Understanding the Digital Generation: The Role of Perceived Ease of Use, Perceived Usefulness and Satisfaction in Users’ Acceptance Intention of the Ruangguru Application Among Generations Y, Z and Alpha

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ABSTRACT

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| The rapid advancement of digital technology has transformed consumer behaviour in the education sector, influencing how users engage with online learning platforms such as Ruangguru. However, user acceptance of these platforms remains inconsistent, necessitating a deeper understanding of the factors driving adoption. This study examines the impact of perceived ease of use and perceived usefulness on acceptance intention while also exploring the role of satisfaction in shaping user engagement. Using an online survey, data were collected from 200 respondents who had previously used Ruangguru and analyzed through PLS-SEM with SmartPLS 4 software. The findings reveal that while perceived ease of use does not directly influence acceptance intention, it significantly enhances perceived usefulness and satisfaction. Perceived usefulness, in turn, has a strong positive impact on both satisfaction and acceptance intention. These insights contribute to marketing literature on consumer adoption of digital services, particularly in the context of online learning. From a practical perspective, this study underscores the importance of feature innovation, service quality improvement, and user experience optimization to enhance consumer satisfaction, drive engagement, and strengthen brand loyalty in the competitive digital education market. |

***Keywords:*** *Perceived Ease of Use, Perceived Usefulness, Satisfaction Acceptance Intention, E-Learning, Ruangguru*

1. INTRODUCTION

The rapid advancement of information and communication technology (ICT) has transformed education, accelerating the growth of e-learning due to increased internet accessibility (GoodStats, 2024a). The shift began during the COVID-19 pandemic when face-to-face learning posed health risks, prompting institutions to adopt online formats (Maatuk et al., 2022). E-learning lowers costs, enhances learning efficiency, and overcomes geographical barriers (Aljawarneh, 2020). It enables knowledge transfer through electronic media and telecommunication, allowing flexible learning anytime and anywhere (Nikou & Maslov, 2021; Nguyen et al., 2020). Originating from distance education via mail, television, and radio, e-learning has evolved to provide personalized, asynchronous learning experiences (Salybekova et al., 2023; Han & Sa, 2022). Unlike traditional "one-size-fits-all" methods, online learning offers specialized modules for independent study (Logan et al., 2021).

Despite its benefits, online learning faces challenges in implementing external regulations and learning orientation, requiring significant resources (Rasheed & Wahid, 2021). E-learning systems must evolve with intelligent technologies to collect, process, and analyze large data volumes (Liu & Yu, 2023). Educators must assess student engagement, as personalized learning reshapes interactions and aims to surpass traditional instruction (Bhardwaj et al., 2021; Han & Sa, 2022). The rise of smartphones, immersive gaming, and advanced technology enhances learning accessibility and effectiveness (Stecuła & Wolniak, 2022). E-learning encompasses various forms like mobile, distance, and digital learning (Djeki et al., 2022), where engagement involves emotional and physical interactions, influencing task performance (Wu et al., 2022).

Despite its potential, internet usage for education in Indonesia remains low due to infrastructure limitations, low digital literacy, and negative perceptions of online learning (Databoks, 2022a). The government and private sector have introduced platforms like PPDB, Rumah Belajar, Ruangguru, and Zenius to address these challenges. Ruangguru, one of the fastest-growing platforms, led the market in 2022 with 32% of users, followed by Zenius with 25% (Databoks, 2022b). Its popularity reflects a shift toward technology-driven learning. Programs like Clash of Champions (CoC) have further increased enthusiasm for education (GoodStats, 2024b; CNN Indonesia, 2024). Ruangguru offers various services, including Ruangbelajar, Brain Academy Online, and Skill Academy, catering to students from Generation Alpha, Z, and Y, who rely heavily on digital learning tools (Ruangguru.com, 2025; Höfrová et al., 2024). This study explores how Ruangguru can enhance education in the digital era.

Satisfaction plays a crucial role in shaping consumers' intentions to adopt and continue using a technology. It refers to the extent to which users perceive their experience with a service as meeting or exceeding their expectations (Yingqing et al., 2024). In the context of e-learning as an information system within an educational environment, student satisfaction with e-learning quality is of great significance (AlMulhem, 2020). According to Zygiaris et al. (2022), satisfaction is defined as the level of fulfilment expressed by individuals after receiving a service. Several studies have examined the relationship between satisfaction and acceptance intention in e-learning, with findings indicating that satisfaction has a positive and significant effect on acceptance intention (Bailey et al., 2021; Puriwat & Tripopsakul, 2021; Saqr et al., 2024; Wang et al., 2021; Zardari et al., 2021). However, this contradicts the findings of Sae-tae & Wang (2024), who reported that satisfaction does not significantly influence acceptance intention.

Acceptance intention is the primary dependent variable in research based on the Technology Acceptance Model (TAM). It is defined as an individual's tendency to utilize information systems and educational technologies (Alturki & Aldraiweesh, 2021). The intention to use digital learning platforms is described as the likelihood that an individual will engage with such platforms (Songkram et al., 2023). According to Shirahada & Zhang (2022), intention reflects the effort an individual invests in a particular behavior and is influenced by three key elements: subjective norms, attitudes, and perceived behavioral control. Moreover, intention is considered a crucial factor in determining whether users will actually adopt a technology (Rizun & Strzelecki, 2020). While research often focuses on students’ intentions to adopt e-learning systems, faculty members also play an essential role in influencing adoption decisions (Kurdi et al., 2020).

Perceived ease of use (PEOU) is a fundamental determinant of users' attitudes and behavioural intentions toward technology adoption (Chawla & Joshi, 2023). It refers to the degree to which users perceive a system as easy to use compared to traditional methods of performing a task (Balakrishnan & Dwivedi, 2024). In the context of e-learning, perceived ease of use pertains to how intuitive the platform is, how well users can understand its features, and how easily they can interact with available tools and resources (Salybekova et al., 2023). Enhancing perceived ease of use is a strategic approach to overcoming consumer resistance to behavioural change (Choe et al., 2021). It also reflects an individual's confidence in how convenient and effortless a particular technology is to use (Yuan et al., 2021).

Equally important is perceived usefulness (PU), which, alongside perceived ease of use, influences users' behavioural intentions and ultimately determines actual technology adoption (Tiwari et al., 2021). Perceived usefulness is defined as the extent to which users believe that using a particular technology will enhance their performance (Naruetharadhol et al., 2021). In the realm of e-services, perceived usefulness is a critical factor affecting various online activities, including searching, shopping, booking, and digital transactions (Kim et al., 2022). Consequently, various strategies have been proposed to improve perceived usefulness. Users' perceptions of a technology's usefulness significantly impact their adoption decisions (Owusu et al., 2021). Although e-learning is considered an e-service provided by universities, students may perceive its usefulness differently from other e-services, given their unique educational needs and expectations (Kim et al., 2022).

Several studies have explored factors influencing satisfaction and acceptance intention in e-learning adoption. Satisfaction is often linked to perceived ease of use (Akdim et al., 2022; Filieri et al., 2021; Mishra et al., 2023; Sayaf et al., 2021) and perceived usefulness (Al-Adwan et al., 2021; Al-Hattami, 2021; Chang & Chen, 2020; Chen et al., 2021). However, some findings contradict this, as Li (2021) reported no significant impact of perceived ease of use on satisfaction, while Tena et al. (2024) found perceived usefulness to be insignificant. Given these inconsistencies, this study aims to further investigate these relationships using the TAM. By re-examining these variables, the research seeks to clarify their role in educational technology adoption.

2. literature review

2.1 The Technology Acceptance Model (TAM) Theory

This study employs the Technology Acceptance Model (TAM), introduced by Davis (1986) as an adaptation of the Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975). TAM focuses on user acceptance of technology, emphasizing perceived usefulness and perceived ease of use (Salybekova et al., 2023). It has been widely applied to predict technology adoption in areas like mobile services, e-commerce, and healthcare (Salybekova et al., 2023). In e-learning research, TAM has successfully predicted adoption and engagement (Mailizar et al., 2021; Al-Adwan et al., 2021), though its impact on learning outcomes remains underexplored. By incorporating key variables, TAM provides a valuable framework for analyzing e-learning adoption (Han & Sa, 2022; Nguyen et al., 2020; Salybekova et al., 2023).

2.2 Perceived Ease of Use and Perceived Usefulness

Studies have shown a strong positive relationship between perceived ease of use and perceived usefulness in e-learning adoption (Gurban & Almogren, 2022; He et al., 2023; Humida et al., 2022; Nikou & Maslov, 2021; Zheng et al., 2023). User-friendly platforms with intuitive designs enhance students' confidence in using technology, leading to higher adoption rates (Salybekova et al., 2023; Kolade et al., 2022; Sayaf et al., 2021). Research confirms that perceived ease of use significantly influences perceived usefulness, as users tend to find easily navigable platforms more beneficial (Baji et al., 2022; He et al., 2023; Saleh et al., 2022). However, some studies, like Sagnier et al. (2020), challenge this link in virtual reality applications, suggesting ease of use may not always determine perceived usefulness. Nonetheless, in e-learning, ease of use remains a critical factor shaping user perceptions, supporting the hypothesis that it enhances perceived usefulness. Based on this discussion, the following hypothesis is proposed:

H1: Perceived ease of use has a positive effect on perceived usefulness in e-learning.

2.3 Perceived Ease of Use and Satisfaction

Research consistently highlights a strong positive relationship between perceived ease of use and satisfaction in e-learning contexts (Chiang et al., 2019; Han & Sa, 2022; Saqr et al., 2024; Sayaf et al., 2021). When students find e-learning platforms easy to navigate and beneficial to their academic performance, their satisfaction increases (Gurban & Almogren, 2022). Ease of use enhances user experience by reducing cognitive load, fostering self-directed learning, and supporting system acceptance (Tsai et al., 2021; Xu et al., 2022).

User satisfaction is a crucial predictor of system success and learning effectiveness (Al-Fraihat et al., 2020). Studies confirm that ease of use positively influences satisfaction, especially when platforms offer intuitive navigation and personalized learning experiences (Chiang et al., 2019; Han & Sa, 2022; Sayaf et al., 2021). However, Li (2021) challenges this, suggesting that among EFL learners using Automated Writing Evaluation (AWE), satisfaction is more strongly influenced by perceived usefulness than ease of use. Despite such discrepancies, ease of use remains a significant factor in student satisfaction and sustainable e-learning adoption (Han & Sa, 2022). Based on this discussion, the following hypothesis is proposed:

H2: Perceived ease of use has a positive effect on satisfaction in e-learning.

2.4 Perceived Usefulness and Satisfaction

Several studies have demonstrated a positive relationship between perceived usefulness and satisfaction in digital learning (Al-Fraihat et al., 2020; Almogren, 2022; Chang & Chen, 2020; Saqr et al., 2024). Similar to perceived ease of use, perceived usefulness is a critical factor influencing satisfaction. It is defined as the extent to which users believe that using a system will enhance their performance or experience (Chiang et al., 2019). According to Rizun and Strzelecki (2020), the perceived usefulness of technology, particularly tools used for remote learning in higher education, is a key element in the Technology Acceptance Model (TAM). Al-Adwan et al. (2021) further emphasized that TAM integrates perceived usefulness and perceived ease of use as primary determinants of e-learning adoption behavior. Users generally feel satisfied with products or services that meet or exceed their expectations in terms of functionality, performance, and benefits (Mishra et al., 2023). In the context of online learning platforms, a high level of confirmation—defined as the alignment between initial expectations and post-usage experiences—is crucial for determining student satisfaction, especially when the experience surpasses their expectations (Wang et al., 2021). More broadly, satisfaction is an emotional assessment of the outcomes obtained, encompassing both subjective views of what is perceived as enjoyable or disruptive (Alzahrani & Seth, 2021).

Research on e-learning systems by Al-Fraihat et al. (2020) highlights that superior technical quality, combined with compatibility with user needs, enhances satisfaction, encourages enthusiastic use, and strengthens perceptions of usefulness. Meanwhile, a study on users of educational platforms such as Blackboard found that perceived usefulness enhances satisfaction, fosters continued use, and contributes to a more effective learning experience, particularly during and after the COVID-19 pandemic (Almogren, 2022). Saqr et al. (2024) reaffirmed the positive relationship between perceived usefulness and satisfaction, emphasizing that higher perceived usefulness leads to greater satisfaction in e-learning environments. However, differing results were observed in a study by Tena et al. (2024) in the context of tourism services, where perceived usefulness did not significantly affect satisfaction. The study suggested that other factors, such as trust in the system, played a more critical role in determining user satisfaction. Despite such variations, perceived usefulness remains a significant predictor of satisfaction in e-learning (Al-Hattami, 2021). Therefore, while perceived usefulness is essential for enhancing satisfaction, other elements, including perceived ease of use, should also be considered when evaluating e-learning systems. Based on this discussion, the following hypothesis is proposed:

H3: Perceived usefulness has a positive effect on satisfaction in e-learning.

2.5 Perceived Ease of Use and Acceptance Intention

Previous studies in the context of e-learning have demonstrated a strong relationship between perceived ease of use and acceptance intention (Han & Sa, 2022; Humida et al., 2022; Zardari et al., 2021; Zheng et al., 2023). Perceived ease of use is a key factor influencing users’ attitudes and behavioral intentions toward systems like e-learning (Weerathunga et al., 2021). A positive perception of ease of use and system usefulness can strengthen user attitudes, ultimately increasing their intention to adopt the technology (Choe et al., 2021). Perceived ease of use refers to the extent to which an individual believes that using a system will be effortless (Tawafakroof et al., 2020). In the context of online education, it describes the extent to which students feel that an e-learning system is easily accessible without requiring significant effort (Al-Rahmi et al., 2021). A study by Baji et al. (2022) confirms that both perceived ease of use and perceived usefulness significantly impact students' intentions to use e-learning. Furthermore, the influence of perceived ease of use on perceived usefulness and the intention to use technology becomes stronger when users have a higher level of technological literacy (Chang & Chen, 2021). Enhancing the perception of a technology’s ease of use positively affects its perceived usefulness and encourages broader adoption and utilization (Tawafak et al., 2023). Additionally, a curriculum design that aligns with students' needs can enhance the learning experience, ultimately leading students to prefer online learning (Lin et al., 2021).

The positive relationship between perceived ease of use and acceptance intention in e-learning has been extensively explored (Han & Sa, 2022; Humida et al., 2022; Zardari et al., 2021). Han and Sa (2022) found that perceived ease of use enhances the usefulness and satisfaction of education, although acceptance intention is also influenced by external factors such as the urgency of adaptation during the COVID-19 pandemic. Similarly, Zardari et al. (2021) revealed that perceived ease of use significantly affects behavioral intention and users’ perceptions of e-learning portals, emphasizing that user-friendly design increases trust in system benefits and promotes technology adoption in higher education. Furthermore, Humida et al. (2022) stated that perceived ease of use in e-learning significantly enhances perceived usefulness and behavioral intention to adopt the system. Their findings highlight a positive relationship between perceived ease of use, perceived usefulness, and acceptance intention, underscoring the importance of positive experiences and supportive resources in encouraging technology adoption. Overall, a positive perception of ease of use strengthens perceived usefulness and enhances students' behavioral intentions to adopt e-learning technology. User-friendly system design, positive experiences, and supportive resources are key factors influencing the adoption of educational technology. Based on this discussion, the following hypothesis is proposed:

H4: Perceived ease of use has a positive effect on acceptance intention in e-learning.

2.6 Perceived Usefulness and Acceptance Intention

The positive relationship between perceived usefulness and acceptance intention has been widely explored in e-learning research (Al-Maroof et al., 2020; Tawafak et al., 2023; T. Wang et al., 2021). Perceived usefulness refers to users’ expectations of the benefits a system provides (Liébana-Cabanillas et al., 2021) and is a central construct in the TAM (Al-Qudah et al., 2024). When students perceive an e-learning system as useful, they are more likely to adopt or continue using it (Alkhawaja et al., 2022). Additionally, attitudes toward mobile learning (M-learning) and perceived usefulness significantly impact students’ adoption intentions (Qashou, 2021). Perceived usefulness often outweighs attitudes toward e-learning in determining usage intention (Liao et al., 2022). A user-friendly design and system effectiveness enhance technology adoption (Almaiah et al., 2022). Technologies perceived as convenient are used more frequently (Han & Sa, 2022). Therefore, focusing on perceived usefulness is crucial for increasing acceptance and sustained engagement in e-learning environments.

Empirical research has consistently demonstrated a strong relationship between perceived usefulness and acceptance intention in e-learning (Al-Maroof et al., 2020; T. Wang et al., 2021). Users' confidence in a technology’s capabilities enhances their performance, leading to higher acceptance intention and adoption. Perceived usefulness has been found to have a greater impact than perceived ease of use in promoting continuous engagement, with a direct correlation to acceptance levels and sustainable usage among teachers and students (Al-Maroof et al., 2020). Findings from T. Wang et al. (2021) further suggest that students with a high perception of e-learning usefulness are more likely to continue using the platform.

However, contrasting results from Mailizar et al. (2021) indicate that during the COVID-19 pandemic, perceived usefulness did not significantly influence students’ behavioral intentions, highlighting a shift where other factors became more critical in technology adoption. Meanwhile, Al-Rahmi et al. (2021) found that students with a strong perception of usefulness were more likely to engage with social media for academic purposes. Overall, perceived usefulness remains a key determinant of technology acceptance and sustained use, particularly in e-learning and social media, as users are more inclined to continue utilizing technology that offers tangible benefits. Based on this discussion, the following hypothesis is proposed:

H5: Perceived usefulness has a positive effect on acceptance intention in e-learning.

2.7 Satisfaction and Acceptance Intention

Previous studies have emphasized the positive relationship between satisfaction and acceptance intention in e-learning (Almogren, 2022; Han & Sa, 2022; Li, 2021; Zardari et al., 2021). Measuring student satisfaction is crucial for ensuring the success of online education for institutions, instructors, and students (Mohammed et al., 2022). Satisfaction reflects the extent to which the collaboration between an information system and its users is successful (Hussein et al., 2021). Providing continuous value-added services enhances user comfort and effectiveness, leading to higher satisfaction (Liébana-Cabanillas et al., 2021). Emotional assessments of perceived outcomes also play a role, as satisfaction arises when expectations are met or exceeded, while dissatisfaction emerges when they are not (Alzahrani & Seth, 2021; Huang, 2021).

Higher satisfaction levels encourage sustainable adoption of online learning by fostering positive learning habits (Lin et al., 2021). Satisfied users are more likely to continue using the system and recommend it to others (Hoang & Le Tan, 2023). This aligns with the idea that customer satisfaction significantly impacts behavioral intentions (Sharabati et al., 2022). Based on the Technology Acceptance Model (TAM), users’ intention to adopt a system is influenced by their satisfaction with its quality and relevance (Elhajjar & Ouaida, 2020). Increasing student satisfaction is key to overcoming resistance to online learning (Han & Sa, 2022).

Several studies highlight satisfaction as a critical factor in e-learning acceptance (Almogren, 2022; Han & Sa, 2022; Zardari et al., 2021). Han and Sa (2022) suggest that educational providers should enhance satisfaction by improving content quality and user experience. Similarly, Silva et al. (2023) found that user satisfaction significantly supports acceptance intention in technology-based services, including e-learning. Satisfaction strengthens users’ intention to reuse the platform, reinforcing e-learning adoption. Almogren (2022) also demonstrated that perceived benefits and ease of use enhance user satisfaction, which, in turn, strengthens behavioral intention. However, Sae-tae and Wang (2024) noted that satisfaction with free e-learning services may discourage users from switching to premium services. Ultimately, satisfaction is a key predictor of e-learning acceptance, influencing continued use and overall system effectiveness. Based on this discussion, the following hypothesis is proposed:

H6: Satisfaction has a positive effect on acceptance intention in e-learning.

3. methodology

3.1 Measurement

This study explores how perceived ease of use and perceived usefulness influence user satisfaction and acceptance intention toward the Ruangguru application. Using a causal relationship approach, it examines cause-and-effect linkages through hypothesis testing. Data were collected via an online questionnaire using a six-point Likert scale to minimize response bias (Yamashita, 2022). The study includes two independent variables (perceived ease of use and perceived usefulness), one mediating variable (satisfaction), and one dependent variable (acceptance intention). The six-point scale, offering nuanced response options, enhances result accuracy compared to traditional five-point scales by encouraging clearer distinctions in opinions.

3.2 Sampling and Data Collection

This study was conducted in Indonesia without geographical limitations, as data collection was carried out online. Ruangguru, one of the most popular e-learning platforms in Indonesia, was selected as the research subject. According to a Databoks (2022) survey with 890 respondents, Ruangguru was the most widely recognized educational startup (98%), followed by Zenius (76%), Akademi (31%), Pahamify (29%), and Cakap (28%). Given Ruangguru’s prominence, Indonesia is an appropriate research location for studying educational startups.

The population consists of Indonesian individuals who have used or are currently using Ruangguru. A convenience sampling technique was applied, allowing quick and efficient data collection. Respondents must be Indonesian citizens and Ruangguru users.The sample size was determined following Hair et al. (2010), using the total number of indicators and latent variables multiplied by five (minimum) or ten (maximum). With 16 question indicators and four latent variables, the target sample size ranges from 80 to 200 respondents (Hair et al., 2019), ensuring sufficient data for robust analysis.

3.3 Data Analysis Techniques

At the initial stage, a pilot test was conducted to ensure the reliability and validity of the research instrument. An online questionnaire was distributed to 43 respondents who met the research criteria. The pilot test aimed to confirm that the questionnaire was suitable for the primary research. Data collected from this phase were analyzed using SPSS software, confirming the validity and reliability of the measurement model.

This study applies both descriptive and statistical analyses. Descriptive analysis systematically presents respondent characteristics, including gender, age, educational background, and e-learning platform usage. It also provides insights into key research variables: perceived ease of use, perceived usefulness, satisfaction, and acceptance intention. The study employs Partial Least Squares-Structural Equation Modeling (PLS-SEM) using SmartPLS 4 software to test hypotheses and analyze relationships between variables. PLS-SEM allows for the simultaneous examination of complex variable relationships through Structural Equation Modeling (SEM) (Dash & Paul, 2021).

The model assessment consists of: (1) the measurement model (outer model), evaluating the relationship between latent variables and their indicators, and (2) the structural model (inner model), assessing hypothesis relationships. Validity in the measurement model is tested through convergent and discriminant validity, ensuring factor loadings exceed 0.7 (Hair et al., 2021) and the average variance extracted (AVE) is above 0.5 (Yu et al., 2022). Discriminant validity is evaluated using the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio, with thresholds between 0.85 and 0.90. Reliability is assessed via Cronbach’s alpha and composite reliability, requiring a minimum of 0.6. The structural model includes collinearity testing, ensuring variance inflation factor (VIF) values remain below 5. R-square and Q-square values assess model fit, while path coefficient analysis determines hypothesis significance.

4. results and discussion

**4.1 Respondent Characteristics**

This section presents the results of data analysis, categorized based on respondent profiles, including factors such as gender, age range, highest level of education, and the e-learning platform used. The respondents' profiles are summarized in Table 1.

**Table 1. Respondents’ Profile**

|  |  |  |
| --- | --- | --- |
| **Categories** | **Frequency** | **%** |
| **Gender**MaleFemale | 24178 | 12.088.0 |
| **Age**< 15 years16 - 28 years29 - 47 years> 48 years | 7182101 | 3.591.05.00.5 |
| **Last education**Junior High School or EquivalentSenior High School or EquivalentDiplomaBachelor's DegreePostgraduate (Master's/Doctoral) | 811019612 | 4.055.09.530.51.0 |

Source: Primary data (2025).

Table 1 indicates that the majority of respondents in this study are female. A total of 178 female respondents accounted for 88% of the sample, while 24 male respondents represented 12% of the total. These findings suggest that most Ruangguru users in this study are female. The results show that most respondents are aged 16-28 years, totalling 182 individuals or 91% of the sample. The majority of respondents in this study have a senior high school education or equivalent. Out of 200 respondents, 110 (55%) have completed senior high school.

**4.2 Measurement Model (Outer Model)**

The measurement model was evaluated for validity and reliability using SmartPLS and the PLS Algorithm. Convergent validity was assessed through outer loading values above 0.7 (Hair et al., 2021) and an average variance extracted (AVE) greater than 0.50 (Yu et al., 2022). Convergent validity ensures that indicators measuring the same construct are strongly correlated. Discriminant validity confirms that indicators within a construct are related but not significantly correlated with other constructs (Neuman, 2014). Reliability testing ensures measurement stability, with higher reliability indicating greater consistency (Sürücü & Maslakçi, 2020; Hair et al., 2019). The results of the convergent validity and reliability tests are presented in Table 2.

**Table 2. Data Convergent Validity and Reliability**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variables** | **Item** | **Loadings** | **CA** | **CR** | **AVE** |
| Acceptance Intention (AI) | AI.1AI.2AI.3AI.4 | 0,8240,7970,8530,813 | 0,840 | 0,893 | 0,676 |
| Perceived Ease of Use (PEOU) | PEOU.1PEOU.2PEOU.3PEOU.4 | 0,8600,9290,9060,784 | 0,840 | 0,893 | 0,760 |
| Perceived Usefulness (PU) | PU.1PU.2PU.3PU.4 | 0,8690,8800,8840,858 | 0,896 | 0,927 | 0,762 |
| Satisfaction (SAT) | SAT.1SAT.2SAT.3SAT.4 | 0,8210,9070,9010,8381 | 0,889 | 0,924 | 0,752 |

*Source: Primary data (2025)*

*\*Notes: Perceived Ease of Use (PEOU); Perceived Usefulness (PU); Satisfaciton (SAT); Acceptance Intention (AI).*

Table 2 confirms that all variable items have outer loading values above 0.7 and AVE values exceeding 0.50 (Hair et al., 2019), validating the measurement model’s convergent validity. Reliability tests further indicate that all variables meet reliability criteria, with Cronbach’s Alpha and Composite Reliability (CR) values exceeding 0.6 (Hair et al., 2021). Higher values suggest stronger internal consistency. For example, perceived ease of use shows values above 0.8, indicating excellent reliability.

Next, Discriminant validity assessed using the Fornell-Larcker criterion and HTMT ratio, confirms acceptable validity, as AVE values exceed 0.50 (Yu et al., 2022). The results of the Fornell-Larcker criterion are presented in Table 3.

**Table 3. Disciminant Validity: Fornell-Larcker**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variables** | AI | PEOU | PU | SAT |
| AIPEOUPUSAT | 0,8220,5780,6070,664 | 0,8720,7750,745 | 0,8730,721 | 0,867 |

*Source: Primary data (2025)*

*\*Notes: Perceived Ease of Use (PEOU); Perceived Usefulness (PU); Satisfaciton (SAT); Acceptance Intention (AI).*

Table 3 presents the square root of the AVE values based on the Fornell-Larcker criterion. The analysis results indicate that the square root of the AVE for each variable is higher than its correlations with other variables, confirming that the measurement meets the criteria established by Fornell and Larcker (1981). For instance, the square root of the AVE for the perceived usefulness variable (0.873) is more significant than its correlation with the satisfaction variable (0.721), and a similar pattern is observed across all variables. These findings confirm that all variables in this study demonstrate acceptable discriminant validity.

The HTMT test was conducted to assess discriminant validity. The HTMT value for perceived usefulness relative to perceived ease of use was 0.866, while other variables remained below 0.85. According to Henseler et al. (2015), values exceeding 0.85 may indicate discriminant validity issues. This suggests that specific indicators within perceived usefulness contributed to the high HTMT value. To resolve this, PU1 was removed based on inter-item correlation analysis, improving discriminant validity. Eliminating this indicator reduced the HTMT value, ensuring the model met validity criteria. The revised HTMT results are presented in Table 4.

**Table 4. Validity Disciminant: Crossloading Test**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variables** | AI | PEOU | PU | SAT |
| AIPEOUPUSAT | 0,6620,6960,766 | 0,8340,837 | 0,806 |  |

*Source: Primary data (2025)*

*\*Notes: Perceived Ease of Use (PEOU); Perceived Usefulness (PU); Satisfaciton (SAT); Acceptance Intention (AI).*

Based on Table 4, the revised HTMT test results indicate that all variables have HTMT values below 0.85, meeting the established criteria. Therefore, the test results are considered acceptable, and all variables in this study can be deemed valid in terms of discriminant validity.

**4.3 Structural Model (Inner Model)**

The structural model assessment was conducted through collinearity testing, path coefficient analysis, determination coefficient (R-square) and Q-square analysis. The bootstrapping results for the structural model assessment are presented in Figure 1.



**Fig. 1. Bootsrapping result model**

*Research model diagram during the bootstrapping process in SmartPLS. Data processing results, 2025.*

First, collinearity testing was conducted based on the variance inflation factor (VIF) values (Hair et al., 2021). The results of the collinearity test are presented in Table 5.

**Table 5. Collinearity Test**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variables** | AI | PEOU | PU | SAT |
| AIPEOUPUSAT | 3,0612,8382,545 |  | 1,000 | 2,5082,508 |

*Source: Primary data (2025)*

*\*Notes: Perceived Ease of Use (PEOU); Perceived Usefulness (PU); Satisfaciton (SAT); Acceptance Intention (AI).*

Table 5 presents the results of the collinearity test, indicating no significant multicollinearity issues in this study. It happens because the variance inflation factor (VIF) values for all variables remain below the threshold of 5 (VIF < 5). In fact, all VIF values are well below 3, suggesting that multicollinearity is not a concern. For instance, the VIF for the relationship between satisfaction and acceptance intention is 2.545, while the VIF for perceived ease of use and satisfaction is 2.508. Based on these findings, there is no disruptive multicollinearity among the variables in this study.

Next, the coefficient of determination test and predictive relevance test are presented in Table 6.

**Table 6. R-Square and Q-Square Results**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variables** | **R-square** | **Adjusted R-square** | **Q-square** |
| Acceptance IntentionPerceived UsefulnessSatisfaction | 0,4760,6010,607 | 0,4680,5990,603 | 0,3280,6050,552 |

*Source: Primary data (2025)*

Table 6 shows the R-square and Q-square results. The R-square test measures how well independent variables explain the dependent variable, with all values above 0.330, indicating a moderate level (Chin, 1998). The Q-square test evaluates predictive relevance, where values above 0 confirm the model’s validity. The results indicate that the model has strong predictive power and fits well with the data, ensuring its reliability for analyzing the relationships between the studied variables.

Finally, the path coefficient test was conducted to assess the direction of the hypotheses and evaluate the hypothesis testing results. The direction of the relationship is represented by the original sample value (β), with path coefficients ranging from -1 to +1. Hypotheses were tested using the T-statistic and P-value, where a hypothesis is supported if the T-statistic exceeds 1.96 (T-statistic > 1.96) and considered statistically significant if the P-value is below 0.05 (P-value < 0.05). Table 7 presents the results of the path coefficient analysis.

**Table 7. The Path Coefficient**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Hypotheses**  | **β** | **T value** | ***P* Value** | **Conclusion** |
| PEOU 🡪 PU | H1 | 0,775 | 16,173 | 0,000 | Supported |
| PEOU 🡪 SAT | H2 | 0,466 | 5,759 | 0,000 | Supported |
| PU 🡪 SAT | H3 | 0,360 | 4,782 | 0,000 | Supported |
| PEOU 🡪 AI | H4 | 0,059 | 0,559 | 0,576 | Not Supported |
| PU 🡪 AI | H5 | 0,238 | 2,635 | 0,000 | Supported |
| SAT 🡪 AI | H6 | 0,448 | 4,296 | 0,000 | Supported |

*Source: Primary data (2025)*

*\*Notes: Perceived Ease of Use (PEOU); Perceived Usefulness (PU); Satisfaciton (SAT); Acceptance Intention (AI).*

Based on the hypothesis testing results presented in Table 7, all direct hypothesis relationships are accepted and significant, except for the direct relationship between perceived ease of use and acceptance intention (H4), which is not significant and therefore rejected. Additionally, all hypothesis relationships exhibit a positive direction, as indicated by β values greater than zero. Furthermore, the research model in this study is adapted from Han & Sa (2022).

**4.3.1 Effect of Ease of Use on Perceived Usefulness**

The findings of this study indicate that perceived ease of use has a positive and significant impact on perceived usefulness in the context of e-learning (T statistic = 16.173 > 1.96 and P value 0.000 < 0.05). Thus, H1 is supported. The easier an e-learning platform is to use, the higher users perceive its benefits (He et al., 2023; Nikou & Maslov, 2021). It aligns with Han and Sa (2022), who emphasize that perceived ease of use and usefulness are crucial in shaping student interactions with online learning. Educational institutions can enhance these perceptions, leading to greater satisfaction and acceptance. According to TAM, these factors influence user behavior in e-learning (Al-Adwan et al., 2021), as ease of access and perceived benefits increase engagement. A seamless, intuitive platform fosters student adaptation and acceptance of digital learning (Gurban & Almogren, 2022). Perceived ease of use and usefulness are linked to respondent age. Most users (91%) are 16–28 years old, showing Ruangguru is popular among digitally literate youth. This group easily navigates the platform, leading to frequent use and stronger recognition of its benefits. The platform’s accessibility and seamless experience enhance their learning. Ultimately, ease of use boosts perceived usefulness, increasing user acceptance of Ruangguru as a preferred e-learning tool.

**4.3.2 Effect of Perceived Ease of Use on Satisfaction**

Perceived ease of use has a positive and significant impact on satisfaction in e-learning (T-statistic = 5.759 > 1.96, P value = 0.000 < 0.05), supporting H2. A user-friendly platform enhances satisfaction by improving accessibility and reducing technical barriers, making learning smoother. Enhancing ease of use encourages technology adoption and minimizes resistance to digital learning (Choe et al., 2021). Studies confirm that accessible platforms help students focus on learning materials without distractions (Chiang et al., 2019; Xu et al., 2022). When users find a system intuitive, they engage more actively, stay motivated, and feel confident in exploring its features, leading to a more effective and enjoyable learning experience (Sayaf et al., 2021). According to the Technology Acceptance Model (TAM), perceived ease of use directly influences perceived usefulness, enhancing user satisfaction (Hoang & Le Tan, 2023). An intuitive platform encourages technology adoption and supports digital learning sustainability. As students grow confident in using technology, they integrate it into their studies, fostering a more inclusive and adaptive digital learning environment.

**4.3.3 Effect of Perceived Usefulness on Satisfaction**

Perceived usefulness has a positive and significant impact on satisfaction, indicating that the higher users’ perception of a platform’s usefulness, the greater their level of satisfaction. (T-statistic = 4.782 > 1.96, P value = 0.000 < 0.05). Thus, H3 is supported. Al-Hattami (2021) states that users assess a system based on its ability to help them achieve their goals. In e-learning, a platform that enhances understanding, learning efficiency, and resource access fosters satisfaction (Al-Fraihat et al., 2020; Chang & Chen, 2020). Saqr et al. (2024) found that user satisfaction in digital learning depends on perceived usefulness, ease of navigation, and interactive features. The willingness to continue using an e-learning platform depends on how well it meets user expectations (Saqr et al., 2024). This aligns with the TAM, which highlights perceived usefulness and ease of use as key factors influencing technology adoption (Han & Sa, 2022). When a system provides clear benefits and seamless access, satisfaction and engagement increase. Implementing intuitive and functional technology enhances learning experiences, encouraging long-term user adoption and improving digital education effectiveness. Most Ruangguru users in this study have a high school education, influencing their perception of usefulness and satisfaction. If a platform provides relevant materials, simplifies complex concepts, and enhances academic performance, satisfaction increases. These learners value adaptive learning, AI, and mentorship, making perceived usefulness a key factor in their learning experience.

**4.3.4 Effect of Perceived Ease of Use on Acceptance Intention**

The findings of this study indicate that perceived ease of use does not have a direct influence on acceptance intention (T-statistic = 0.559 > 1.96, P value = 0.576 < 0.05), indicating that H4 is not supported. The study reveals that perceived ease of use does not directly influence acceptance intention (T-statistic = 0.559 > 1.96, P value = 0.576 < 0.05), meaning H4 is not supported. Users’ perception of ease does not necessarily increase their willingness to adopt technology, aligning with previous studies (Al-Adwan et al., 2023; Alassafi, 2022). While ease of use enhances user experience, it is not the primary factor in adoption decisions. Users prioritize tangible benefits over usability—if a system is easy but lacks efficiency, long-term adoption is unlikely. Research by Han and Sa (2022) confirms that perceived ease of use influences perceived usefulness and satisfaction but does not directly drive acceptance. Similarly, Sprenger and Schwaninger (2023) argue that technological adoption depends more on perceived usefulness than ease of use. People embrace technology when they see clear benefits, such as improved productivity or efficiency, rather than just user-friendliness. These findings highlight that while ease of use is important, it must be complemented by real value to drive adoption in digital learning environments.

Alassafi (2022) found that perceived ease of use does not significantly impact e-learning adoption, with academic motivation and perceived usefulness playing a greater role. This suggests students prioritize benefits over usability. Similarly, Al-Adwan et al. (2023) noted that ease of use enhances enjoyment and usefulness but does not directly influence adoption. While usability matters, technology must provide clear benefits to drive acceptance. Developers should focus on value-driven features rather than just ease of use, ensuring functionality that enhances engagement and long-term adoption of e-learning platforms. This reinforces the idea that perceived usefulness and motivation outweigh usability in adoption decisions.

**4.3.5 Effect of Perceived Usefulness on Acceptance Intention**

Perceived usefulness has a positive and significant effect on acceptance intention in the context of e-learning (T-statistic = 2.635 > 1.96, P value = 0.000 < 0.05). Thus, H5 is accepted. The more users perceive an application as useful, the more likely they are to adopt it. High perceived usefulness enhances learning effectiveness and motivation, making it a key factor in user acceptance (Alkhawaja et al., 2022; To & Trinh, 2021). In digital services like Ruangguru, users evaluate a platform based on its ability to support learning goals. If a system effectively aids task completion and goal achievement, users are more inclined to adopt it (To & Trinh, 2021).

As a core element of the Technology Acceptance Model (TAM), perceived usefulness also applies to telemedicine services (Kissi et al., 2020). Users' perception of both the benefits and usability of a system determines its adoption (Almaiah et al., 2022). When a digital tool is both beneficial and user-friendly, users are more motivated to engage with it. A strong belief in its usefulness reinforces adoption intention, further enhanced by an intuitive and efficient interface (Kissi et al., 2020). Ultimately, perceived usefulness plays a critical role in shaping user engagement and long-term commitment to digital learning platforms.

**4.3.6 Effect of Satisfaction on Acceptance Intention**

The findings of this study indicate that satisfaction has a positive and significant impact on acceptance intention (T-statistic = 4.296 > 1.96, P value = 0.000 < 0.05); thus, H6 is accepted. Higher user satisfaction increases the intention to adopt and integrate a system into daily activities, particularly in e-learning (Kashive et al., 2020; Lin et al., 2021; Mohammed et al., 2022). In digital learning, students’ satisfaction with information and communication technology (ICT) predicts their continued use of technology for learning (Sayaf et al., 2021). When technology offers a practical and satisfying learning experience, students are more motivated to engage with it long-term. Additionally, acceptance intention is influenced not only by satisfaction but also by perceived ease of use and usefulness. If an e-learning system is easy to navigate and effective, users are more likely to adopt it. The TAM explains that users' acceptance of technology is influenced by perceived ease of use and usefulness (Han & Sa, 2022). Educational institutions must design user-friendly and beneficial systems to enhance adoption. Optimizing features and service quality fosters engagement, satisfaction, and long-term acceptance in digital education.

4. Conclusion

This study provides insights into the key factors influencing acceptance intention in e-learning, focusing on the Ruangguru platform. Using data from 200 respondents, the research examines the relationships between perceived ease of use, perceived usefulness, and satisfaction in driving acceptance intention. The findings reveal that all three factors significantly contribute to acceptance intention, with satisfaction mediating the relationship between perceived ease of use and perceived usefulness. Additionally, perceived ease of use impacts perceived usefulness (T-statistic = 16.173, *P* value = 0.000), aligning with He et al. (2023), who state that an intuitive platform enhances users’ perception of its benefits. This strengthens users’ intention to accept and engage with Ruangguru. The study reinforces the Technology Acceptance Model (TAM) and its role in shaping user behavior toward digital learning. It also provides practical implications for optimizing technology adoption, particularly among Generations Y, Z, and Alpha, who exhibit distinct technological behaviors (Höfrová et al., 2024).

This study benefits students, researchers, and e-learning providers. Students gain insights into factors influencing technology acceptance in digital learning, while researchers receive empirical evidence on the relationships between perceived ease of use, usefulness, and satisfaction. E-learning providers can use these findings to develop better marketing strategies and user-friendly systems. Platforms that are both accessible and beneficial enhance satisfaction and reinforce long-term adoption of e-learning services (Filieri et al., 2021; Han & Sa, 2022; Sayaf et al., 2021).

This study reveals that perceived ease of use does not directly increase acceptance intention; instead, its effect is mediated by user satisfaction. In contrast, perceived usefulness has a direct impact, as users are more likely to adopt e-learning if they perceive it as beneficial. Therefore, optimizing technological design should focus on enhancing perceived benefits rather than just improving navigation. The study also highlights a strong relationship between perceived ease of use and perceived usefulness (P-value = 16.173), suggesting that an intuitive system enhances users’ perceived benefits. These insights guide e-learning providers in designing intuitive, functional, and user-aligned platforms to foster sustainable adoption.

This study has several limitations that should be considered for future research to enhance the understanding of e-learning contexts. First, the respondent age distribution is skewed, with 91% aged 16–28, limiting generalizability to older users. Second, the sample is predominantly female (88%), meaning findings mainly reflect female experiences. Third, 55% of respondents have a high school education, with fewer holding higher degrees, making the results more representative of high school users. Additionally, the study focuses only on Ruangguru, limiting applicability to other platforms with different features and demographics. Lastly, the cross-sectional design captures user behavior at a single point, limiting insights into long-term e-learning adoption.

As e-learning adoption evolves, further research is needed to understand user acceptance across different platforms. Future studies should compare multiple e-learning platforms to explore factors influencing perceived ease of use, usefulness, and satisfaction. Additionally, analyzing demographic factors such as gender, age, and education is crucial for identifying variations in acceptance. Since this study mainly included young female respondents, future research should include a more diverse sample to enhance representativeness.

A longitudinal approach is recommended to evaluate changes in perceived ease of use, usefulness, satisfaction, and acceptance over time. Future studies should explore key e-learning features such as virtual classrooms, exams, interactive tutoring, feedback, and certification. Understanding these features’ impact can help enhance user experience and support long-term e-learning adoption.

**Disclaimer (Artificial intelligence)**

Author(s) hereby declare that this is a original paper that written by author. AI technologies is used to correct the citation writing.

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APPENDIX

The item scale used to measure the construct of this study was adapted from Han & Sa (2022). The item scale of measurement in this study presented in Table A1

**Table A1. Item Scale**

|  |  |
| --- | --- |
| **Construct** | **Item** |
| Perceived Ease of Use | PEOU1PEOU2PEOU3PEOU4 | I can clearly understand how to use Ruangguru. I can use Ruangguru proficiently. Learning how to use Ruangguru feels easy. Ruangguru is easy to use. |
| Perceived Usefulness | PU1PU2PU3PU4 | Using Ruangguru allows me to access educational information efficiently.Using Ruangguru enables me to obtain useful and engaging educational information.The educational information obtained through Ruangguru is highly beneficial.Using Ruangguru can help me improve my academic performance. |
| Satisfaction | SAT1SAT2SAT3SAT4 | I am satisfied with my choice of using the Ruangguru. I am satisfied with my experience using the Ruangguru. I am satisfied with the quality of the Ruangguru. I agree with the fees charged for using the Ruangguru. |
| Acceptance Intention | AI1AI2AI3AI4 | I plan to use Ruangguru in the future. I will choose Ruangguru in the future. I will speak positively about Ruangguru to others in the future. I will recommend Ruangguru to others in the future. |