceived Usefulness is a phase where someone believes that using an information system will increase productivity, performance, work performance, and bring benefits for those who use it [7][25]. Someone who will use information technology has an understanding of its usefulness [26], which results in the ease of
use. A study comparing the factors that influence e-commerce adoption shows that PEU has a positive effect on AU [27]. Whereas in other studies related to online shopping on Instagram, shows that the user has proven and felt the benefits [28]. Based on the results of the study, the second hypothesis is:

H2: Perceived Ease of Use (PEU) influences Attitude toward Using (AU).

2.5 Effect of attitude toward using (AU) on behavior intention to use (BIU)

Attitudes and subjective norms influence the intention of human behavior [29]. If someone tends to have a positive attitude towards technology, then that person tends to accept and use the technology, or vice versa [24]. One study related to factors influencing student adoption and the use of e-learning shows the results that attitude towards the use of mobile learning influence the intention to use [30]. Attitude toward Using (AU) is also obvious in the use of internal banking systems because it makes it easier to use technology. That increases the interest of users to use technology in their work [31]. The most dominant intention is influenced by attitude because Attitude toward Using (AU) is a strong mediator between belief and interest to use [32]. Based on the results of the study, the third hypothesis is:

H3: Attitude toward Using (AU) influences Behavior Intention to Use (BIU).

2.6 Effect of perceived usefulness (PU) on behavior intention to use (BIU)

Behavioral intention to use is the tendency for a person's behavior to continue to apply the technology, including the desire to keep using it and to influence other users [7]. Increased user interest in the system is seen when the usefulness of the system has been felt [33]. One researcher who examined mobile services has proven that perceived usefulness is one of the factors supporting the intention of users to use technology [34]. The use of technology by users shows that the level of user confidence in the method of delivering information is beneficial and is considered as a choice [35]. Thus, positively perceived usefulness will directly affect intention to use [36]. Based on the results of the research, the fourth hypothesis is:

H4: Perceived Usefulness (PU) influences Behavior Intention to Use (BIU)

2.7 Effect of perceived ease of use (PEU) on behavior intention to use (BIU)

Behavioral intention to use is a form of one's belief in the use of technology accompanied by increased interest in using it, and finally using information technology to complete the work [37]. The higher one's perception of the ease of using the system, the higher the level of utilization [38]. This means that when the user believes that the information system is easy to use, the user will use it or vice versa [39]. Several previous studies have mentioned that perceived ease of use has a positive effect on the attitude of technology use [40] and [41]. Based on the results of the research, the fifth hypothesis is:

H5: Perceived Ease of Use (PEU) influences Behavior Intention to Use (BIU)
3  Result and Discussion

3.1 Correlation Test

The correlation tests between variables are shown in figure 3. AU and BIU shows the strongest correlation ($\rho=0.64$), compared to other correlations. Correlation test between PU and AU; and correlation test between PU and BIU also gave strong correlation score with $\rho=0.57$ and $\rho=0.48$ respectively, which can be classified as moderate correlation. Lastly, the correlation related to PEU shows the weakest correlation among other correlations. Even though AU has strong correlation with PU and BIU, it has weak correlation of $\rho=0.3$ with PEU.

Fig. 3. Correlation between Variables

3.2 Hypothesis test

Linear regression explains the pattern of relationships between two or more variables. The results of this analysis determine whether between the variables being studied against the relationship, influence each other, and how much the level of
relationship. The results of testing the hypothesis using linear regression can be seen in figure 4.

![Fig. 4. Linear Regression Analysis Result](image)

- **Hypothesis 1 Testing**

  The linear regression model shows the relationship between PU to AU based on the data collected as follow:

  \[
  AU = 1.1911 + 0.5750 \times PU + \varepsilon
  \]

  This linear regression model explains that there is a positive influence between PU on AU. The slope value of 0.5750 can be interpreted as an increase in the average perception of utilization due to an increase in attitude towards use. T-test result indicates that the effect of PU is statistically significant at \( \alpha = 0.05 \) (\( p < 0.001 \)). Thus the H1 hypothesis is proven that PU influences AU.

  The regression line shown in figure 5 depicts the relationship between PU and AU.

![Fig. 5. Regression Plot between Perceived Usefulness (PU) of Attitude toward Using (AU)](image)
As given by the fitted linear model, the R^2 of the linear model in figure 5 is 0.322. This means that only 32.2% of the variability in AU can be explained by the variability in PU.

- **Hypothesis Testing 2**

  The linear regression model also found relationship between PEU and AU based on the data collected is:
  
  \[ AU = 2.0832 + 0.2976 \times PEU + \epsilon \]

  This linear regression model explains the positive effect on PEU between AU. It is possible to interpret the estimated slope value of 0.2976 as an increase in the PEU due to an increase in AU. T-test result shows a statistically significant effect of PEU at \( \alpha = 0.05 \) (\( p = 0.019 \)), so the H2 hypothesis is proven to affect the AU.

  The following line of regression describes the relationship between PEU and AU (figure 6).

  ![Perceived Ease of Use vs Attitude Toward Using](image)

  **Fig. 6.** Regression Plot between Perceived Ease of Use (PEU) and Attitude toward Using (AU)

  Based on the linear model figure 6, the R-squared value is 0.093. This means that the variation in PEU will explain 9.3% of the variability in AU.

- **Hypothesis Testing 3**

  The results of the analysis show that the linear regression model that showing the correlation between AU to BIU based on sample data is:
  
  \[ BIU = 0.5033 + 0.7879 \times AU + \epsilon \]

  This linear regression model explains that the AU and BIU has a positive influence. The reported slope value of 0.7879 can be interpreted as an increase in the AU due to an increase in BIU. T-test result shows a statistically significant effect at \( \alpha \)
= 0.05. This is shown by the p-value magnitude that is much smaller than 0.001. Therefore, the H3 hypothesis is proven.

The following regression line explains the relationship between AU and BIU (figure 7).

Fig. 7. Regression Plot between Attitude toward Using (AU) and Behavior Intention to Use (BIU)

As inferred from the linear model in figure 7, the R-squared value is 0.409, that means only 40.9% of the variability in AU will be stated by the BIU variation.

- **Hypothesis Testing 4**

A linear regression analysis is again adopted to find a relation between PU and BIU, which is found to be:

\[
BIU = 1.0076 + 0.5964 \times PU + \varepsilon
\]

The model is visualized on the data set in figure 8 and has R2 value of 0.5964. T-test demonstrates that the effect of PU on BIU is statistically significant at \( \alpha = 0.05 \) (p-value < 0.001), implying the H4 hypothesis is accepted.

Fig. 8. Regression Plot between Perceived Usefulness (PU) and Behavior Intention to Use (BIU)
• **Hypothesis Testing 5**

Assuming a linear regression model between PEU and BIU (figure 9), the resulting equation can be written as:

\[
BIU = 1.3767 + 0.5036 \times PEU + \varepsilon,
\]

Where the value of R² is 0.174. The t-test result demonstrates a statistically significant relation between the two variables with p-value of 0.001. The result firmly implies that H5 hypothesis is accepted.

![Regression Plot between Perceived Ease of Use (PEU) and Behavior Intention to Use (BIU)](image)

**Fig. 9.** Regression Plot between Perceived Ease of Use (PEU) and Behavior Intention to Use (BIU)

4 **Conclusion**

The correlation test that produces a low correlation is found in the correlation between PEU and AU, which is equal to 0.30. The correlation test that produces a moderate correlation is found in the correlation between PU and AU of 0.56, PEU and BIU of 0.41 and PU and BIU of 0.47. Finally, the correlation test that produces a strong correlation is found in the correlation between AU and BIU of 0.63.

Based on the results of the t-test showed that the effect of perceived usefulness on attitude toward using was statistically significant at α = 0.05. Likewise, the effect of PEU on AU, AU towards BIU, PU towards BIU, and PEU towards BIU are significant (p < 0.05).

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