PERCEPTION AND BARRIERS TO MOOC ADOPTION: A CASE STUDY OF *KARTU PRAKERJA* RECIPIENTS

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Abstract*—The Indonesian government launched the Pre-Employment Card (Kartu Prakerja) program to enhance workforce skills and address economic challenges. This program provides training through online platforms, including Massive Open Online Courses (MOOCs). The UTAUT2 model was employed as a framework to understand the factors influencing the acceptance and use of educational technology in this context. This study examines the effects of UTAUT2 variables—performance expectancy, effort expectancy, habit, traditional barriers, platform content, access limitations, interaction limitations, facilitating conditions, hedonic value, price value, and social influence—on the intention and adoption of MOOCs among Pre-Employment Card participants. The sample consisted of 222 respondents who were users of the Prakerja platform. Data were collected using a questionnaire and analyzed through Structural Equation Modeling (SEM) with the support of PLS-SEM software. In addition, a sentiment analysis was conducted on comments posted on the official Instagram account @prakerja.go.id to explore public perceptions of the program. The findings reveal that 46.2 percent of public sentiment was negative, particularly related to the program implementation and the use of partner MOOC platforms. SEM analysis further indicates that hedonic value, habit, and social influence have positive and significant effects on the intention and adoption of MOOCs. The moderation analysis by gender shows that performance expectancy, hedonic value, and social influence are stronger among males, whereas effort expectancy, habit, and platform content are stronger among females.*

Keywords: *MOOC, PLS-SEM, pre-employment card, sentiment analysis.*

Abstrak*—Pemerintah Indonesia meluncurkan program Kartu Prakerja untuk meningkatkan keterampilan tenaga kerja sekaligus menghadapi tantangan ekonomi. Program ini menyediakan pelatihan melalui platform daring, termasuk Massive Open Online Courses (MOOC). Model UTAUT2 digunakan sebagai kerangka untuk memahami faktor-faktor yang memengaruhi penerimaan dan penggunaan teknologi pendidikan dalam konteks program tersebut. Penelitian ini menguji pengaruh variabel UTAUT2, yaitu ekspektasi kinerja, ekspektasi usaha, kebiasaan, hambatan tradisional, konten platform, keterbatasan akses, keterbatasan interaksi, kondisi yang memfasilitasi, nilai hedonis, nilai harga, dan pengaruh sosial terhadap niat dan adopsi penggunaan MOOC pada peserta Kartu Prakerja. Sampel penelitian terdiri atas 222 responden pengguna platform Prakerja yang diperoleh melalui kuesioner dan dianalisis menggunakan Structural Equation Modeling (SEM) berbantuan perangkat lunak PLS-SEM. Selain itu, dilakukan analisis sentimen terhadap komentar pada akun Instagram resmi @prakerja.go.id untuk mengeksplorasi persepsi publik. Hasilnya menunjukkan bahwa 46,2 persen sentimen publik bersifat negatif, terutama terkait implementasi program dan penggunaan platform MOOC mitra. Analisis SEM menemukan bahwa nilai hedonis, kebiasaan, dan pengaruh sosial berpengaruh positif dan signifikan terhadap niat serta adopsi MOOC. Temuan moderasi berdasarkan gender menunjukkan bahwa ekspektasi kinerja, nilai hedonis, dan pengaruh sosial lebih kuat pada laki-laki, sedangkan ekspektasi usaha, kebiasaan, dan konten platform lebih kuat pada perempuan.*

Kata Kunci*: MOOC, SEM PLS, kartu prakerja, analisis sentimen.*

INTRODUCTION

The digital era has brought significant transformations in the field of education, particularly through the introduction of Massive Open Online Courses (MOOCs). MOOCs serve as essential platforms for distance learning, providing learning opportunities with high-quality resources for anyone with internet access. Shah (2020) noted that more than 180 million people worldwide have enrolled in various MOOC courses, indicating a significant increase in online learning. MOOCs have reshaped access to higher education by offering broad and inclusive learning opportunities. The key characteristics of MOOCs are their openness, flexibility, and accessibility to a wide audience, which help reduce the digital divide and expand access to education. However, despite numerous advantages such as access to materials from prestigious universities and the convenience of learning at one's own pace, many developing countries still experience low enrollment and completion rates for MOOC courses (Pörzse & Kenesei, 2025).

In Indonesia, the government has launched the Pre-Employment Card program (Indonesian: *Kartu Prakerja*) in response to the need for workforce skill development and economic challenges. This program provides skill training through online platforms, including MOOCs, to enhance workforce capabilities in facing labor market uncertainties, particularly during and after the COVID-19 pandemic. The program relies heavily on MOOC platforms as its training medium. It is designed for various groups, ranging from those affected by layoffs to individuals seeking to improve their skills (Kemnaker, 2023). The application of the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) in the context of MOOCs and the Pre-Employment Card program provides a framework for understanding the factors influencing the acceptance and use of educational technology. UTAUT2, an extension of the UTAUT model, incorporates additional aspects such as perceived value, habit, and facilitating conditions, making it highly relevant in the context of online learning (Gimpel et al., 2025). Several studies have applied UTAUT2 to understand technology adoption in education (Dhewandrie & Yuniawan, 2023) but few have investigated its applicability to government-subsidized MOOCs within the unique structure of a national policy like Kartu Prakerja.

Recent literature also highlights the growing integration of sentiment analysis with adoption models to uncover user’s emotional and cognitive responses toward MOOCs. Ahmad et al. (2023) demonstrated how sentiment analysis could provide a deeper understanding of public acceptance of MOOC platforms. Although MOOCs present various opportunities, such as self-paced and accessible learning, traditional learning, and time constraints (Islam et al., 2025). Therefore, this study integrates sentiment analysis to offer a more comprehensive perspective on how both perceptions and emotional reaction influence MOOC adoption, especially within the Pre-Employment Card program.

To date, few studies have specifically examined the intersection between UTAUT2-based behavioral modeling and sentiment analysis in the context of state-sponsored learning programs. This study addresses that gap by exploring how perceptions and external influences (including online sentiments) affect MOOC usage among Kartu Prakerja participants. Additionally, this research investigates the moderating role of gender, which remains underexplored in MOOC adoption literature in Indonesia. Thus, this study aims to answer the following research questions: How do UTAUT2 variables and social media sentiment influence MOOC adoption among recipients of the Kartu Prakerja program and how does gender moderate these effects?

MATERIALS AND METHODS

This study used a quantitative research design with a survey approach. This approach was chosen because it allowed for the collection of numerical data from a representative sample to test hypotheses related to the relationships between variables in the UTAUT2 model and MOOC adoption (Creswell, 2019). Additionally, sentiment analysis was used to evaluate the Pre-Employment Card policy based on sentiment from social media. The types of data used in this study were primary and secondary data. Primary data were obtained from respondents through questionnaire distribution, while secondary data were collected from comments on Instagram posts of @prakerja.go.id.

Data were collected through an online questionnaire distributed to respondents via social media platforms. The questionnaire was designed to be easy to understand and respond to, ensuring a high response rate. Data collection was conducted among respondents from the sample, specifically Pre-Employment Card users. The estimated sample size was determined using several practical rules and guidelines available in the SEM-PLS literature. One of the most commonly used methods was the 10 times rule, which states that the sample size should be at least 10 times larger than the number of the largest paths leading to a latent variable in the model or 10 times the number of indicators of the largest latent variable in the model (Sarstedt et al., 2021). The highest number of indicators from the formulated latent variable was five, so the ideal total sample size used in this study was 50. According to Sarstedt, Ringle, & Hair (2021) explain if a model had a high level of complexity, a conservative approach could be used with a larger sample size, which is approximately 100–200 samples. Then, for sentiment analysis to address perception-related questions, scraping was performed on comment data from Instagram posts on the @prakerja.go.id account.

Based on the research problem and hypotheses, the variables examined and analyzed in this study were categorized into two types: dependent variables (Y) and independent variables (X). The dependent variables were MOOC usage intention and actual MOOC usage. Meanwhile, the independent variables included Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Habit, Hedonic Value, and Price Value. The collected data were analyzed using Structural Equation Modeling (SEM) with the assistance of SmartPLS software. SEM was chosen due to its ability to examine the relationships between independent and dependent variables in a complex model (Sarstedt et al., 2021). The data used a Likert scale ranging from 1 to 6, where 1 represented the lowest level of acceptance, indicating that respondents strongly disagreed with the given statement, and 6 represented the highest level of acceptance, indicating that respondents strongly agreed with the given statement. Additionally, the demographic data of the respondents examined in this study included gender, age, education level, the number of training programs attended, and the number of MOOC Mitra Prakerja (English: Pre-Employment Card Partners) platforms participated in, The names of the MOOC Prakerja partner platforms. In addition to the quantitative survey approach, this study also integrated sentiment analysis as an additional method to understand the perceptions and attitudes of Pre-Employment Card users. Sentiment analysis was conducted using natural language processing (NLP) tools and machine learning. The techniques used included:

1. Sentiment Extraction: Used NLP algorithms to identify keywords and phrases that indicate positive, negative, or neutral sentiment (Chowdhury, 2024)
2. Sentiment Classification: Used machine learning models that had been trained to classify sentiment from the extracted text.

Data collection for this sentiment analysis was conducted using Apify.com to extract data related to the Pre-Employment Card. The author collected data from the official Pre-Employment Card Instagram account, @prakerja.go.id. Sentiment analysis using Instagram comments has also been conducted by Khoirunnisa & Rumaisa (2025). In their study, 800 Instagram comments were collected and categorized into several categories, including health, education, administration, economy, infrastructure, citizenship, social, and environment. The results of the sentiment analysis were combined with survey data to provide a more comprehensive understanding of the factors affecting MOOC adoption. This analysis helped identify whether there was a correlation between the sentiment expressed on social media and the survey responses regarding the UTAUT2 variables (Creswell, 2019).

RESULTS AND DISCUSSION

Sentiment Analysis Results

The first discussion begins with the results of the sentiment analysis. The sentiment analysis of the Pre-Employment Card, which was taken from comments on Instagram posts on the @prakerja.go.id account, used the Python programming language and the Natural Language Processing (NLP) method to classify sentiment into three categories, namely positive, negative, and neutral. The total number of comments that were collected was approximately 945 comments from various posts. The distribution of sentiment analysis results on the Pre-Employment Card can be seen in Table 1.

Table 1. Sentiment Distribution

Category	Percentage
Negative	46.2%
Neutral	29.8%
Positive	24%

Source: (Research Results, 2024)

From the sentiment distribution results, it can be observed that the majority sentiment toward the Pre-Employment Card is negative. Furthermore, the representation of the most frequently appearing words in Instagram comments related to the Pre-Employment Card is shown in Figure 1.

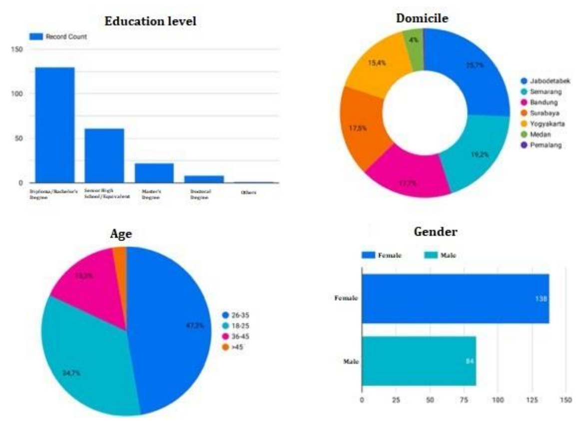
Source: (Research Results, 2024)

Figure 1. *Word Cloud* Comment

It can be seen from the word cloud results that the most frequently appearing words are *"Prakerja"* (Pre-Employment Card), *"Min"* (short for "Admin," referring to the administrator of the Instagram account), *"Pelatihan"* (training), and *"Gelombang"* (wave, referring to different enrollment batches for the Pre-Employment Card program). It is evident that many users are questioning when the *Pre-Employment Card* waves and training will start again. Some users also inquire about *"Cair"* (disbursement, referring to the release of Pre-Employment Card funds). Others ask technical questions related to *"Akun"* (account) and *"Email"* (email), which refer to MOOC usage. These issues align with the findings of the Supreme Audit Agency (Indonesian: *Badan Pemeriksa Keungan*; BPK), as published in Warta Pemeriksa, which can be accessed on the bpk.go.id website. The findings indicate that 165,544 Pre-Employment Card participants, with a total aid value of IDR 390.32 billion, were placed on the blacklist after being designated as participants in the program. This resulted in a waste of IDR 390.32 billion (Badan Pemeriksa Keuangan, 2022). In addition, a study by Fasri et al (2023) also showed that Pre-Employment Card recipients were still not well-targeted due to the lack of a proper database, based on their research conducted in Makassar. Based on these findings, it can be seen that social media users' questions regarding the Pre-Employment Card program schedule and fund disbursement are relevant to the reality that the Pre-Employment Card policy is still not well-targeted.

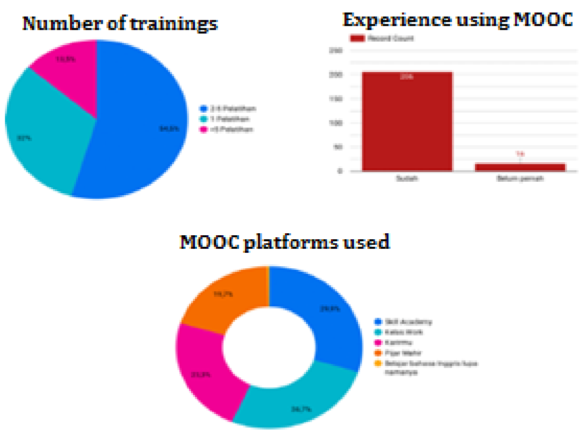
Data Description

The discussion then continued with the main method, SEM-PLS, beginning with an explanation of the data description. This study involved 222 respondents, all of whom were users of the Prakerja platform. Based on the data collection results, the characteristics of respondents are presented according to gender, age, education level, domicile, number of training programs attended, MOOC usage, and the MOOC Mitra Prakerja platforms they utilized. The overall distribution of respondents' demographics is illustrated in Figure 2.



Source: (Research Results, 2024)
Figure 2. Respondent Demographics Chart

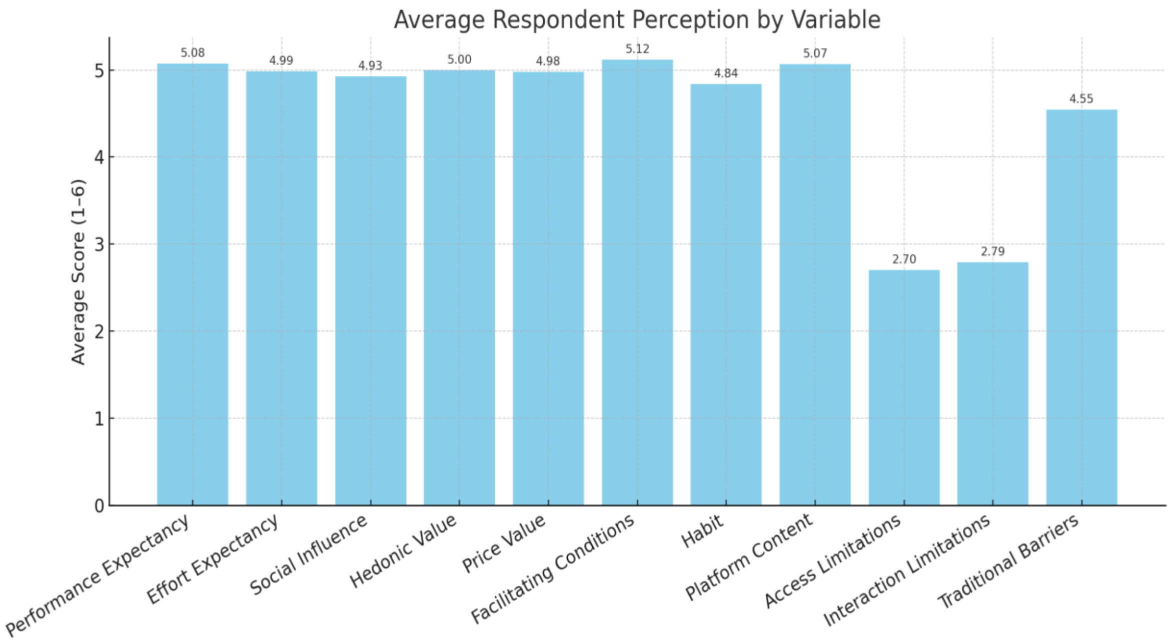
As shown in Figure 2, the majority of respondents were female graduates with a diploma or bachelor's degree, aged 26–35 years, and residing in the Greater Jakarta area (Jabodetabek). Although the majority were female, the number of male respondents was also significant, approximately 40% fewer than females. The minority distribution was found outside major cities and outside Java, specifically in Pemalang and Medan. In addition to demographics, the usage of MOOC Mitra Prakerja platforms was also analyzed. The distribution of respondents based on MOOC usage is depicted in Figure 3.



Source: (Research Results, 2024)
Figure 3. Respondent Chart Based on MOOC Usage

As illustrated in Figure 3, the majority of respondents had previously used MOOC platforms. They regularly participated in training programs, averaging 2–5 sessions, with most utilizing the Skill Academy platform provided by Ruang Guru. In addition to the description of respondent characteristics, descriptive analysis was also conducted on the respondents' answer scores. This analysis was used to examine the overview of research variables based on respondents' perceptions. Following Sekaran & Bougie (2016), mean scores on a six-point Likert scale were categorized as follows: 1.00–2.67 indicates a low perception, 2.67–4.34 indicates a moderate perception, and 4.34–6.00 indicates a high perception.

To provide a more concise overview of respondents' perceptions across the measured constructs, the following bar chart summarize the average score of each variables. This visualization replaces the descriptive tables presented earlier and highlights the relative strength of each factor based on participant responses. All items were rated on a six-point Likert scale. By presenting the data in a single cart, it becomes easier to identify which factors were perceived most positively or negatively by the participants.



Source: (Research Results, 2024)

Figure 4. Average Respondent Perception by Variable

The bar chart in Figure 4 provides an overview of the average scores of respondents perceptions across the key variables measured in this study. The findings can be thematically grouped into three categories: drivers of adoption, moderately influential factors, and barriers to adoptions.

Drivers Adoption

Variables such as Facilitating Conditions, Platform Content, and Performance Expectancy recorded the highest average scores. These results indicate that participants generally perceive that:

1. The technical infrastructure and support available to access MOOCs are adequate;
2. The content provided on MOOC platforms is relevant, well-organized, and helpful for improving competencies;
3. Using MOOCs is expected to enhance their job readiness and productivity.

Moderately Influential Factors

Effort Expectancy, Social Influence, and Habit received moderate ratings. This suggest that:

1. While MOOCs are perceived as relatively easy to use, ease of use alone may not be a decisive factor.
2. Social influence, such as encouragement from peers or mentors, play a supportive but not dominant role.
3. Habitual use is emerging but has not yet become a strong behavioral driver in this context.

This is consistent with previous research indicating external motivation (e.g., incentives) may play a more central role than peer influence in adoption behavior, particularly in government-supported programs (Abubakar et al., 2024; Hoya et al., 2024).

Barriers to Adoption

Variables related to limitations are Access Limitations and Interaction Limitations received the lowest scores. These findings point to:

1. Ongoing challenges in internet connectivity, device access, or digital literacy among some users;
2. Limited interaction with instructors or peers, which may hinder engagement and satisfaction with the learning experience.

Interestingly, Traditional Barriers such as preference for face to face learning still recorded relatively high scores, though these factors were not statistically significant in influencing adoption intention. This may reflect a broader cultural transition toward accepting digital learning as a variable alternative, particularly post-pandemic. Overall, the results suggest that while technical readiness and perceived usefulness remain key drivers of MOOC adoption, efforts should be made to address access and interaction limitations.

In a structural model, the exogenous variables in the research model simultaneously affect the endogenous variable. The magnitude of the contribution of all exogenous variables to the endogenous variable can be observed from the coefficient of determination. The coefficient of determination can be seen from the Adjusted R Square value. This value ranges from 0 to 1 or can also be interpreted as a percentage (0 – 100%). The larger the coefficient of determination, the greater the variance of the endogenous variable explained by its exogenous variables. Meanwhile, a small coefficient of determination indicates that the effect of the exogenous variables on the endogenous variable is still low. This is because there are still many other factors outside those exogenous variables that may affect the endogenous variable.

Table 13. Coefficient of Determination

	R Square	R Square Adjusted
MOOC Adoption Intention	0.755	0.742

Source: (Research Results, 2024)

The analysis results in Table 13 show that the Adjusted R Square value for the MOOC adoption intention variable is 0.742, or 74.2%. This indicates that MOOC adoption intention is affected by performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic value, habit, price value, platform content, access limitations, interaction limitations, and traditional barriers. Meanwhile, the remaining 25.8% of MOOC adoption intention is affected by factors outside performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic value, habit, price value, platform content, access limitations, interaction limitations, and traditional barriers.

To further examine how gender moderates the relationship between independent variables and the intention to adopt MOOCs, a multigroup analysis (MGA) was conducted. The analysis compared the path coefficients between male and female participants across key constructs of the model. The results indicate that certain variables demonstrate stronger effects depending on gender. Table 14 summarizes the key findings from the multigroup moderation analysis, providing an overview of which relationships are significantly influenced by gender and how these differ between male and female participants.

Table 14. Multigroup Analysis Results

Variable	Moderation Effect by Gender	Significant for	Interpretation
Performance Expectancy (EK → Y)	Stronger for male participants	Male	Males with higher performance expectancy are more likely to adopt MOOCs
Effort Expectancy (EU → Y)	Stronger for female participants	Female	Females are more influenced by ease of use when adopting MOOCs
Habit (HA → Y)	Stronger for female participants	Female	Online learning habits have a stronger effect on adoption among females
Platform Content (KP → Y)	Slightly stronger for females	Female (not significant)	Content quality matters more to females, though not statistically significant
Hedonic Value (NH → Y)	Stronger for male participants	Male (not significant)	Males are more motivated by enjoyment when using MOOCs
Social Influence (PS → Y)	Stronger for male participants	Male (not significant)	Social pressure has more influence on males, though not statistically significant
Other Variables (HT, KA, KI, KM)	No significant gender difference	–	No meaningful moderation effect was found

Source: (Research Results, 2024)

The Effect of Performance Expectancy on MOOC Adoption Intention

Performance expectancy does not have a positive and significant effect on the intention to adopt MOOC, as shown by a p-value of 0.070 (> 0.05) and a t-statistic of 1.818 (< 1.96). This means that the high or low-performance expectancy does not affect the high or low intention to adopt the MOOC platform. The effect of performance expectancy on adoption intention is a concept that is frequently studied in the context of technology or innovation adoption. The UTAUT theory emphasizes that high-performance expectancy will increase the intention to adopt a technology. This theory states that a person is more likely to adopt a technology if they expect positive outcomes (high-performance expectancy) and if they place a positive value on those outcomes.

However, the results of this study actually show that performance expectancy does not affect the intention to adopt MOOCs. This may be because the effect of performance expectancy on the intention to adopt MOOCs is only significant when the user is male. The results of the moderation test show a difference in the intention to adopt MOOCs between male and female users. For males, if they have high-performance expectancy toward the platform, their intention to adopt the MOOC platform will definitely be high. However, for females, the intention to adopt the MOOC platform is not always high, even if they have high-performance expectancy. Additionally, it can also be observed from the sentiment data that many users focus more on the money they expect to receive rather than on learning itself. The results of this study are consistent with the findings of which

(Candra et al., 2024; Iranmanesh et al., 2024; Islam et al., 2025; Mohd Suki et al., 2023; Pörzse & Kenesei, 2025; Yang & Lee, 2021) also show that performance expectancy does not affect users' intention.

The Effect of Effort Expectancy on MOOC Adoption Intention

The analysis results in this study show that effort expectancy does not have a positive and significant effect on the intention to adopt MOOC, as indicated by a p-value of 0.828 (> 0.05) and a t-statistic of 0.218 (< 1.96). This means that the high or low effort expectancy does not affect the high or low intention to adopt the MOOC platform. Previous studies have shown an effect of effort expectancy on user intention, but the results of this study indicate that the effect is insignificant. This may be due to differences in how effort expectancy affects user intention. Based on the analysis results in this study, it was found that the effect of effort expectancy on adoption intention is positive for female users, while for male users, it is negative.

Effort expectancy reflects the extent to which users believe that using the technology will be easy for them. As examined by Salsabila & Febriani (2022), the easier a technology is to use, the more useful it will be for users. If users perceive the technology to be difficult to use, even if it provides benefits, this can reduce their adoption intention. In addition, if users encounter technical difficulties or perceive the functionality of the technology as inadequate, it will undoubtedly make it difficult for them to use. If this issue is not addressed, adoption intention may decrease. A lack of training and education can also reduce user intention. Users may not have a sufficient understanding of how to use the technology. If the lack of education or training leads to low effort expectancy, users may be reluctant to adopt the technology. In addition, a lack of trust in sustainability or technical support also causes effort expectancy to not affect user intention. If users are not confident that the technology will continue to be supported, or if the technical support is inadequate, this can impact effort expectancy and adoption intention.

Although effort expectancy is low, if users feel that the benefits obtained from the technology are insufficient or irrelevant, adoption intention remains low. To increase adoption intention, it is important to analyze the causes of the low impact of effort expectancy and take appropriate actions. This may involve improvements in user interface design, providing training or support, or ensuring that the technology offers clear and relevant benefits for users. The results of this study are consistent with the findings of (Dagnoush & Khalifa, 2021; Hassaan & Yaseen, 2024; Irawan, 2024; Mogaji et al., 2024) which show that effort expectancy does not affect user intention. Also, the study by Ananda & Nuriyah (2023) found that effort expectancy, or in this case, the perception of ease, does not affect the intention to use technology services.

The Effect of Price on User Adoption Intention

Price does not have a positive and significant effect on the intention to adopt MOOC, as shown by a p-value of 0.733 (> 0.05) and a t-statistic of 0.341 (< 1.96). This means that the high or low price value does not affect the high or low intention to adopt MOOCs. The results of this study are not aligned with previous research. Instead, this study shows that price is not a factor influencing user adoption intention. If the price of a product or service is considered high or disproportionate to the value provided, the user intention to adopt may decrease. Users often compare the value they receive with the cost they have to pay. Understanding the target market and its price sensitivity is also an important factor. If the target market has a limited budget and the price is considered a barrier, this can affect user intention.

Pricing strategy and how the product or service is positioned in relation to competitors also play a role. If users feel that the price is in proportion to the value provided, user intention may remain high. In some cases, certain market segments may be more or less sensitive to price changes. Understanding the dynamics of these market segments can provide further insight into the impact of price on user intention. In this context, it could be because MOOC Prakerja users do not incur any costs to access the training, as it is a government program. However, the results of this study are consistent with the findings of Tahir et al (2024), Pratisthita et al (2022), and Ayub & Kusumadewi (2021), which show that price is not a factor influencing user intention.

The Effect of Habit on Adoption Intention

Habit has a positive and significant effect on MOOC user adoption intention, as indicated by a p-value of 0.019 (< 0.05), a t-statistic of 2.354 (> 1.96), and a coefficient of 0.188. This means that the higher the habit, the higher the adoption intention to use MOOCs. Conversely, the lower the habit, the lower the adoption intention to use MOOC. Habit can significantly effect the adoption intention of a technology. When someone has developed a habit of using a particular technology, their adoption intention can become higher. If users are already accustomed to a technology and feel comfortable using it, they are more likely to continue adopting it. Strong habits can serve as a significant driver in maintaining the use of a product or service.

Habits create consistency in user behavior. Users who have the habit of regularly using technology are more likely to continue adopting that technology, as it has become part of their routine. Habits reduce the mental effort required to make decisions or take action. Once a technology has become a habit, users no longer need to think about or consider alternatives, which can increase adoption intention. Habits create a sense of psychological security for users. They feel familiar and comfortable with the technology environment they are accustomed to, which can increase their desire to continue adopting it. Habits can also become a factor of resistance to adopting new technologies. If users have developed a habit with a particular technology, they may be reluctant to switch to a new technology because such a change could disrupt their established habits.

Habits in user behavior can help developers create user experiences that facilitate the formation of positive habits. Designing technology that is easy to integrate into users' daily routines can increase adoption intention and build long-term relationships. Additionally, in the context of MOOC Prakerja, it can be seen that one of the strengthening indicators is HK2, which states: "I automatically switch to MOOC Prakerja whenever I need information or want to learn a new topic." This means that learning on MOOC Prakerja is already sufficient to summarize users' desires for a particular topic. The results of this study are consistent with the findings of Venkatesh (2022), which revealed that habit plays an important role in predicting usage intention.

The Effect of Traditional Barriers on MOOC User Adoption Intention

Traditional barriers do not have a negative and significant effect on MOOC user adoption intention, as indicated by a p-value of 0.658 (> 0.05) and a t-statistic of 0.443 (< 1.96). This means that the high or low level of traditional barriers does not affect the high or low intention to adopt MOOCs. In the context of technology or innovation adoption, traditional barriers may refer to obstacles or challenges arising from old practices or habits that might conflict with the acceptance or use of new technology. Adoption intention, on the other hand, refers to the extent to which an individual or group is willing to adopt or use an innovation or technology. This statement may refer to situations where, despite the presence of traditional barriers, the intention to adopt remains high. For example, this may involve a situation where an individual's environment has certain traditional practices that initially seem to conflict with the adoption of new technology. However, despite these traditional barriers, people still have the intention to adopt the technology because they recognize its significant value or benefits. The results of this study align with the findings (Febrian & Fadly, 2021b, 2021a; Jalalkamali & Doratli, 2022; Khan et al., 2024).

The Effect of Access Limitations on MOOC User Adoption Intention

Access limitations do not have a negative and significant effect on MOOC user adoption intention, as indicated by a p-value of 0.939 (> 0.05) and a t-statistic of 0.076 (< 1.96). This means that the high or low level of access limitations does not affect the high or low intention to adopt MOOCs. Access limitations can include restrictions in terms of physical, financial, or knowledge access. Access limitations may involve difficulties in obtaining internet access in certain areas, lack of technological understanding, or financial constraints that prevent someone from adopting a particular technology. In many cases, access limitations can be a major barrier to user adoption intention, as they may not have sufficient access to familiarize themselves with, test, or use the technology. Therefore, efforts to overcome access limitations can increase the likelihood of user adoption intention. However, in this study, access limitations were not a barrier, possibly because the platform's access was already well-established, making it insignificant in influencing user intention. Moreover, the majority of respondents were from major cities, where access is generally easy to obtain. The results of this study are consistent with the findings (Dahal & Krisjanti, 2021; Festa et al., 2025; Jebarajakirthy & Shankar, 2021).

The Effect of Interaction Limitations on MOOC User Adoption Intention

Interaction limitations do not have a negative and significant effect on MOOC user adoption intention, as indicated by a p-value of 0.502 (> 0.05) and a t-statistic of 0.672 (< 1.96). This means that the high or low level of interaction limitations does not affect the high or low intention to adopt MOOCs. If there are significant interaction limitations, they can become a serious barrier to user adoption intention toward a product, service, or technology. Interaction limitations in this context include interactions with other participants, interactions with instructors, and interactions with platform operators. If there are interaction limitations that hinder ease of use or result in an unsatisfactory experience, user adoption intention may decrease. It is important to create intensive interactions, such as by establishing communities for idea exchange and networking. Significant interaction limitations can be a hindering factor, and developers or service

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providers need to pay attention to user feedback to continuously improve and enhance the user experience to increase adoption intention. The results of this study are consistent with the findings (Jebarajakirthy & Shankar, 2021; Naruetharadhol et al., 2021; Owusu et al., 2021; Shankar, 2021).

The Effect of Facilitating Conditions on MOOC User Adoption Intention

Facilitating conditions do not have a positive and significant effect on MOOC user adoption intention, as indicated by a p-value of 0.288 (> 0.05) and a t-statistic of 1.672 (< 1.96). This means that the high or low level of facilitating conditions does not affect the high or low intention to adopt MOOCs. The results of this study are not consistent with several previous studies, which found that facilitating conditions affect user intention. This is likely related to trust because even if facilitating conditions are present if users do not trust the innovation or technology, their intention to adopt may not increase. Additionally, unclear value perception also contributes to the lack of effect of facilitating conditions on user intention. If users do not see a clear value or benefit from the innovation, their adoption intention may remain low despite the presence of facilitating conditions. Uncertainty and risk also contribute to the insignificant effect of facilitating conditions on user adoption. If users perceive that adopting the innovation involves high risk or uncertainty, their adoption intention may remain low even in the presence of facilitating conditions.

The results of this study are not consistent with the findings of Venkatesh (2022), which showed that facilitating conditions have a positive effect on technology adoption.

The Effect of Platform Content on User Adoption Intention

Platform content does not have a positive and significant effect on MOOC user adoption intention, as indicated by a p-value of 0.306 (> 0.05) and a t-statistic of 1.025 (< 1.96). This means that the high or low quality of platform content does not affect the high or low intention to adopt MOOCs. This is possibly due to the perceived quality of the content, which may not be considered sufficiently engaging to encourage users' adoption intention of the platform. Users may be more likely to adopt the MOOC Pre-Employment Program if the content is high-quality, relevant to their needs, and capable of enhancing their skills or knowledge. Instructional design and user experience may also be important considerations. How the material is delivered, its interactivity, and how it is accessed by users can affect adoption intention. A well-structured instructional design and a positive user experience can increase motivation to use the program. The reputation of the online learning platform and the instructors delivering the program can also affect user adoption intention. If users trust the quality of the platform and instructors, they may be more likely to adopt the program. Additionally, the support and facilitation provided may be perceived as insufficient, preventing the formation of high adoption intention. The availability of support and facilitation, whether from the platform or instructors, can help resolve issues and increase user adoption intention.

The results of this study are consistent with the findings Stracke et al (2023) and Wang et al (2021), which evaluated the instructional quality of several MOOCs and found that many courses had low instructional quality. These findings align with the results of this study, indicating that platform content may not always affect adoption intention, especially if the content quality is perceived as inadequate.

The Effect of Hedonic Value on User Adoption Intention

Hedonic value has a positive and significant effect on MOOC user adoption intention, as indicated by a p-value of 0.043 (< 0.05), a t-statistic of 2.026 (> 1.96), and a coefficient of 0.178. This means that the higher the hedonic value, the higher the adoption intention of MOOC users. Conversely, the lower the hedonic value, the lower the adoption intention of MOOC users. Hedonic value refers to the satisfaction users gain from aspects that provide pleasure, enjoyment, or emotional fulfillment when using a product or service.

In the context of the MOOC Pre-Employment Platform, where the primary goal is education and skill development, hedonic value may play a role in influencing user adoption intention. If users experience the MOOC Pre-Employment Platform as an enjoyable and emotionally satisfying experience, this can increase adoption intention. Factors such as engaging videos, comfortable audio, or interactive elements may contribute to enhancing hedonic value and further affect user adoption intention.

An engaging design can provide hedonic value. If users feel a sense of achievement and gain self-satisfaction through their learning progress, this can serve as a hedonic value that motivates them to continue using the platform and pursue more courses or programs. If the platform offers creative or interactive elements that enhance aesthetic satisfaction or user experience, this can contribute to hedonic value and affect adoption intention. Additionally, if users can experience social aspects or engagement in a learning community, this can also provide hedonic value and further increase adoption intention.

Referring to the highest indicator, NH3, which states, "I find the training on the MOOC Prakerja platform very enjoyable to complete," indicates an interest in completing the MOOC platform as soon as possible. The results of this study are consistent with the findings of Darmanto et al (2025), which revealed that engaging and interactive design elements can enhance student engagement in adopting MOOCs.

The Effect of Social Influence on User Adoption Intention

Social influence has a positive and significant effect on MOOC user adoption intention, as indicated by a p-value of 0.014 (< 0.05), a t-statistic of 2.565 (> 1.96), and a coefficient of 0.250. This means that the higher the social influence, the higher the adoption intention of MOOC users. Conversely, the lower the social influence, the lower the adoption intention of MOOC users. Social influence can have a positive and significant effect on the intention to adopt MOOCs (Massive Open Online Courses). It can be observed from the highest indicator, PS3, which states, "The trust of other participants in the MOOC Mitra Prakerja platform encourages me to use the platform," indicating that reviews and ratings play a significant role in strengthening users' intention to use the platform. Additionally, recommendations or influence from friends, colleagues, or family members who have previously participated in MOOCs can have a significant impact on adoption intention. Personal recommendations from trusted sources can increase user trust and interest. MOOCs that have partnerships or associations with leading educational institutions or renowned instructors can provide an element of social prestige. This can be a factor influencing adoption intention, especially if users feel a sense of prestige or gain social recognition through their participation. Social influence can add significant value to adoption intention.

The results of this study are consistent with the findings of Cabanlit & Domingo (2024), which found that social influence affects MOOC adoption. One of the social influence elements examined in their study includes friend recommendations and social prestige. Additionally, these findings align with the study by Zhu (2022), which also stated that there is an effect between user evaluations and loyalty in technology adoption.

Managerial Implications

Based on the research findings, several managerial implications can be adopted by both the government and MOOC vendors/startups to increase MOOC platform adoption, particularly in the context of gender differences, including:

1. Implementation Strategy for the Government

The government should conduct awareness campaigns and training programs targeting both genders, emphasizing the benefits of using MOOCs to enhance skills and job opportunities, especially for men, who, according to this study, tend to have higher performance expectancy compared to women. Performance expectancy should also be supported with clear strategic objectives, such as realistic outcome goals, as highlighted in the study by (Rizkalla et al., 2023; Utomo et al., 2021), which emphasizes that a relevant vision, mission, and strategic goals are crucial for education. For women, special training programs can be organized to introduce technology and the MOOC platform, considering that, according to this study, women have higher effort expectancy compared to men. Therefore, the government can focus on providing programs for men to make the initiative more effective, as the research findings indicate that men have higher performance expectancy than women.

2. Implementation Strategy for MOOC Vendors/Startups

MOOC vendors must develop and offer content that aligns with modern needs for both genders, especially for men, by considering their higher performance expectancy. Additionally, MOOC vendors/startups also need to pay attention to interface design that facilitates ease of use, particularly for women. Because women have higher effort expectancy compared to men, implementing personalization features that allow users to customize their learning experience based on personal preferences and learning habits is essential. Williamson & Hogan (2021) emphasize the importance of personalization in enhancing the intention to use MOOCs.

CONCLUSION

Based on the data analysis results and discussion through the testing of hypotheses related to the research problem, the following conclusions can be drawn:

Performance expectancy does not have a positive and significant effect on MOOC user adoption intention, meaning that the high or low level of performance expectancy does not affect the high or low adoption intention of MOOC users.

Effort expectancy does not have a positive and significant effect on MOOC user adoption intention, meaning that the high or low level of effort expectancy does not affect the high or low adoption intention of MOOC users.

Social influence has a positive and significant effect on MOOC user adoption intention, meaning that the higher the social influence, the higher the adoption intention of MOOC users. Conversely, the lower the social influence, the lower the adoption intention of MOOC users.

Facilitating conditions do not have a positive and significant effect on MOOC user adoption intention, meaning that the high or low level of facilitating conditions does not affect the high or low adoption intention of MOOC users.

Habit has a positive and significant effect on MOOC user adoption intention. The higher the habit, the higher the adoption intention of MOOC users. Conversely, the lower the habit, the lower the adoption intention of MOOC users.

Hedonic value has a positive and significant effect on MOOC user adoption intention. The higher the hedonic value, the higher the adoption intention of MOOC users. Conversely, the lower the hedonic value, the lower the adoption intention of MOOC users.

Price value does not have a positive and significant effect on MOOC user adoption intention, meaning that the high or low price value does not affect the high or low adoption intention of MOOC users.

Platform content does not have a positive and significant effect on MOOC user adoption intention, meaning that the high or low platform content quality does not affect the high or low adoption intention of MOOC users.

Access limitations do not have a negative and significant effect on MOOC user adoption intention, meaning that the high or low level of access limitations does not affect the high or low adoption intention of MOOC users.

Interaction limitations do not have a negative and significant effect on MOOC user adoption intention, meaning that the high or low level of interaction limitations does not affect the high or low adoption intention of MOOC users.

Traditional barriers do not have a negative and significant effect on MOOC user adoption intention. The higher the social influence, the higher the adoption intention of MOOC users. Conversely, the lower the social influence, the lower the adoption intention of MOOC users. Then, the moderation analysis with gender resulted in three significant variables: performance expectancy, which is stronger for male users, effort expectancy, which is stronger for female users, and habit, which is also stronger for female users.

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