# AI in Social Commerce: The Moderating Role of Privacy Concerns in the Link Between Customer Engagement and Repurchase Intention

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## Abstract

**Background:** Artificial intelligence (AI) is changing the way consumers interact in social commerce transactions. Therefore, it is essential to understand how consumers perceive this technology. **Objectives:** This study aims to evaluate consumer perceptions of AI technology in functional and socio-emotional terms. The study also examines whether privacy concerns moderate the association between customer engagement and repurchase intention. **Methods/Approach:** A total of 353 social commerce consumers in Indonesia were sampled using a quantitative, structural equation modelling approach. **Results:** Social presence and perceived convenience were positively associated with both engagement and conversion. Perceived usefulness and ease of use showed small positive associations with engagement, and neither was significantly associated with conversion. Engagement and conversion were positively associated with repurchase intention. Conclusions: Both associations with repurchase intention were stronger among consumers with greater privacy concerns.

**Keywords:** artificial intelligence; engagement; privacy concern; social commerce; structural equation modelling

**JEL classification:** M31; D83; O33
**Paper type:** Research article

**Received:** 24 March 2026
**Accepted:** 26 July 2026

**Citation:** Febrian, A., Fihartini, Y., Roslina, Alif, M. I., Setyawan, D., Nugroho, D., Riyoko, S., Brata, A., Maulana, Y., & Mirza, A. D. (2026). AI in Social Commerce: The Moderating Role of Privacy Concerns in the Link Between Customer Engagement and Repurchase Intention. Business Systems Research, 17(2), 41-66.
**DOI:** https://doi.org/10.2478/bsrj-2026-0018

# Introduction

The increase in social media users drives economic development through social commerce. (Al-Omoush & Shuhaiber, 2024; Leong et al., 2024). Social commerce (s-commerce) is defined as a transaction process delivered through social media and is part of electronic commerce (e-commerce) (Turban et al., 2017). Unlike e-commerce, which involves direct interaction between sellers and buyers (Febrian et al., 2025), s-commerce involves user interaction with content they create and virtual communities (Febrian, 2023; Sheikh et al., 2019). The community helps users find desired products by using features such as live videos, hashtags, and photos that increase product visibility. (Febrian et al., 2022; Song et al., 2019). These features are optimised through artificial intelligence (AI) technology based on user data. (Febrian, 2025; Senyapar, 2024). Examples of the application of AI in s-commerce include metaverse commerce, live-streaming commerce, conversational commerce, and shared commerce. (Koohang et al., 2023; Tan et al., 2023; Theadora et al., 2022). Through this platform, customers get an interactive virtual shopping experience, more relevant product recommendations, and real-time responses from sellers. (Febrian et al., 2024).

However, research gaps remain, limiting the understanding of AI's functional aspects within the Technology Acceptance Model (TAM) framework. (Hossain & Biswas, 2024), such as the benefits of its use (Cheng, 2025; J. Kim et al., 2021). These studies ignore users' emotional responses, which AI utilisation can affect. They also ignore the nature of AI, which operates through behavioural and personal data. This approach can raise privacy and intrusion concerns. (Nazneen et al., 2023; Soliman et al., 2023). Users have concerns about how companies use their data. (Shoukat et al., 2025). Explain that privacy issues may increase purchase intentions. Several previous studies have focused solely on privacy issues as risks of data use, without linking them to emotional dynamics or the functional benefits of AI. (Belli & Leon, 2024; Durovic & Corno, 2024; Pejić-Bach & Marić, 2025). Therefore, it is essential to consider the indirect effects of privacy issues on the success of AI utilisation in e-commerce. The security and privacy that consumers feel when using AI technology can form positive attitudes that benefit the company (Alka'awneh et al., 2025). Thus, this study offers a novel approach to the research model by investigating not only functional but also social-emotional factors arising from AI use. We also investigate the moderating role of privacy issues in strengthening the relationship between customer engagement and repurchase intentions, a factor that has not been previously studied.

This study aims to explore how functional and social emotional factors from AI influence customer engagement in s-commerce, analyse their impact on repurchase intentions, and examine how privacy concerns moderate these relationships. The findings can inform businesses in designing effective AI-based marketing strategies. The study also contributes theoretically by integrating the Technology Acceptance Model and the Theory of Planned Behaviour to explain AI use in social commerce. (Ajzen & Driver, 1992a; Morgan & Hunt, 1994a). Although the three theories have been widely used separately in studies on technology acceptance and consumer behaviour, no study has comprehensively combined them to examine how commitment, attitude, and behavioural intention influence customer engagement

with AI in the s-commerce environment. Thus, this study presents a novel approach that offers more profound insights into the factors that drive or hinder consumer adoption of AI, thereby enriching the literature on technology acceptance models in the digital era.

Furthermore, this paper is structured in three stages: a literature review that develops a conceptual framework and research hypotheses to support the study's direction while maintaining focus on the main objective. The second part describes the research methodology used and presents the results of the empirical data analysis. Finally, the last part concludes the findings based on the study results.

## Literature review

AI is a new technology widely used across industries; social commerce is one industry that has successfully leveraged its benefits. (Shoukat et al., 2025). AI is based on algorithms designed to work like the human mind. As a result, social media services include human-like features. To evaluate the use of AI in online shopping activities, Mustofa et al. 2025) suggest using the Technology Acceptance Model approach, which consists of two dimensions: perceived ease of use and usefulness. This method aims to understand the user's perception of experience after using AI. (Davis, 1989) Defines ease of use as referring to an individual's perception of the level of comfort associated with using a particular system or technology. Usefulness refers to the extent to which a person can benefit from a system in improving their work. Perceived ease of use can influence positive attitudes towards AI services when shopping online. (Hur & Kim, 2022). The cognitive dissonance AI triggers in customers increases conversion rates and customer engagement. (Bag et al., 2022; Y. Gupta & Khan, 2024) . This is especially true in social commerce, which has successfully utilised AI (Perez-Vega et al., 2021). AI does this by improving the relationship between users and marketers, helping users feel comfortable using it. (Allagui & Breslow, 2016).

- *H1a: Perceived usefulness has a significant positive effect on social media user engagement*
- *H1b: Perceived usefulness has a significant positive effect on conversion*
- *H2a: Perceived ease of use has a significant positive effect on social media user engagement*
- *H2b: Perceived ease of use has a significant positive effect on conversion*

The evaluation of artificial intelligence use can also take a social-emotional approach. (Cominelli et al., 2018; Sethi & Jain, 2024). (Cheng, 2025) Emphasises two aspects of social emotion, namely social presence and perceived convenience. Social presence facilitates understanding of interpersonal communication and relationship-building in a business environment, particularly when using technological media to influence whom individuals choose to communicate with. (Short, 1976). Communication becomes more effective when the media used have a level of social presence aligned with the needs of interpersonal engagement. (Wei et al., 2017). (Kietzmann et al., 2012) Suggests a positive relationship between social presence and engagement because social presence accelerates human interactivity and contact. Other social emotions can also be explained by perceived convenience, which is defined as the ease of using technology by considering place, time, acquisition, implementation, and use (Brown, 1989), so that it can reduce the cognitive, emotional, and physical burden of users (Chang et al., 2012). Perceived convenience is an antecedent factor that can influence the intention to use technology in online shopping. (S. Gupta & Kim, 2007). When people feel the technology used is useful, it can increase consumer engagement and conversion rates on social media platforms. (Nazir et al., 2023).

- *H3a: Social presence has a significant positive effect on social media user engagement*
- *H3b: Social presence has a significant positive effect on conversion*
- *H4a: Perceived convenience has a significant positive effect on social media user engagement*
- *H4b: Perceived convenience has a significant positive effect on conversion*

Social media platforms have changed consumers' role from passive observers to active participants who help produce and create content. (Dolan et al., 2019). This behaviour reflects customer engagement on social media, which includes activities such as creating, contributing, and consuming brand-related content. (Hallock et al., 2019; Muntinga et al., 2011). The development of artificial intelligence (AI) technology has strengthened this engagement by customising content and recommending products based on customer preferences and behaviour, thereby driving higher engagement and conversion. (Nguyen et al., 2024). Previous studies have shown that effective and efficient customer engagement is crucial to increasing conversion rates on social media platforms. (Hollebeek et al., 2024). In addition, emotional attachments built through intensive interactions can also drive repurchase intentions. (Grisaffe & Nguyen, 2011). Efficient and effective consumer engagement is a prerequisite for optimising conversion rates on social media platforms. (Yin & Qiu, 2021). Thus, exploring customer engagement as a predictor of repurchase intention and conversion rate becomes essential for marketers in designing effective digital strategies. (Majeed et al., 2022).

- *H5: User engagement on social media has a significant positive effect on conversion*
- *H6: User engagement on social media has a significant positive effect on repurchase intention*

Social media has become a significant intermediary in online travel, enabling companies to connect with consumers more personally and thereby increase sales conversions (W. G. Kim & Park, 2017). In digital marketing, conversion is a key indicator of a strategy's effectiveness (Bag et al., 2022). According to Nazir et al., 2023)conversion is defined as the interaction between a website and consumers, explicitly referring to the proportion of users who make a purchase of a particular product compared to the total number of visitors. A low conversion rate indicates that the marketing strategy used is not yet effective and needs to be redesigned. Although website traffic is high, it is not always directly proportional to high conversions. Therefore, a targeted strategy is necessary to optimise conversions. Digital marketers need a deep understanding of consumer purchasing behaviour on social media to effectively increase conversion rates, particularly through artificial intelligence (AI) technology (Bag et al., 2022). Companies are also increasingly utilising AI on social media platforms to attract users' attention and convert them into loyal customers (McDowell et al., 2016). On the other hand, a high conversion rate not only reflects success in driving initial purchases but also significantly increases repurchase intention (Bag et al., 2022). This is because a positive purchasing experience strengthens trust, satisfaction, and brand loyalty. When consumers perceive the purchasing process as efficient, relevant, and personal, they are more likely to make repeat purchases (Meng et al., 2023). The analytical model of conversion behaviour can predict the purchase opportunities of individual visitors based on their previous visits to the website and purchases (Moe & Fader, 2004). This consumer attitude has implications for increasing a person's intention to visit and make repeat purchases of the marketed products (Nazir et al., 2023). Therefore, optimising conversion not only improves short-term sales but also plays a crucial role in fostering long-term consumer relationships.

- *H7: Conversion has a positive and significant effect on repurchase intention*

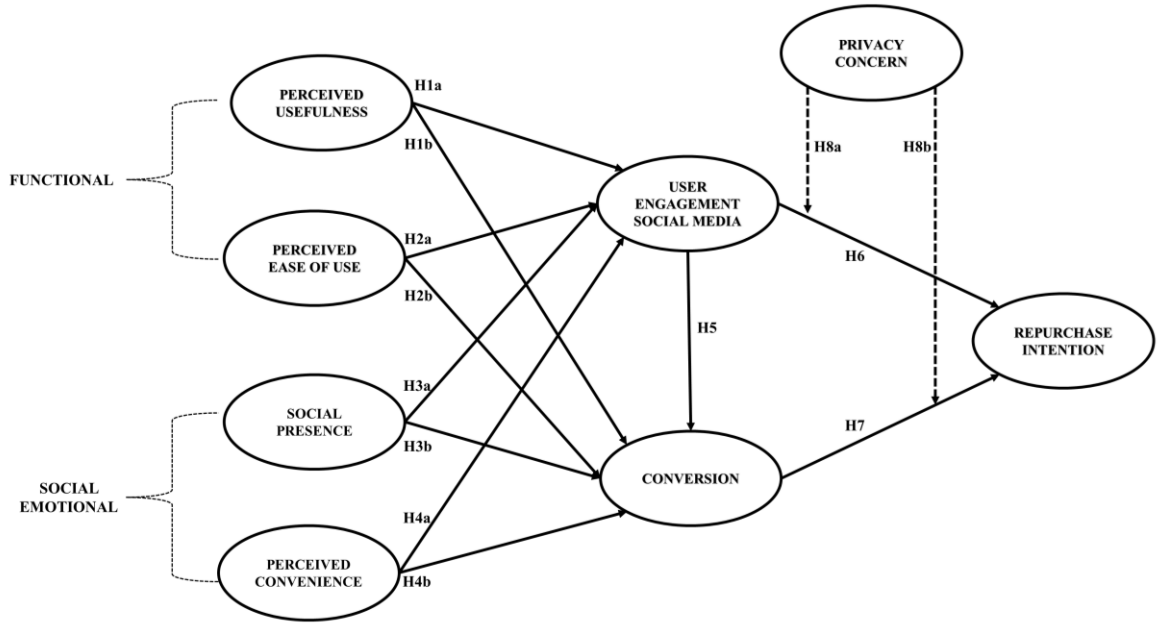
Data privacy regarding personal information is becoming increasingly important due to the use of AI, which increases the risk to individual privacy. (Manheim & Kaplan, 2019). For example, making transactions on online platforms often requires disclosing large amounts of personal information, which has become a requirement of e-commerce. (R. Smith & Shao, 2007). Privacy in online shopping should include respect for users' personal space and assurance that their data is collected, stored, and utilised while respecting individual rights. (Sanchez et al., 2024). Many empirical studies show a negative correlation between trust and privacy issues during online transactions. (Akhter, 2014; Liao et al., 2011; Sreejesh & Anusree, 2016). Although the loss of personal data does not necessarily result in direct financial loss, the perception of a threat to individual privacy is enough to reduce a person's interest in making a transaction. (Dinev & Hart, 2006). Additionally, receiving unwanted information about a product can create negative expectations and feelings in consumers' minds, drastically reducing their desire to repurchase the product or service. (Sánchez-Cañizares et al., 2021).

(Shabankareh et al., 2024) A strong correlation shows that privacy issues moderate the role of engagement in repurchase intention. Privacy issues can directly affect repurchase intentions (Trivedi & Yadav, 2020). Thus, mental risk mitigation is necessary to shift users' perceptions and increase the likelihood of repurchasing the same product or service (Larchenko, 2020). Therefore, strategies that address privacy issues can strengthen engagement in social commerce and increase repurchase intention. Retaining existing customers and encouraging repeat purchases makes customer retention crucial. (Singh et al., 2024). Another issue to consider is whether the increase in conversions driven by AI can be translated into actual sales. Because stagnant conversion rates will be a problem for online marketers, they must study the factors that positively influence conversion rates for e-commerce growth. (Naveen Gudigantala Pelin Bicen Mike (Tae-in) Eom, 2016).

- *H8a: Privacy concerns moderate the relationship between social media user engagement and repurchase intention*
- *H8b: Privacy concerns moderate the relationship between conversion and repurchase intention*

We propose a research model (Figure 1) that investigates the impact of AI on repurchase intentions. The concept is based on the Service Robot Acceptance Model, which focuses on the functional and socio-emotional aspects of consumer acceptance of AI-powered digital services. (Cheng, 2025; J. Kim et al., 2021; Wirtz et al., 2018). Functionality encompasses a person's considerations, including perceived ease of use and usefulness. Socio-emotional encompasses social presence and perceived convenience (Cheng, 2025). To explain the model, we link TAM, Commitment–Trust Theory, and TPB. Although each captures different aspects, they can complement each other in AI adoption in social commerce. TAM focuses on AI functionality (perceived usefulness and ease of use), Commitment–Trust Theory emphasises socio-emotional factors, and TPB explains consumer behaviour and repurchase intentions. Therefore, this research is essential to understanding how AI is not just a technological tool but also an entity that interacts with and influences its users' emotional experiences and social dynamics.

*Figure 1*
Research model




*Source:* Authors' work

# Methodology

## *Sample description*

Research data were collected on consumer perceptions of Artificial Intelligence (AI) utilised in Social Commerce in Indonesia. Respondents were selected using purposive sampling based on specific criteria (Creswell & Guetterman, 2024), targeting respondents who have at least visited or frequently engaged in trading activities through social commerce. The survey was distributed through social media channels (Instagram, WhatsApp) over four weeks in September–October 2024. We gathered data using a structured online questionnaire developed in Google Forms, which served as the primary data collection instrument. We collected data from 363 respondents but removed 10 as outliers. The final dataset included 353 respondents, with a demographic composition of 66.9% women, 33.1% men, and 83.6% aged 17-28 years. Additionally, 72.2% of the respondents held a bachelor's degree. All question items use a scale of 1 (strongly disagree) to 5 (strongly agree).

The first step is to conduct an initial analysis to assess data normality and identify any outliers that could affect the validity of the research data. This analysis aims to determine whether the data are normally distributed, as data normality is an essential assumption in many statistical methods, especially parametric methods. (Vrbin, 2022). In this process, the SPSS tool was used to facilitate the analysis. One of the main steps in SPSS is to test data normality by examining the Z-score for each item. The Z-score identifies data that deviates significantly from the normal distribution. Z-score values that exceed a threshold, such as those below -2.58 or above 2.58, are often considered outliers. (Park & Lee, 2021). Structural Equation modelling is appropriate to use because it does not show significant deviations due to value violations. (Griffin & Steinbrecher, 2013). Based on the normality test results, the research data are normally distributed and suitable for structural equation modelling (SEM) analysis. SEM was chosen because its statistical integrity is superior to that of other approaches, such as multiple regression analysis (Byrne, 2013).

## *Research instrument*

The questionnaire questions were adopted from previous research. The construct Perceived Usefulness (PU) (Shoukat et al., 2025) consists of four statement items; Perceived Ease of Use (PEU) (Venkatesh et al., 2003) consists of four statement items; Social Presence (SP) (Toader et al., 2020) consists of five statement items: Perceived Convenience (PC) (Akdim & Casaló, 2023; Lautenschläger, 2020) consists of five statement items, User Engagement on Social Media (UESM) (Bag et al., 2022) consists of six statement items, Conversion (CONV) (Bag et al., 2022) consists of four statement items, Privacy Concern (PCO) (Shoukat et al., 2025) consists of three statement items, and Repurchase Intention (REI) (Shang & Bao, 2020) consists of three statement items. Table 1 summarises the variables used.

*Table 1*
Overview of research constructs

| Construct | Key Definition | Role in This Study |
|---|---|---|
| **Perceived Usefulness** | The extent to which using AI provides benefits and improves user performance (Davis, 1989) | Functional aspect of AI that enhances user experience and drives engagement and conversion in e-commerce. |
| **Perceived Ease of Use** | The degree of comfort and effortlessness associated with using AI systems (Davis, 1989) | A functional factor that influences a positive attitude toward AI and encourages engagement and conversion. |
| **Social Presence** | The degree to which AI facilitates interpersonal connection and human-like interaction (Short, 1976) | Factors that influence a positive attitude toward AI and encourage engagement and conversion. |
| **Perceived Convenience** | The ease of using technology, considering time, place, effort, and implementation (Brown, 1989) | A factor that reduces cognitive burden, increasing engagement and conversion on social media. |
| **User Engagement** | Active participation in creating, consuming, and interacting with content on social media (Voorveld et al., 2018) | Central behavioural construct predicting conversion and repurchase intention. |
| **Conversion** | The proportion of users who perform a purchase relative to total visitors; a key effectiveness metric in digital marketing (Nazir et al., 2023). | Behavioural outcome connecting engagement to repurchase intention. |
| **Repurchase Intention** | An individual's likelihood to make repeat purchases in the future(Meng et al., 2023) | Outcome reflecting long-term consumer behaviour in AI-enabled s-commerce. |
| **Privacy Concerns** | Perceived threats and risks associated with disclosing personal information on AI-driven platforms. (Dinev & Hart, 2006). | A moderating variable influencing how engagement and conversion translate into repurchase intention. |

Source: Authors' work

### *Statistical methods*

The statistical method used is Structural Equation Modelling (SEM), a multivariate analysis approach that allows researchers to examine complex relationships between latent variables and indicators simultaneously. SEM combines confirmatory factor analysis (CFA) to ensure construct validity and reliability, and structural models to assess the strength and direction of relationships between variables within a predetermined theoretical framework (Hair et al., 2017). This method is particularly relevant for examining abstract concepts such as perceptions, attitudes, or intentions that cannot be directly measured. (Dash & Paul, 2021). In data collection, this study used an online questionnaire distributed via Google Forms, enabling respondents to complete it easily and efficiently. With SEM, researchers can evaluate the overall model's fit, thereby gaining a more comprehensive understanding of the phenomenon under study.

Before testing the validity and reliability of all constructs, we checked whether the collected data were free of bias. We followed the suggestions. (Kock et al., 2021; Mahmud et al., 2017)We focused on measurement methods by following Herman's single-factor statistical approach. This test is most widely used to assess common method bias. All constructs were analysed using an explanatory factor analysis (EFA), and Common Method bias was assumed if any factor emerged from an unrotated factor solution. AMOS was used to test the data. In this study, the variance explained by a single factor with confirmatory factor analysis (CFA) was found to be <50% according to the recommended criteria. (Harman, 1976) Moreover, the results show the absence of common-method bias in the dataset used.

## Results

We applied Covariance-Based Structural Equation Modelling (CB-SEM) using AMOS 24 to test the hypothesis using a multivariate approach across latent variables in a complex model, and tested it simultaneously. (J. Hair Jr et al., 2019). Table 2 shows the factor loadings, average values, standard deviations, and reliabilities for each construct used.

*Table 2*
Measurement Model per-item construct

| Constructs | Items | Factor Loading | CR | AVE | CA | Mean | SD |
|---|---|---|---|---|---|---|---|
| **Perceived Usefulness (PU)** | PU2 | 0.73 | 0.80 | 0.58 | 0.80 | 4.01 | 0.75 |
| | PU3 | 0.77 | | | | 3.93 | 0.74 |
| | PU4 | 0.78 | | | | 3.80 | 0.77 |
| **Perceived Ease of Use (PEU)** | PEU1 | 0.75 | 0.83 | 0.56 | 0.83 | 3.92 | 0.72 |
| | PUE2 | 0.70 | | | | 3.93 | 0.75 |
| | PUE3 | 0.77 | | | | 4.06 | 0.62 |
| | PUE4 | 0.77 | | | | 3.97 | 0.66 |
| **Social Presence (SP)** | SP1 | 0.70 | 0.87 | 0.63 | 0.86 | 3.55 | 0.87 |
| | SP2 | 0.79 | | | | 3.54 | 0.84 |
| | SP3 | 0.82 | | | | 3.23 | 0.94 |
| | SP4 | 0.87 | | | | 3.24 | 0.93 |
| **PC** | PC1 | 0.74 | 0.87 | 0.58 | 0.87 | 3.80 | 0.76 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | PC2 | 0.75 | | | | 3.89 | 0.74 |
| | PC3 | 0.79 | | | | 4.03 | 0.62 |
| | PC4 | 0.80 | | | | 3.73 | 0.70 |
| | PC5 | 0.72 | | | | 3.76 | 0.75 |
| **UESM** | UESM1 | 0.73 | 0.87 | 0.58 | 0.86 | 3.70 | 0.85 |
| | UESM2 | 0.73 | | | | 3.97 | 0.74 |
| | UESM3 | 0.75 | | | | 3.67 | 0.75 |
| | UESM4 | 0.81 | | | | 3.96 | 0.73 |
| | UESM5 | 0.79 | | | | 3.70 | 0.80 |
| **CONV** | CONV1 | 0.76 | 0.81 | 0.59 | 0.76 | 4.31 | 0.71 |
| | CONV2 | 0.77 | | | | 4.07 | 0.76 |
| | CONV3 | 0.77 | | | | 3.91 | 0.77 |
| **PCO** | PCO1 | 0.71 | 0.75 | 0.51 | 0.73 | 3.85 | 0.74 |
| | PCO2 | 0.86 | | | | 3.62 | 0.88 |
| | PCO3 | 0.55 | | | | 3.11 | 0.93 |
| **REI** | REI1 | 0.79 | 0.83 | 0.62 | 0.83 | 3.77 | 0.73 |
| | REI2 | 0.82 | | | | 3.64 | 0.77 |
| | REI3 | 0.76 | | | | 3.82 | 0.70 |

*Notes*: CR = Compositeeliability, AVE = Average Variance Extracted, CA = Cronbach Alpha, SD = Standard Deviation
Source: Author's work

## *Measurement Model (Validity and Reliability)*

Confirmatory Factor Analysis (CFA) uses AMOS 24 to test convergent and discriminant validity. In this analysis, the maximum likelihood estimation method is used. Convergent validity refers to the principle that indicators of a construct should have at least a moderate correlation with each other (Blanco et al., 2010). According to Steenkamp & Geyskens 2006), factor loadings in the confirmatory model must be statistically significant ($p < 0.05$ in this study) and have a value of more than 0.5. The Average Variance Extracted (AVE) values of the eight constructs tested were all above the minimum limit of 0.5, confirming convergent validity (J. Hair Jr. et al., 2019).

The results also showed satisfactory reliability, with composite reliability and Cronbach's alpha values of≥ 0.70 for all constructs, indicating internal consistency and construct reliability above the minimum limit of 0.6 (J. F. Hair Jr. et al., 2010). In addition, composite reliability is also used as an additional measure (Jöreskog, 1971; K. W. Smith, 1974). Table 2 presents the mean and standard deviation for all items.

Discriminant validity (Table 3) shows that indicators of different constructs should not be highly correlated, as this could lead to the conclusion that the indicators measure the same thing (Blanco et al., 2010). To ensure discriminant validity, the square root of the AVE (shown in the diagonal elements in Table 3) must be greater than the correlation with other constructs (off-diagonal elements) (Fornell & Larcker, 1981).

Additionally, we checked the assumptions of common method bias and linearity and found no violations of either. Thus, the average value across all constructs is above 3.5, indicating that respondents agree with moderate to high responses across all constructs.

*Table 3*
Assessment of Discriminant Validity

| Latent Construct | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| **1. Perceived Usefulness (PU)** | 0.76 | | | | | | | |
| **2. Perceived Ease of Use (PEU)** | 0.66 | 0.75 | | | | | | |
| **3. Social Presence (SP)** | 0.56 | 0.58 | 0.80 | | | | | |
| **4. Perceived Convenience (PC)** | 0.68 | 0.68 | 0.64 | 0.76 | | | | |
| **5. User Engagement on Social Media (UESM)** | 0.63 | 0.61 | 0.63 | 0.66 | 0.76 | | | |
| **6. Conversion (CONV)** | 0.55 | 0.64 | 0.36 | 0.64 | 0.40 | 0.77 | | |
| **7. Privacy Concern (PCO)** | 0.39 | 0.39 | 0.39 | 0.46 | 0.37 | 0.38 | 0.72 | |
| **8. Repurchase Intention (REI)** | 0.58 | 0.61 | 0.52 | 0.67 | 0.59 | 0.66 | 0.41 | 0.79 |

*Note: Diagonal line (Bold) is the root AVE of correlations between constructs of AVE, n = 353.*
*Source: Authors' work*

## *Structural model*

In the conceptual research model, causal relationships are tested using goodness-of-fit and path coefficient significance. Overall, the data show good model fit, as evidenced by the estimation of several model fit test statistics. The absolute fit indices calculated include the Absolute fit measures, the Incremental fit index, and the Parsimonious fit indices (J. F. Hair Jr. & Sarstedt, 2019).

Table 4 shows that the absolute fit measures category has a high fit tendency, followed by the incremental fit indices category, and the parsimonious fit indices category also exhibits a strong model fit tendency (0.78 to 0.90).

Based on the recommended criteria, the fit indices indicate that the model fits the data well and is suitable for hypothesis testing (Etezadi-Amoli & Farhoomand, 1996; Seyal et al., 2002; Steiger, 1980).

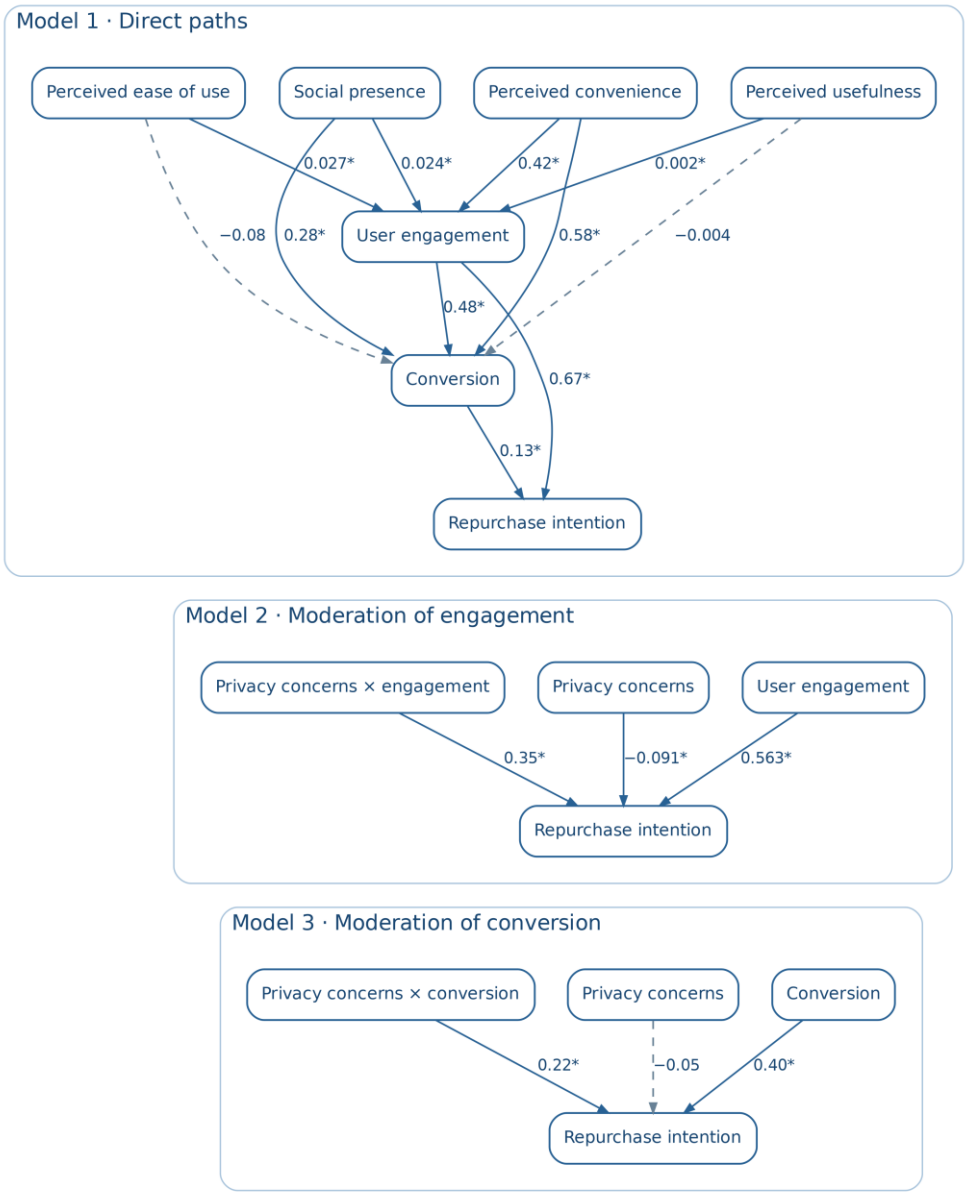
*Table 4*
The Goodness of Fit (GOF) Index for the Structural Equation Modelling

| GOF indices | Indicator | Cut-off point | Estimate | Result |
|---|---|---|---|---|
| **Absolute fit measures** | *Chi- square* ($\chi^2$)/CMIN | | 627.741 | Good Fit |
| | Degrees of freedom/df | | 307 | |
| | CMIN/df | Interval [2≤5] | 2.042 | Good Fit |
| | *P* | | 0.001 | |
| | GOF | ≥0.90 | 0.925 | Good Fit |
| | RMSEA | ≤0.08 | 0.054 | Good Fit |
| **Incremental Fit Indices** | AGFI | ≥0.90 | 0.9 | Good Fit |
| | TLI | ≥0.90 | 0.935 | Good Fit |
| | NFI | ≥0.90 | 0.894 | Marginal Fit |
| **Parsimonious Fit Indices** | PNFI | ≥0.90 | 0.782 | Marginal Fit |
| | PGFI | ≥0.90 | 0.825 | Marginal Fit |

*Source*: *Authors' work;* AMOS 24 output analysis

Hypotheses were evaluated at the 5% significance level (a = 0.05). Support for the directional hypotheses required a statistically significant coefficient in the hypothesised direction. Figure 2 presents the direct paths and the two moderation models.

*Figure 2*
Structural models and standardised path coefficients




Standardised coefficients (β). * p < 0.05. Dashed paths: p ≥ 0.05.

*Source: Authors' work*

Tables 5 and 6 report the direct estimates, and Table 5 also reports the moderation models.

Perceived usefulness (H1a, β = 0.002, p = 0.023) and perceived ease of use (H2a, β = 0.027, p = 0.006) showed small positive associations with user engagement. Neither was significantly associated with conversion (H1b, β = −0.004, p = 0.065; H2b, β = −0.08, p = 0.055). Social presence was positively associated with user engagement (H3a, β = 0.024, p < 0.001) and conversion (H3b, β = 0.28, p < 0.001). Perceived convenience was positively associated with user engagement (H4a, β = 0.42, p < 0.001) and conversion (H4b, β = 0.58, p < 0.001). User engagement was positively associated with conversion (H5, β = 0.48, p < 0.001) and repurchase intention (H6, β = 0.67, p < 0.001).

Conversion was positively associated with repurchase intention (H7, β = 0.13, p = 0.011).

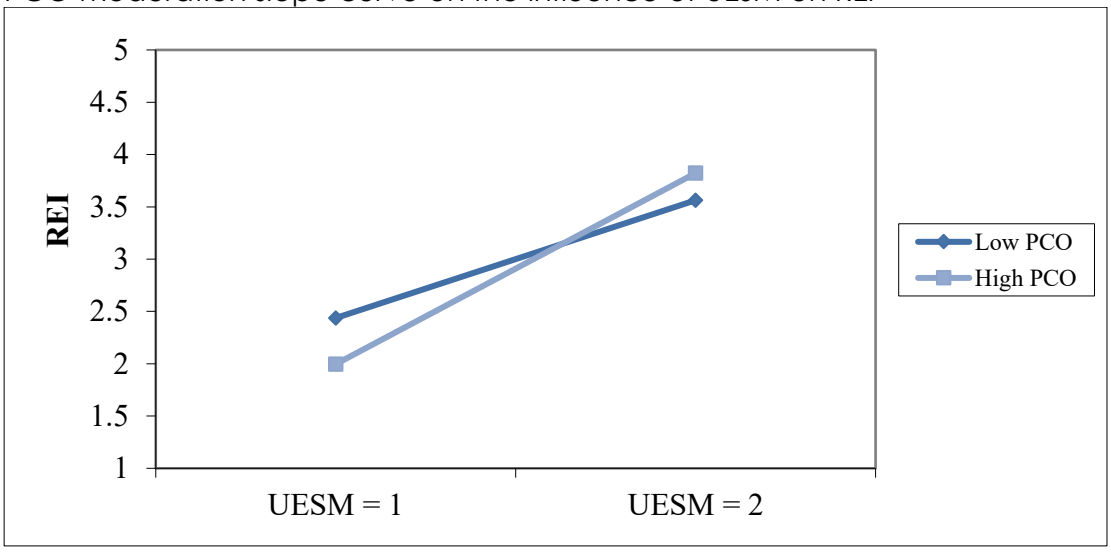
*Table 5*
Results of the structural model analysis.

| Path Analysis | Path-to (β and p-value) | | |
|---|---|---|---|
| | Model 1 | Model 2 | Model 3 |
| UESM <---- PU | 0.002* | | |
| UESM <---- PEU | 0.027* | | |
| UESM <---- SP | 0.024* | | |
| UESM <---- PC | 0.42* | | |
| CONV <---- PU | -0.004 | | |
| CONV <---- PEU | -0.08 | | |
| CONV <---- SP | 0.28* | | |
| CONV <---- PC | 0.58* | | |
| CONV <---- UESM | 0.48* | | |
| REI <---- UESM | 0.67* | | |
| REI <---- CONV | 0.13* | | |
| REI <---- UESM | | 0.563* | |
| REI <---- PCO | | -0.091* | |
| REI <---- Interaksi PCO*UESM | | 0.35* | |
| REI <---- CONV | | | 0.40* |
| REI <---- PCO | | | -0.05 |
| REI <---- Interaksi PCO*CONV | | | 0.22* |

*Note. n = 353. * p < 0.05. Source: Authors' work.*

Model 2 in Table 5 shows a positive interaction between privacy concerns and user engagement on repurchase intention, supporting H8a (β = 0.35, p < 0.01). Figure 3 illustrates a stronger positive association between engagement and repurchase intention at higher levels of privacy concerns.

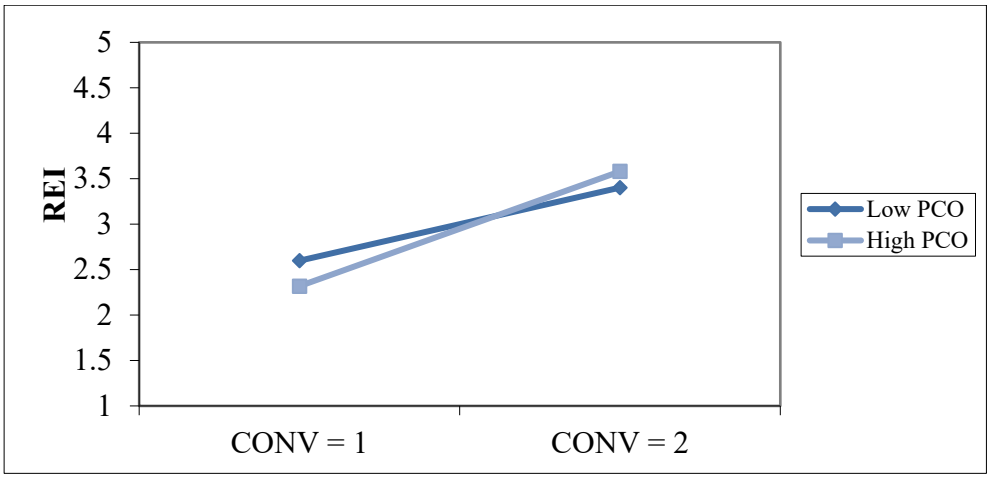
*Figure 3*
PCO moderation slope curve on the influence of UESM on REI




*Source: Authors' work*

Model 3 in Table 5 shows a positive interaction between privacy concerns and conversion in the model for repurchase intention, supporting H8b (β = 0.22, p < 0.01). Figure 4 illustrates a stronger positive association between conversion and repurchase intention at higher levels of privacy concerns.

*Figure 4*
PCO moderation slope curve on the influence of CONV on REI




Source: Authors' work

Table 6 shows that nine of the eleven direct hypotheses were supported at the 5% significance level. Perceived usefulness and perceived ease of use were positively associated with social media user engagement (H1a and H2a). Their associations with conversion did not reach statistical significance (H1b and H2b). Social presence and perceived convenience were positively associated with both engagement and conversion (H3a–H4b). Engagement was positively associated with conversion and repurchase intention (H5 and H6), and conversion was positively associated with repurchase intention (H7).

*Table 6*
Results of the structural model analysis.

| | Path analysis | Standard Estimate | p-value | Hypothesis Decision |
|---|---|---|---|---|
| **H1a** | Perceived usefulness -> social media user engagement | 0.002 | 0.023 | Supported |
| **H1b** | Perceived usefulness -> conversion | -0.004 | 0.065 | Not supported |
| **H2a** | Perceived ease of use -> social media user engagement | 0.027 | 0.006 | Supported |
| **H2b** | Perceived ease of use -> conversion | -0.08 | 0.055 | Not supported |
| **H3a** | Social presence has a significant positive effect on social media user engagement | 0.024 | < 0.001 | Supported |

| | | | | |
|---|---|---|---|---|
| **H3b** | Social presence has a significant positive effect on conversion | 0.28 | < 0.001 | Supported |
| **H4a** | Perceived convenience has a significant positive effect on social media user engagement | 0.42 | < 0.001 | Supported |
| **H4b** | Perceived convenience has a significant positive effect on conversion | 0.58 | < 0.001 | Supported |
| **H5** | User engagement on social media has a significant positive effect on conversion | 0.48 | < 0.001 | Supported |
| **H6** | User engagement on social media has a significant positive effect on repurchase intention | 0.67 | < 0.001 | Supported |
| **H7** | Conversion has a positive and significant effect on repurchase intention | 0.13 | 0.011 | Supported |

Note. Hypothesis decisions are based on a = 0.05. Source: Authors' work.

Overall, perceived convenience and social presence were positively associated with both engagement and conversion. In the baseline structural model, engagement and conversion were both positively associated with repurchase intention, with a larger standardised coefficient for engagement. The positive interaction coefficients supported H8a and H8b, indicating that the associations of engagement ($\beta = 0.35$, $p < 0.01$) and conversion ($\beta = 0.22$, $p < 0.01$) with repurchase intention were stronger at higher levels of privacy concerns.

## Discussion and Conclusion

This study aims to identify the factors that influence engagement and conversion in AI use in social commerce. Additionally, this study aims to investigate how privacy issues influence repurchase intention. The study's results reveal several key findings that can serve as considerations for academics and practitioners in the field of social commerce. More specifically, the findings indicate that optimising AI to consider social-emotional aspects has a significant positive impact on digital consumer behaviour. These findings support previous studies, which state that the success of AI depends not only on technical effectiveness, but also on its ability to build emotional connections that influence consumer perceptions and decisions (Adikari et al., 2021; Rehman et al., 2024). Perceived usefulness and ease of use showed small positive associations with engagement, consistent with prior research on technology acceptance, including (Scherer et al., 2019) . . . The Technology Acceptance Model (TAM) emphasises that the success of AI utilisation is primarily determined by perceptions of its ease and usefulness. In fact, (Cheng, 2025) also confirmed that these two aspects are able to encourage user engagement on social media.

The results of this study indicate that functional aspects such as perceived usefulness and ease of use were not significantly associated with conversion in the context of social commerce. This finding can be explained by the main characteristics of social commerce, which are driven more by social factors than technical ones. This is because consumer decisions in social commerce are influenced by social interaction, trust, and social proof (Patwa et al., 2024; Tseng et al., 2025). As users become familiar with social commerce platforms, they may come to expect basic

functionality and ease of use. Furthermore, purchasing behaviour in social commerce is often impulsive and emotional (Wu et al., 2024), making cognitive factors derived from the Technology Acceptance Model (TAM) less relevant. Thus, the finding for conversion aligns with the literature, which shows a shift in consumer behaviour from utilitarian to socio-relational aspects in social commerce.

Users' familiarity with basic digital features may help explain the small coefficients for perceived usefulness and ease of use in the engagement model. Perceived convenience had a larger coefficient for engagement and was also positively associated with conversion. This pattern suggests that it is useful to distinguish general perceptions of a platform's functionality from the convenience of completing specific shopping tasks.

User engagement was positively associated with conversion and repurchase intention. Conversion was also positively associated with repurchase intention, with a smaller standardised coefficient than engagement in the baseline model. AI can process large amounts of algorithmic data to see patterns, consumer tendencies, make predictions, and provide insights (Borges et al., 2021; Sipior, 2020). These findings link customer engagement to conversion and to the intention to buy again. Public opinion analysis using artificial intelligence can improve the quality of service to customers and influence consumer interest in promoted goods (Sydorenko et al., 2020). A positive first purchase experience and pleasant interactions can increase users' tendency to make repeat purchases. Thus, customer engagement with AI mediation is not only transactional, but also relational.

In addition, this study contributes by examining the moderating role of privacy concerns, which are often assumed to be obstacles but can strengthen the relationship between user engagement and repurchase intention. The study measured consumers' privacy concerns. Privacy assurances, transparency, data security and user controls are separate practices that platforms can consider when addressing those concerns. In online buying and selling activities, customers need assurance of privacy, not just information (Hua et al., 2024). Thus, customer privacy protection has a significant impact on long-term customer satisfaction (Plangger & Watson, 2015). Although a security system has been systematically implemented to minimise customer concerns, complex procedures may lead customers to assume the online system is not secure and may not fully protect their privacy. Protecting consumer data privacy is essential to building user trust and loyalty in the digital world. Customer concerns about privacy can affect a customer's purchase intention towards a product (Shankar et al., 2016; Fortes & Rita, 2016) and can even negatively impact consumer purchase intention (Hew et al., 2017). In this sample, the associations of user engagement and conversion with repurchase intention were stronger among consumers who reported greater privacy concerns.

## *Theoretical implications*

The findings of this study make essential contributions to the development and enrichment of the Technology Acceptance Model (Davis, 1989) and Commitment-Trust Theory (Morgan & Hunt, 1994c) in the context of utilising artificial intelligence-based technology in social commerce activities. Perceived usefulness and ease of use were positively associated with engagement, consistent with the Technology Acceptance Model. The small coefficients for engagement and the lack of significant associations with conversion suggest that the relevance of these constructs varies across outcomes in social commerce. Thus, these results highlight the need to develop a TAM model that is better suited to the context of platforms that integrate social media and e-commerce.

The results of this study also provide theoretical contributions to the development of the Commitment-Trust Theory concept (Morgan & Hunt, 1994b) by emphasising that success in building long-term relationships between consumers and digital service providers does not only depend on trust factors, but is also greatly influenced by the level of emotional and rational commitment formed through consistent and relevant interaction experiences. This study expands the theory by adding empirical evidence that, in the context of using AI in social commerce, trust can form not only through the provider's integrity and competence but also through perceived added value and personalised experiences. Thus, the results underscore the importance of affective commitment as a mediator in strengthening loyalty and repurchase intentions and highlight the need to update the model in the context of a more dynamic digital economy.

## *Practical implications*

These findings provide strategic guidelines for business actors and social commerce platform developers to optimise AI use. It is important to note that this study's findings are based solely on Indonesian respondents. Indonesia is characterised by high collectivism, where social influence and community approval strongly affect consumer behaviour. In addition, social commerce in Indonesia is predominantly mobile-first, with users primarily engaging on smartphones. Privacy perceptions are also shaped by cultural factors, with users being susceptible to personal data security and transparency. Therefore, while these results provide valuable insights, their applicability to other cultural contexts may be limited and should be interpreted with caution.

Emotional factors, such as social presence and perceived convenience, are key drivers of user engagement and conversion, thereby enhancing the user's digital experience. Consumers will be more loyal if they receive an emotional experience and feel the presence of a human behind each AI system. This study also emphasises the importance of building strong relationships and trust through transparency and personal data protection. Privacy protection systems must be comprehensive and accountable. By combining technological effectiveness and efficiency with digital emotional experiences and a commitment to privacy, companies can increase loyalty and encourage repeat purchases.

Social commerce managers should implement concrete AI features that enhance social presence and emotional engagement. For instance, AI-powered live chat can interact with users using local language nuances, offering personalised product suggestions and culturally relevant greetings. Additionally, AI-generated storytelling can present product information in ways that resonate with individual preferences and regional context, increasing user immersion and engagement. For privacy management, platforms should adopt transparent, participatory mechanisms that let users clearly consent to data use, review and update their personal information, and delete it if they choose. Communicating these policies in an accessible, culturally appropriate way helps build trust, ensures compliance, and strengthens long-term user loyalty and repurchase intentions.

Social commerce managers also do not focus solely on developing artificial intelligence features that emphasise ease of use and technical usefulness (perceived usefulness). Both aspects showed small positive associations with engagement, and neither was significantly associated with conversion. The findings also point to social presence and convenience as considerations when designing AI features for social commerce. To avoid unethical behaviour from the use of AI on a person's emotional condition, such as the misuse of information (Dolunay & Temel, 2024).

This can be achieved by providing relevant, contextual content tailored to user preferences, delivering adaptive product recommendations that mimic human communication, and creating more immersive and engaging interactions. This affection-based, personal-closeness approach is believed to be more effective at increasing active user participation and encouraging purchase intentions in the context of social commerce. In managing privacy issues in social commerce, managers must view them not only as a matter of regulatory compliance but also as a key factor in building trust and increasing customer repurchase intentions. Effective privacy management includes several essential steps. First, provide a transparent, easy-to-understand privacy policy; second, give users complete control over their data, including the right to access, update, and delete their information. Third, we ensure data security through encryption and strong authentication, and actively and convincingly communicate privacy protection efforts at every digital touchpoint with customers. By incorporating data protection into their brand value, social commerce platforms can not only alleviate customer concerns but also foster a deeper emotional connection to the platform, thereby positively impacting loyalty and conversion.

### *Conclusion*

Social presence and perceived convenience were positively associated with customer engagement and conversion. Perceived usefulness and ease of use showed small positive associations with engagement. Both engagement and conversion were positively associated with repurchase intention. These findings offer new insights for social commerce businesses, as a good user experience is not determined by technical benefits alone. Marketers must understand which types of AI services can build emotional engagement. For example, AI can understand the user's local language style and provide personalised recommendations. This can increase user engagement and conversions, benefiting the company. Both of these attitudes illustrate the importance of building ongoing interactions between marketers and consumers. The associations of engagement and conversion with repurchase intention were stronger among consumers who reported greater privacy concerns. This finding concerns consumers' perceptions. Data protection measures are a separate consideration for platform design.

While this study contributes to understanding digital consumer behaviour, it has limitations that can inform future research. First, this study used a quantitative approach utilising questionnaires. This method may have weaknesses in providing in-depth interpretation due to the limited choice of respondents. Future research could use a qualitative or mixed-methods approach to explore respondents' experiences in more depth. Second, this study's sample was limited to a single country. Future research could use the same conceptual model in other countries to generalise the results. Adding variables to explore different perspectives is also needed to enrich the research findings.

## Acknowledgements

This research was funded by the Direktorat Riset, Teknologi, dan Pengabdian kepada Masyarakat (DRTPM), BIMA Program, Kementerian Pendidikan Tinggi, Sains, dan Teknologi Republik Indonesia. The authors would like to thank Universitas Lampung for its financial and resource support.

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