# THE INTENTION OF GENERATION Z TO USE MOBILE LEARNING: THE ROLE OF SELF-EFFICACY AND ENJOYMENT

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## ABSTRACT

The Technology Acceptance Model (TAM) is a concise and efficient predictive model used to explain the acceptance of m-learning technology. However, several studies have shown that TAM cannot fully explain the acceptance of m-learning among Generation Z. This study aims to formulate TAM as a model of m-learning acceptance for Generation Z. TAM developed based on self-efficacy and enjoyment is expected to explain the behavior of Generation Z in accepting m-learning. This study uses a survey approach, utilizing PLS-SEM as an analysis tool and primary data collected through questionnaires. Participants in this study were 563 students who used m-learning (on class application) at the Muhammadiyah University of Purwokerto, Indonesia. The results contribute to the formulation of a successful m-learning implementation model for Generation Z. These results provide empirical support indicating that self-efficacy and perceived enjoyment cause them to use m-learning now and in the future. Generation Z, who grew up in the digital era, has a high level of proficiency in using technology. Self-efficacy increases user optimism. They are confident in their ability to complete tasks and solve problems when using m-learning. Enjoyment can increase the belief that m-learning is user-friendly and useful. The results of this study support the theory of self-efficacy which states that user beliefs serve as the best predictors of their behavior in using technology in mobile learning.

**Keywords:** Technology acceptance model, mobile learning, Generation Z, self-efficacy, enjoyment, intention to use.

## INTRODUCTION

The inclusion of ICT in educational institutions and the use of mobile learning (m-learning) are crucial in the era of the Industrial Revolution 4.0 and Society 5.0 (Weeden & Cornwell, 2020). The term ICT (Information and Communication Technology) is a synonym for digital technology, or all forms of technology used to store, display, process, transmit, share, or exchange information via electronic means (Nikolopoulou, 2022). IR 4.0 is a stage of technological development that develops vital interactions between humans and machines. IR 4.0 has changed the landscape of educational innovation, driven by artificial intelligence and digital physical frameworks that make human-machine interfaces more universal (Shahroom & Hussin, 2018). Meanwhile, Society 5.0 is a societal structure built to realize a prosperous, human-centered society, where economic development and solving social challenges can be achieved, and people can enjoy a high quality of life actively and comfortably (Fukuyama, 2018).

Mobile learning (m-learning) is an educational and learning activity through mobile technology that includes wireless networks, the Internet, mobile devices, and e-learning applications so that learning can be done anywhere and anytime (Danish & Hmelo-Silver, 2019; Alowayr & Al-Azawei, 2021). M-learning used effectively, will encourage autonomous learning (Cheung et al., 2021). This is also an efficient learning strategy that allows students to utilize their academic abilities related to the learning process (Zimmerman, 2013). M-learning can meet students' needs, speed up search and access to information, mobility of the learning environment, faster and more timely interactions, develop learning motivation, and make it easier for students to learn. M-learning has become an important learning activity, because it is easily accessible (available), low-cost, easy to use, and interactive (Kumar et al., 2019; Aljawarneh, 2020). It creates self-directed learning, which will be used in the future (Al-Emran et al., 2020). Its use requires readiness, optimism, and self-directed learning from lecturers and students (Lin et al., 2016).

The successful implementation of m-learning relies on user willingness and acceptance (Almaiah & Alismaiel, 2019). Both lecturers and students, as well as education providers, need to adapt to this technology to ensure high-quality learning experiences (Herliandry et al., 2020; Fadli et al., 2020). Failure to utilize m-learning can hinder the realization of its advantages and benefits (Almaiah & Al-Khasawneh, 2020). Therefore, it is important to resolve any issues so that its use is effective (Saade & Kira, 2007).

Several studies examine the failure of m-learning implementations (Teo et al., 2020; Almaiah & Al-Khasawneh, 2020; Al-araibi et al., 2019). In developing countries, it has been reported that 45% of projects have failed, 40% have partially failed, and only 15% have succeeded. The primary cause of failure is often the discomfort and lack of confidence experienced by users when using m-learning (Al-Araibi et al., 2019). This failure represents a loss for educational institutions.

The Technology Acceptance Model (TAM) is commonly used to study the success of m-learning. TAM explores user intentions and actual usage (Mailizar et al., 2021; Ritter, 2017). TAM has been used as an effective and concise model to explain the acceptance of m-learning technology. This model has been empirically validated and replicated in various studies (Teo et al., 2019; Mohammadi, 2015). TAM focuses on user intentions and actual usage behavior, providing insight into factors that influence technology adoption. However, several studies have questioned the ability of TAM to explain the acceptance of m-learning, especially for Generation Z (Li et al., 2021; Sukendro et al., 2020). This study argues that additional factors should be included in the TAM framework.

This research proposes a model of m-learning success. This research uses a sample of mostly m-learning users from Generation Z. According to Gupta & Pathania (2021), Generation Z is known to be adaptable and skilled in using technology. This generation has a high interest in new technology and often utilizes digital technology. They often access information via the internet using their smartphones. This generation also has high self-efficacy and enjoyment when using m-learning (Lai et al., 2021; Ching-ter et al., 2017). This research develops a technology acceptance model (Davis, 1989) using self-efficacy and enjoyment as variables that influence m-learning acceptance. This model can be used for different technology acceptance and age ranges. However, because they have different characteristics, other results are possible (IBIlI et al., 2023).

Many studies have investigated factors influencing the successful adoption of m-learning and have identified enjoyment as a significant determinant (Wang et al., 2020; Wang et al., 2019; Ching-ter et al., 2017; Jiang et al., 2021; Al-Gahtani, 2016). Enjoyment refers to the intrinsic motivation and pleasure derived from using m-learning which positively influences the willingness to accept and utilize it (Wang et al., 2019; Ching-ter et al., 2017). When users enjoy the experience, they tend to tend to perceive the technology as more usable and convenient.

However, there are research findings on the impact of enjoyment on m-learning usage that have been inconsistent. Some studies support the notion that enjoyment influences m-learning usage positively, while others have found no significant effect (Wang et al., 2020; Jiang et al., 2021; Al-Gahtani, 2016). It is important to consider these differing perspectives and further investigate the relationship between enjoyment and m-learning adoption to gain a comprehensive understanding of the factors influencing its success.

Indeed, self-efficacy is another key factor that influences the success of m-learning (Thongsri et al., 2020). Self-efficacy refers to users' belief in their capabilities to effectively use the system. Higher levels of self-efficacy have been found to positively affect user satisfaction (Hammouri & Abu-Shanab, 2018). However, some studies have reported no significant impact of self-efficacy on the success of m-learning (Kosycheva & Tikhonova, 2021). Further research is needed to explore and reconcile these divergent findings regarding the relationship between self-efficacy and m-learning adoption. The results of this study are expected to be a reference for developing a successful model of m-learning implementation, especially for Generation Z.

## METHOD

### Research Design

The research design used is a survey that uses quantitative measurements. Component-based Structural Equation Modeling (SEM) using Partial Least Square (PLS) is the analytical approach adopted in this research. PLS-SEM is used to explain the relationships between latent variables in complex models. SEM was used to evaluate the proposed research model. The PLS-SEM model consists of two submodels: a measurement model (outer) and a structural model (inner).

### Participants

The population of this study has used students as m-learning users at the Muhammadiyah University of Purwokerto (UMP). UMP is one of the universities in Indonesia, which uses offline and online methods. The m-learning application "onclass" has been implemented at UMP since 2020. Other populations can be studied in further research.

Participants are undergraduate and postgraduate students of UMP. Their ages range from 20 - 35 years. Participants are generally Generation Z who are the internet generation or digital natives. They are considered very potential in utilizing technology, especially for the implementation of m-learning.

### Data Collection

Determination of the minimum sample size using power analysis (Hair et al., 2022). Sampling using the random sampling method. Students filled out the questionnaire using a Google form. Data was collected for 1 month (February 2024), so the number of participants collected was 563 students. The time of data collection varies, the study used a non-response bias test to prevent sample bias. The test uses the common method bias (Podsakoff et al., 2003), using the highest full collinearity variance inflation factor (FCVIF) test (Kock, 2015). Based on the test results, it is known that the highest FCVIF in the research model is less than 3.3. This shows that the bias that occurs is not a significant problem.

This research uses latent variables, namely perceived enjoyment, self-efficacy, usefulness, ease of use, and m-learning usage. Table 1 presents the questionnaire statements that are indicators for measuring the variables. The data collected is primary data, and the instrument used for data collection is a questionnaire, using a 1-5 Likert scale (from strongly disagree to strongly agree). The average indicator score is categorized into five levels from 1 to 5 which indicates very low to very high levels. This research also used a questionnaire with open questions for respondents.

Based on Table 1., there are 17 items from 5 constructs in the conceptual research model (self-efficacy, enjoyment, perceived usefulness, ease of use, and m-learning usage). Five items are used to measure self-efficacy. This indicator refers to Hammouri & Abu-Shanab (2018) and Mutahar et al. (2018). Enjoyment is calculated using three indicators referring to Al-Gahtani (2016) and Ching-ter et al. (2017). Perceived usefulness, ease of use, and m-learning usage are measured using three indicators each referring to Davis (1989) and Al-Fraihat et al. (2020).

**Table 1.** Operational definition and measurement of variables

| Variables | Indicators |
|---|---|
| Self-efficacy (Hammouri & Abu-Shanab, 2018); (Mutahar et al., 2018) | Confidence can use m-learning through the user guide<br>Confidence can solve problems using m-learning<br>Confidence can use m-learning even though it has never been used before<br>Confidence can use m-learning because there is a tutorial.<br>Confidence can use m-learning with learning in a short time |
| Enjoyment (Al-Gahtani, 2016)"ISSN":"22108327","abstract":"E-learning has become progressively more vital for academia and corporate training and has potentially become one of the most significant developments and applications in Information Technologies (ITs; (Ching-ter et al., 2017) | Using m-learning is comfortable<br>Enjoyment of using m-learning<br>Using m-learning happily |
| Perceived Usefulness (Al-Fraihat et al., 2020); (Davis, 1989) | The use of m-learning causes learning to be more effective and efficient<br>The use of m-learning causes increased activity in learning.<br>The use of m-learning facilitates the achievement of learning objectives |
| Perceived ease of use (Al-Fraihat et al., 2020); (Davis, 1989) | Ease of learning m-learning<br>Ease of operating m-learning<br>Ease of becoming proficient with m-learning |
| M-learning Usage (Al-Fraihat et al., 2020); (Davis, 1989) | Frequency of using m-learning<br>Regular use of m-learning<br>Dependence on the use of m-learning in studies |

## Validity and Reliability

The measurement model in the PLS-SEM model is tested to assess the quality of the indicators. Evaluation is used to test the validity and reliability of indicators of research variables. Significance criteria for factor loading tests, average variance extracted (AVE), composite reliability (CR), and Fornell-Larcker criteria (Hair et al., 2022).

## Data Analysis

The model developed in this study, as in Figure 1, has seven hypotheses. The hypothesis is formulated that partially perceived usefulness and ease of use have a positive effect on m-learning usage. Another hypothesis is that self-efficacy and enjoyment have a positive effect on perceived usefulness and ease of use.

The analysis technique used is component or variant-based Structural Equation Modeling (SEM) using Partial Least Square (PLS). PLS-SEM is used to explain the relationship between latent variables. We are using PLS-SEM to estimate variable relationships with complex models (Hair et al., 2022).

The PLS-SEM model constructed comprises two sub-models: the structural (inner) model and the measurement (outer) model. The structural model illustrates the relationship between latent variables whether they are exogenous or endogenous. According to Hair et al. (2022), structural model evaluation is used to test the coefficient of determination ($R^2$), effect size ($f^2$), and the significance of the path coefficient. Hypothesis testing uses the significance of the path coefficient (p-value less than 0.05).

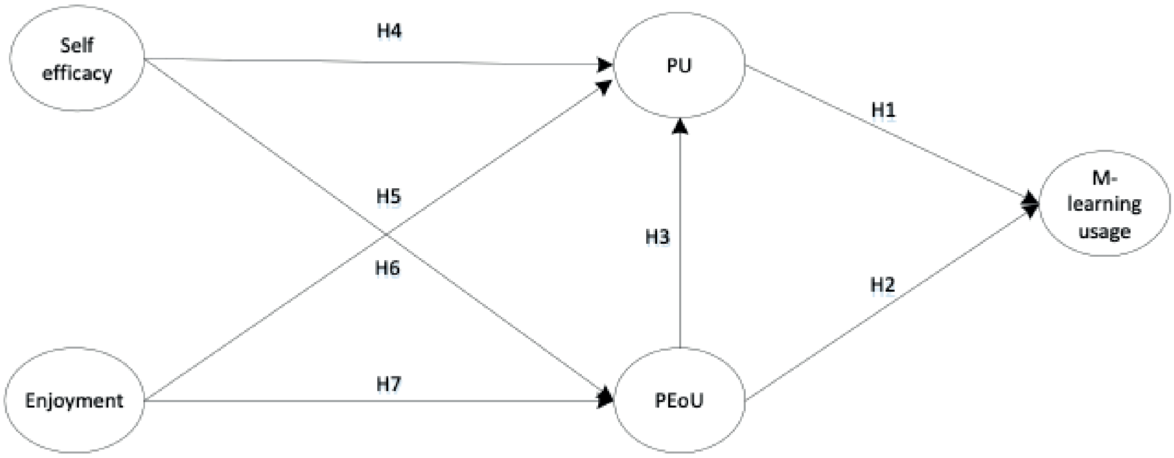


**Figure 1.** M-learning success model

Based on the phenomena and review of previous research results, a model was proposed as in Figure 1. The hypotheses formulated in this research are:

$H_1$: Perceived usefulness has a positive effect on m-learning usage.

$H_2$: Perceived ease of use has a positive effect on m-learning usage.

$H_3$: Perceived ease of use has a positive effect on perceived usefulness.

$H_4$: Self-efficacy has a positive effect on perceived usefulness.

$H_5$: Self-efficacy has a positive effect on perceived ease of use.

$H_6$: Enjoyment has a positive effect on perceived usefulness.

$H_7$: Enjoyment has a positive effect on perceived ease of use.

# FINDINGS

## Demographic Profile and Characteristics of Participants

The demographic profile and characteristics of the participants are presented in Table 2.

**Table 2.** Demographics of participants' profiles

| Characteristics | % |
|---|---|
| Gender | |
| Female | 69.02 |
| Male | 30.98 |
| Age | |
| <30 years old | 92.45 |
| ≥30 years old | 7.35 |
| Times to use m-learning | |
| ≤ 3 years | 81.18 |
| > 3 years | 18.82 |

Table 2 shows that there were 69.02% females and 30.98% males among the 563 participants. Most participants have used m-learning for less than 3 years (81.18%), while those who have used it for more than 3 years are 18.82%. Participants are undergraduate and postgraduate students of UMP. Their ages range from 20 - 35 years. They are Generation Z (92.45%), with users under 30 years old (born in 1995 or later). This generation is known to have a high interest in new technology and often utilizes digital technology. They are the first digital generation, use a lot of communication technology, and are always connected to the world. They are often and familiarly interacting with the web, internet, smartphones, laptops, and digital media, so they are more adaptable and skilled in using m-learning (Gupta & Pathania, 2021; Szymkowiak et al., 2021). Generation Z has diverse learning styles. They also have a lot of knowledge and experience in using information technology and information systems. They are very participative, proactive, and productive in the use of IS (Szymkowiak et al., 2021).

## Validity and Reliability

Validity and reliability testing using measurement model test. The measurement model test uses outer loading, CR, AVE, and Fornell-Larcker values. The results of validity and reliability testing are presented in Tables 3 and 4.

**Table 3.** The validity and reliability (AVE, CR, and outer loading)

| Variables | AVE | CR | Indicators | Outer Loading | |
|---|---|---|---|---|---|
| | | | | Original | p-value |
| Self-efficacy | 0.57 | 0.87 | SE1 | 0.72 | 0.00 |
| | | | SE2 | 0.71 | 0.00 |
| | | | SE3 | 0.75 | 0.00 |
| | | | SE4 | 0.86 | 0.00 |
| | | | SE5 | 0.71 | 0.00 |
| Enjoyment | 0.81 | 0.93 | E1 | 0.93 | 0.00 |
| | | | E2 | 0.89 | 0.00 |
| | | | E3 | 0.87 | 0.00 |
| PU | 0.70 | 0.88 | PUI | 0.83 | 0.00 |
| | | | PU2 | 0.86 | 0.00 |
| | | | PU3 | 0.78 | 0.00 |
| PEoU | 0.68 | 0.87 | PEoU1 | 0.83 | 0.00 |
| | | | PEoU2 | 0.86 | 0.00 |
| | | | PEoU3 | 0.78 | 0.00 |
| M-learning usage | 0.46 | 0.52 | Usg1 | 0.83 | 0.00 |
| | | | Usg2 | 0.84 | 0.00 |
| | | | USg3 | 0.81 | 0.00 |

**Table 4.** The discriminant validity (Fornell-Larcker criterion)

| Variables | M-Learning usage | Enjoyment | PEoU | PU | Self-efficacy |
|---|---|---|---|---|---|
| M-Learning usage | 0.83 | | | | |
| Enjoyment | 0.52 | 0.89 | | | |
| PEoU | 0.51 | 0.48 | 0.83 | | |
| PU | 0.49 | 0.52 | 0.59 | 0.94 | |
| Self-efficacy | 0.46 | 0.52 | 0.52 | 0.37 | 0.75 |

The measurement model test results show the outer loading value above 0.7, p-value below 0.05, CR above 0.7, and AVE above 0.5 (Table 3). The Fornell-Larcker value for each variable is higher than the other variables (Table 4). Based on these findings, it can be concluded that the measurement model meets the criteria for validity and reliability. Thus, all indicators used in this research reflect latent variables.

## Data Analysis

Descriptive statistics are used to describe the characteristics of research variables. Table 5 provides a summary of participants' responses regarding self-efficacy, enjoyment, perceived usefulness, ease of use, and actual use of m-learning.

Based on Table 5, self-efficacy, enjoyment, perceived usefulness, ease of use and actual use of m-learning obtained an average score for all indicators ranging from 3.41 – 4.20, including in the high category. Users show high self-efficacy in utilizing m-learning. They quickly adapt to m-learning systems with the help of user guides, training, or tutorials, even when they have no previous experience. They also have the confidence to solve any problems encountered while using it.

Users feel happiness and comfort when using m-learning, which influences perceived usefulness and ease of use. Users consider m-learning to be a valuable tool that increases the effectiveness and efficiency of online learning. It functions as an alternative learning media that users need. Overall, users feel that using this application facilitates the learning process because m-learning is easy to learn and operate. As a result, they believe it is easy to become proficient in using m-learning.

**Table 5.** Recapitulation of participants' responses

| Variables | Indicators | Scores | Average |
|---|---|---|---|
| Self-efficacy | SE1 | 4.03 | 4.02 |
| | SE2 | 3.98 | |
| | SE3 | 4.11 | |
| | SE4 | 4.09 | |
| | SE5 | 3.87 | |
| Enjoyment | E1 | 3.97 | 3.98 |
| | E2 | 4.09 | |
| | E3 | 3.89 | |
| Perceived Usefulness | PU1 | 3.38 | 3.93 |
| | PU2 | 4.31 | |
| | PU3 | 4.11 | |
| Perceived Ease of Use | PEoU1 | 4.24 | 4.21 |
| | PEoU2 | 4.24 | |
| | PEoU3 | 4.16 | |
| M-learning usage | Usg1 | 3.96 | 4.01 |
| | Usg2 | 4.12 | |
| | Usg3 | 3.95 | |

The average score for actual use of m-learning is also in the high category. Both students and lecturers consistently use the application during m-learning. They rely on the application to fulfill all their learning-related tasks and assignments. The application seamlessly integrates their tasks and work processes.

The structural model illustrates the relationship between latent variables whether they are exogenous or endogenous. The evaluation of the structural model encompasses tests for the significance of path coefficients, the coefficient of determination ($R^2$), and the effect size ($f^2$). Detailed results of the evaluation are presented in Tables 6 and 7.

**Table 6.** Path coefficient, statistic-t, p-value

| Hypothesis | Path coefficient | t-statistic | p-value | Result |
|---|---|---|---|---|
| $H_1$ | 0.29 | 4.24 | 0.00 | Supported |
| $H_2$ | 0.34 | 4.82 | 0.00 | Supported |
| $H_3$ | 0.47 | 7.99 | 0.00 | Supported |
| $H_4$ | 0.04 | 0.62 | 0.43 | Not Supported |
| $H_5$ | 0.37 | 8.95 | 0.00 | Supported |
| $H_6$ | 0.31 | 5.12 | 0.00 | Supported |
| $H_7$ | 0.29 | 8.12 | 0.00 | Supported |

**Table 7.** The coefficient of determination ($R^2$) and the effect size ($f^2$)

| Variables | $R^2$ | $f^2$ |
|---|---|---|
| Self-efficacy | | 0.15 |
| Enjoyment | | 0.11 |
| Perceived usefulness | 0.63 | 0.08 |
| Perceived ease of use | 0.53 | 0.11 |
| M-learning usage | 0.52 | |

The strength and direction of influence between latent variables can be observed from the path coefficient values. According to Table 6, at the significance level $\alpha$ = 5%, enjoyment has a positive effect on perceived usefulness while self-efficacy does not show any effect. Both self-efficacy and enjoyment, however, do have an impact on perceived ease of use. Perceived usefulness and ease of use, in turn, affect the usage of m-learning. Additionally, perceived ease of use influences perceived usefulness.

The standard $f^2$ values of 0.02, 0.15, and 0.35 are used to indicate small, medium, and large effects of exogenous variables on endogenous variables (Hair et al., 2022). Referring to Table 7, it is observed that self-efficacy and enjoyment variables have a medium effect on m-learning usage, while the perceived usefulness variable has a small effect. Additionally, perceived ease of use has a medium effect on m-learning usage.

The $R^2$ value demonstrates the proportion of variability in perceived usefulness that can be explained by changes in the variables of self-efficacy, enjoyment, and perceived ease of use, amounting to 0.63 or 63%. It implies that variables outside the study account for 37% of the variability. Similarly, the $R^2$ value for perceived ease of use is 0.53, indicating that self-efficacy and enjoyment influence 53% of the variability in perceived ease of use. Furthermore, the $R^2$ value for m-learning usage suggests that perceived usefulness and ease of use contribute to a change in the variability of m-learning usage by 52%.

## DISCUSSIONS AND CONCLUSION

### The Effect of Perceived Usefulness and Ease of Use on M-learning Usage

Based on Table 6, perceived usefulness and ease of use have a positive effect on the use of m-learning. This means that when users find m-learning useful and easy to use, they are more likely to use it frequently. This research defines perceived usefulness as the potential of m-learning to facilitate learning for users. Perceived ease of use is reflected in users who are easy to operate and proficient in using m-learning. This perception is a motivating factor to continue using m-learning. This research states that users who have a high perception of the usefulness and ease of use of m-learning applications tend to use them more often.

Usability and ease of use play an important role in influencing the acceptance and implementation of m-learning. Users feel that m-learning can be used anywhere and anytime. So, the learning becomes more efficient. They can save time and money by studying offline. The m-learning application used at UMP has also been designed to meet the needs and be user-friendly so that they feel comfortable using it. This causes them to use it regularly and will continue to use it in the future.

User-friendly and easy-to-implement m-learning design increases users' ability to learn how to use it and increases their willingness to adopt it. When users find m-learning easy to use, this positively influences their willingness to utilize it. Simple and accessible m-learning design with interactive functions contributes to user comfort and dependability on the system, thereby leading to continued use.

M-learning that is easy to use will increase the user's proficiency in using it. Perceived ease of use directly influences perceived usefulness. The easier it is to use m-learning technology, the more users will experience its benefits in supporting their learning. In addition, when users find m-learning easy to use and useful, this will encourage them to continue using it. These findings are consistent with Li et al. (2021); Ang et al. (2021); and Baber (2021) that explained if m-learning is too complicated and users have negative experiences, they may avoid or refuse its use.

This study found that students' perceptions that m-learning causes learning to be more effective and efficient had an average value of 3.38, which is quite sufficient. The average perceived usefulness score was high, but they felt that the use of m-learning applications was not optimal for improving their understanding and skills. They understand learning materials better when using offline learning methods. This is possible because the technological devices (such as laptops, smartphones, or other gadget specifications and internet speed) they use are inadequate (Asghar et al., 2023; Asgari et al., 2021). Lecturers and students who use m-learning have the perception that m-learning and offline learning are the same except for the media. It is different. In offline classes, lecturers find it easier to understand student behavior. As for m-learning, lecturers must design learning tools that motivate and encourage active participation from students (Bao, 2020; Abduljawad & Ahmad, 2023).

Nikolopoulou (2022) stated that offline and mobile learning have different characteristics. Offline learning makes it easier to create closeness and interaction with lecturers, as well as active student participation. However, the problem that occurs is limited time and place. The benefits of using m-learning include flexibility in time and place, as well as familiarity with digital technology. Meanwhile, m-learning problems are related to more complex technical usage and a lack of social interaction between lecturers and students.

Currently, the role of m-learning cannot completely replace offline learning. This learning method is still in its early stages of development and there are still many problems that need to be resolved. Many higher education institutions have failed to achieve the expected benefits of this system (Kumar & Chand, 2018; Almaiah et al., 2020). Some studies even report a decline in acceptance rates among students (Alrawashdeh et al., 2020; Almaiah & Al Mulhem, 2018). Hybrid or blended learning is an alternative learning that combines offline and m-learning (Lee et al., 2022; Li, 2022).

### The Effect of Self-efficacy on Perceived Usefulness and Ease of Use

Table 6 shows that self-efficacy affects perceived ease of use but not usefulness. The path coefficient shows a positive relationship (p-value = 0.00) indicating that the higher the self-efficacy, the greater the perceived ease of use. Since the Covid-19 pandemic occurred, in 2020, Universitas Muhammadiyah Purwokerto (UMP) has implemented m-learning as an alternative learning solution that can be done anywhere and anytime. The success of its implementation depends on the willingness and self-efficacy of the user. Self-efficacy acts as a predictor that influences the ease of use of m-learning. Self-efficacy refers to users' beliefs about their ability to use m-learning effectively. As seen in Table 3, m-learning users show high self-efficacy. This belief makes users optimistic and confident in their ability to complete tasks and solve learning problems. Users with high self-efficacy increase their confidence in their abilities and predictions, thus opening their minds to relevant actions. Based on Table 2, it is known that the respondents are dominated by Generation Z. They have high motivation and curiosity in using technology. These conditions play an important role in increasing self-efficacy. Motivated students will spend more time studying. This will increase their self-confidence in using m-learning. Users with high self-efficacy feel their ability to use m-learning effectively. Users get guidance and tutorials on using m-learning. This will increase their self-confidence and self-efficacy in operating it. Users who have previous experience with m-learning can also increase their self-confidence in using it. Generation Z has high self-confidence in their knowledge and skills in interacting with m-learning technology and tends to have a more positive attitude towards its use. Increasing self-efficacy can also be achieved through technical trials of using m-learning.

However, there are often problems related to the technological infrastructure used, be it hardware, software, facilities, or network capabilities. Common problems that occur when using m-learning are inadequate hardware such as laptops, smartphones, or other devices, as well as unstable internet speeds. Lack of integration between hardware and software can also cause problems in its implementation. With high self-efficacy, they try to solve these problems. This is in line with Asgari et al. (2021) and Hammouri & Abu-Shanab (2018) that people who have higher levels of self-efficacy have a positive impact on user satisfaction.

This study found that self-efficacy did not affect the perceived usefulness of m-learning. The research findings show that users have high self-efficacy and perceived usefulness towards m-learning, but perceived usefulness is not influenced by self-efficacy. Users are aware of the benefits provided by m-learning. At UMP, the implementation of m-learning has been going on for six semesters. Users have realized the benefits of flexibility because they can access m-learning from anywhere and anytime. The findings of this study are in line with Thongsri et al. (2020) and Hammouri & Abu-Shanab (2018), that self-efficacy is one of the factors that influence the success of m-learning for Generation Z.

This study also found that the effectiveness of m-learning depends on the behavior of lecturers and students. Lecturers should act as facilitators, not just provide materials through m-learning applications. Unfortunately, lecturers do not provide the right instruments to use in m-learning. Learning only relies on the delivery of materials and direct online interactions between lecturers and students. Therefore, instruments are needed that can improve students' understanding and skills independently. M-learning utilizes technology to increase the accessibility and effectiveness of learning. M-learning is also expected to create an interactive environment that encourages effective and positive learning experiences. Lecturers need to have a positive influence in building students' mindsets and behaviors towards independent learning and understanding of content through m-learning. In addition, lecturers can encourage positive attitudes towards the use of m-learning. In utilizing m-learning, lecturers must design various learning methods and tools to improve students' understanding and skills. Creative, innovative, and practical learning methods and tools are created to encourage student involvement. These instruments should encourage focus, provide feedback, and trigger student autonomy in the learning process.

Students are also expected to be more responsible in their learning. With self-awareness, they should use all the instruments and features available in the application to improve their understanding and skills. During online meetings, they and the lecturer can discuss and find solutions to problems according to the subject matter studied. These ideal conditions have not yet occurred in the implementation of m-learning at UMP. They have felt the usefulness and ease of use of m-learning as a flexible learning method, but students and lecturers do not report that the use of m-learning can improve the expected understanding and skills.

Mumford & Miller (2018) emphasize how the use of m-learning can influence users' access to feedback. M-learning has characteristics that facilitate student feedback and engagement, which should be carefully monitored. Blended learning between offline and mobile learning can help reduce potential problems. In offline learning, lecturers have better control over student behavior, allowing for more effective management.

## The Effect of Enjoyment on Perceived Usefulness and Ease of Use

Table 6 shows that enjoyment has a positive effect on perceived ease of use and usability. Users who feel comfortable will feel that m-learning provides usability and ease of use. Based on Table 2, users feel high enjoyment, usefulness, and ease of use. Users who are comfortable using m-learning will find it easy to operate and useful. Enjoyment contributes to the ease and higher usability of m-learning applications. These are extrinsic motivators that can be incorporated into TAM.

The use of m-learning has been implemented for six semesters. Before using m-learning, users have received a lot of information and experience through video tutorials to familiarize themselves with its functions. Students acquire the skills necessary to use m-learning effectively. So, students have found m-learning user-friendly, useful, and beneficial.

M-learning should be designed to be visually appealing and user-friendly. This will further strengthen users' perceptions that the application is easy to use and can facilitate their learning tasks more efficiently. The user-friendly approach makes them feel enjoyment and contributes to its use. Furthermore, the findings of this study indicate that perceived enjoyment plays an important role in users' intention to use m-learning. Ease of use and perceived usefulness will increase users' intentions to adopt and continue to use m-learning now and in the future.

M-learning becomes effective if lecturers and students have the responsibility to support its success. The comfortable and attractive m-learning design makes it easy for users to adapt to various m-learning applications and platforms. This design provides a higher-quality learning experience.

This research found that self-efficacy and enjoyment influence perceptions of usefulness and ease of use, and impact actual use of m-learning. Future research is expected to develop m-learning success models by incorporating other characteristics of Generation Z. This generation is more adaptable and skilled in using technology. Thus, the m-learning model was found to be successful and appropriate for Generation Z.

This research has expanded the m-learning success model using TAM by adding self-efficacy and enjoyment variables. The success of m-learning of Generation Z can be measured through reflective indicators: including perceived usefulness, ease of use, and m-learning usage. Indicators that reflect self-efficacy include the belief that users can utilize m-learning effectively through guides and tutorials, even without previous experience and limited time. Enjoyment is reflected through feelings of joy, enthusiasm, and comfort when using it.

These findings have indicated that enjoyment is an external variable that influences perceptions of usefulness and ease of use. Generation Z has demonstrated a high level of proficiency in using technology from an early age. The existence of guides and tutorials further enriches their experience and increases their confidence in using it.

Additional findings suggest that enjoyment has a positive effect on perceived ease of use and usefulness. Enjoyment makes individuals believe that m-learning is user-friendly and offers benefits. This is an extrinsic factor that influences acceptance of technology. Motivation also plays an important role in m-learning adoption.

Even though students and lecturers have realized the usefulness and ease of use of m-learning as a flexible learning method, they have not experienced an increase in understanding of learning. Based on the results of the questionnaire, it is known that technically learning becomes more efficient when using m-learning. However, the effectiveness of using m-learning to improve learning objectives has a lower score. Lecturers and students have not reported an increase in students' understanding and skills when using m-learning. They feel that m-learning has made learning techniques easier. Lecturers should not only provide material and interact with students online but should also motivate students to learn autonomously.

M-learning is proposed to use diverse learning tools to improve students' understanding and skills. Apart from that, lecturers should prepare creative, innovative, and practical learning materials to foster student learning independence. Lecturers should develop learning tools that support students to be actively involved in learning and problem-solving discussions. M-learning must also be interactive to create an effective and meaningful learning environment. The implementation of M-learning at UMP through onclass applications has only been three years. This causes the implementation to not obtain optimal results. In this research, it is proposed that optimal learning outcomes can be done by combining it with face-to-face learning.

In further research, it is proposed to test the effectiveness of using m-learning in improving student understanding and skills. Future research can also be expanded by including additional variables, dimensions, and indicators to strengthen confidence and general acceptance of the research conducted. In addition, it is necessary to examine the key factors for the success of information systems, both internal and external, which are useful for further research.

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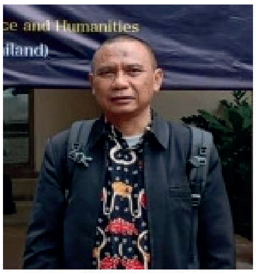

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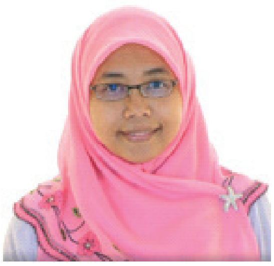

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