Studi Akuntansi, Keuangan, dan Manajemen (SAKMAN)
ISSN 2798-0251, Vol 5, No 4, 2026, 107-126 https://doi.org/10.35912/sakman.v5i4.6263

The Impact of AI Adoption on Customer Perceived Value, Satisfaction, and Loyalty in Social Commerce

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Article History:
Received on 04 February 2026
1st Revision on 06 February 2026
2nd Revision on 18 February 2026
3rd Revision on 23 February 2026
Accepted on 06 March 2026

Abstract

Purpose: This study investigates how AI-based personalization, marketing analytics capability, and perceived privacy assurance influence customer loyalty in social commerce and whether these effects operate through perceived value and customer satisfaction.

Research Methodology: A cross-sectional online survey was administered to 510 active social commerce users in South Sulawesi, Indonesia, to collect data. The hypothesized relationships and mediation effects were examined using PLS-SEM.

Results: AI-based personalization significantly increased customer satisfaction and loyalty but had no significant effect on perceived value. Marketing analytics capability significantly strengthens perceived value; however, it has no significant direct effect on satisfaction or loyalty. Perceived privacy assurance positively affects perceived value, satisfaction, and loyalty. Both perceived value and customer satisfaction significantly enhance the loyalty. The mediation results indicate that marketing analytics capabilities indirectly strengthen loyalty via perceived value, whereas privacy assurance strengthens loyalty via both perceived value and customer satisfaction. AI-based personalization primarily drives loyalty through customer satisfaction.

Conclusions: Customer loyalty in AI-enabled commerce is reinforced through complementary cognitive and affective pathways.

Limitations: The findings are constrained by the cross-sectional design, self-reported data, and single-region sample. In addition, the privacy construct reflects assurance-oriented perceptions rather than anxiety.

Contributions: This study clarifies the distinct roles and indirect mechanisms through which personalization, analytics capabilities, and privacy perceptions shape loyalty in social commerce.

Keywords: *AI Personalization, Customer Satisfaction, Customer Loyalty, Marketing Analytics, Privacy Assurance*

How to Cite: Aris, V., Sobirov, B., Maupa, H., Ruslan, A., Aris, A, L. (2026). The Impact of AI Adoption on Customer Perceived Value, Satisfaction, and Loyalty in Social Commerce. *Studi Akuntansi, Keuangan, dan Manajemen*, 5(4), 107-126.

1. Introduction

Recent advances in information technology, particularly the rapid diffusion of Artificial Intelligence (AI) have reshaped the contemporary marketing landscape. Firms are moving beyond experimentation and are increasingly making systematic investments while redesigning processes to capture value from AI. McKinsey reports that 2024 marked an inflection point in which AI generated its highest business impact, with the largest gains occurring in marketing and sales compared to other functions (Singla, Sukharevsky, Yee, Chui, & Hall, 2025). In Indonesia, adoption has expanded quickly, with 28 percent of firms reporting AI use, representing a 47 percent year year-over-year increase; reported outcomes include revenue growth for 59 percent of firms and cost reductions for 64 percent (Amazon Web, 2025). Beyond productivity and top line effects, AI enabled marketing is also associated with improved customer experience, which can reinforce loyalty (Hermann & Puntoni, 2024). These developments suggest that the strategic value of AI in marketing lies not only in efficiency gains but also in building and sustaining customer relationships. Customer loyalty denotes a sustained attitudinal and behavioral commitment, whereby customers repeatedly favor a given brand even when attractive alternatives exist (Kotler et al., 2022). Loyalty remains a central performance indicator because loyal customers repurchase more frequently, advocate positively, and contribute to more stable revenue streams (Kim, Jindabot, & Yeo, 2024; Mittal et al., 2023). Accordingly, many marketing efforts focus on strengthening the processes that generate customer loyalty. Prior studies indicate that technology-enabled marketing innovations can accelerate loyalty formation by improving how customers evaluate and experience the offering (Chotisarn & Phuthong, 2025; Hossain, Akter, & Yanamandram, 2020; Teepapal, 2025).

From a relationship marketing perspective, loyalty is shaped by how customers evaluate what they receive relative to what they sacrifice and by the affective responses that follow repeated usage experiences. Perceived value represents a holistic appraisal of benefits relative to sacrifices, and it is often positioned as an early driver of loyalty formation (Zauner, Koller, & Hatak, 2015). Some evidence supports a direct positive link between perceived value and loyalty (Basrowi, Ali, & Suryanto, 2023; Sirdeshmukh, Singh, & Sabol, 2002). However, other findings suggest that value does not always translate directly into loyalty and that satisfaction may be required as a proximal mechanism through which value is converted into sustained commitment (Aqabneh, 2025). This implies that value can be an important starting point, but its effect depends on whether the experience remains consistently satisfactory over time.

Customer satisfaction is widely recognized as a key determinant of loyalty because it captures an overall affective evaluation of performance relative to expectations (Croitoru, Capatina, Florea, Codignola, & Sokolic, 2024; Yum & Kim, 2024). When satisfaction is consistently realized across marketing touchpoints, customers are more likely to develop attitudinal loyalty that later manifests as behavioral loyalty (Arabella, Mani, Sahabu, & Aras, 2025; Mittal et al., 2023; Reitsamer & Becker, 2024). Conversely, repeated dissatisfaction increases the risk of switching and weakens the customer-brand relationship. In this sense, satisfaction functions as a psychological channel that stabilizes loyalty by reinforcing positive evaluations generated through value and performance.

Marketing technology adoption can strengthen perceived value and satisfaction by enabling personalization, automation, predictive analytics, and richer and more interactive experiences (Labib, 2024; Teepapal, 2025). Personalization can improve the relevance of content and recommendations, thereby supporting customer outcomes. Prior studies have reported that personalization can influence loyalty through perceived value and satisfaction and can also show a direct effect on loyalty beyond mediation (Chandrakumar, 2024; Sucidha, 2025). These findings position personalization not only as an operational feature but also as a strategic lever that can improve customer evaluations and strengthen the conditions under which loyalty develops.

Marketing analytics capability is defined as an organization's integrated ability to convert customer and market data into actionable insights that improve decision quality, speed, and effectiveness (Basu & Lim, 2023). At the consumer level, capability becomes visible through market-facing outcomes, such as the relevance of offerings, responsiveness, and consistency in execution across the customer journey. Prior work suggests that analytics capability supports better customer understanding and more relevant experiences, which can enhance perceived value and trust (Agag et al., 2024; Basal & Moulai, 2025; Sáenz, Ortiz de Guinea, & Peñalba-Aguirrezabalaga, 2022; Zanon, Arantes, Calache, Martins, & Carpinetti, 2025). Other studies indicate that analytics capability can improve satisfaction and, through satisfaction, contribute to loyalty (Agag et al., 2024; Alfadhel, 2025; Fetais, Algharabat, Aljafari, & Rana, 2023; Jabado & Jallaoli, 2024). Collectively, this literature reflects a shift from treating data as a passive asset to deploying analytics as an experience-shaping capability that supports high-value customer journeys.

Despite these benefits, data-driven marketing raises concerns regarding privacy and security. Consumers increasingly recognize that online interactions can be collected, analyzed, and used for commercial purposes, which makes privacy perceptions central to the sustainability of data-driven marketing practices. Perceived Privacy Assurance (PPA) refers to customers' belief that a platform's privacy practices are clear and trustworthy and that they have adequate control over their personal data (Magrizos, Campora, Lamprinakos, Giovanis, & Christofi, 2025). Importantly, prior work showing reduced trust and less favorable brand attitudes typically refers to privacy concern or privacy anxiety, rather than assurance (Hsu, Liao, Lee, & Chan, 2022; Martin & Murphy, 2017; Pavlou & Gefen, 2004). In contrast, higher privacy assurance is expected to function as risk mitigation by lowering perceived privacy costs and supporting more-favorable evaluations. Empirical evidence further suggests that privacy-related perceptions can spill over to key relationship outcomes by shaping perceived value, satisfaction, and loyalty (Anshori, Karya, & Gita, 2022; Dienlin, 2023; Irgui & Qmichchou, 2024). Thus, understanding the PPA is essential for balancing marketing innovation with the protection of consumer privacy while sustaining trust-based relationships.

This study draws on the Stimulus-Organism-Response (SOR) framework to explain how technology-enabled marketing features translate into customer loyalty. In the SOR model, environmental stimuli shape individuals' internal states, which subsequently guide their behavioral responses (Mehrabian & Russell, 1974; Vieira, 2013). In AI-enabled social commerce, personalization and marketing analytics capabilities are treated as salient technological stimuli because they influence how content is tailored, how recommendations are delivered, and how customers perceive platform responsiveness. These stimuli affect two organismic states: cognitive evaluation captured by perceived value and affective evaluation captured by customer satisfaction, which then shapes loyalty as a response. Framing perceived value and satisfaction as parallel routes allows the model to capture both the cognitive and affective mechanisms of loyalty formation.

To theorize privacy in this setting, the study complements SOR with privacy calculus, which proposes that consumers balance expected benefits against privacy related costs when engaging with data driven services (Dienlin, 2023; Xu, Luo, Carroll, & Rosson, 2011). Rather than treating privacy solely as anxiety, this study focuses on perceived privacy assurance, which reflects confidence in transparent and dependable privacy practices and meaningful control over personal data. Within the privacy calculus, PPA functions as a risk-mitigating stimulus because it reduces perceived privacy costs and supports more favorable evaluations, thereby strengthening perceived value, satisfaction, and ultimately loyalty. This framing offers a clearer theoretical contribution because it distinguishes privacy assurance from privacy concerns and specifies the psychological pathways through which privacy perceptions operate in technology-intensive marketing contexts.

Accordingly, this study tests the effects of personalization, marketing analytics capabilities, and perceived privacy assurance on customer loyalty through perceived value and customer satisfaction. Its contribution lies in clarifying mixed evidence by specifying where and how the effects unfold in the customer value chain. Prior findings are inconsistent because personalization strengthens perceived value mainly when benefits are salient and not perceived as intrusive, and because the value-loyalty link is not uniform, with some studies supporting a direct path and others suggesting that value must first translate into satisfaction (Akdim & Casaló, 2023; Aqabneh, 2025; Basrowi et al., 2023; Teepapal, 2025).

Evidence on analytics capability is also fragmented, as its impact often appears strongest in cognitive evaluations unless insights are translated into consistent execution across customer touchpoints (Agag et al., 2024; Alfadhel, 2025; Basal & Moulai, 2025; Fetais et al., 2023; Jabado & Jallaoli, 2024; Sáenz et al., 2022; Zanon et al., 2025). Privacy findings are similarly difficult to reconcile because privacy is frequently framed as a concern, whereas this study captures assurance-oriented perceptions of control, transparency, and protection that operate as risk mitigation (Hsu et al., 2022; Martin & Murphy, 2017;

Pavlou & Gefen, 2004). By integrating these drivers into a serial mediation model in which perceived value and satisfaction transmit effects to loyalty, this study provides a more precise account of the cognitive and affective pathways through which AI-enabled marketing fosters loyalty.

2. Literature Review and Hypothesis Development

2.1 AI-Based Personalization

AI-based personalization refers to dynamically tailoring content, recommendations, and interactions based on individual customers' behaviors, preferences, and contextual data. In digital marketing, personalization is often expected to enhance perceived value by improving relevance and reducing search and decision efforts; however, its benefits are not uniform across settings. Prior studies suggest clear boundary conditions: personalization tends to strengthen perceived value when customers perceive the recommendations as useful and congruent with their goals, and when personalization is not experienced as intrusive or privacy threatening (Akdim & Casaló, 2023; Teepapal, 2025).

When customers attribute personalization to excessive tracking or feel that it limits their autonomy, the perceived benefits may be offset, weakening value perceptions, even if the content is tailored. This contingency helps explain why the empirical evidence on personalization-related outcomes is mixed and why the value pathway should not be assumed to be automatic. Against this backdrop, the present study tests whether AI-based personalization increases perceived value while recognizing that the magnitude of this effect may depend on customers' interpretation of personalization as beneficial rather than intrusive.

Beyond perceived value, the literature more consistently links personalization to favorable brand perceptions and relationship outcomes, including satisfaction and loyalty, either directly or indirectly (Chandrakumar, 2024; Hussain, 2025; Lin, Jeong, Zhang, & Liu, 2024; Shahzad, Xu, An, & Javed, 2024; Sherly Steffi et al., 2025; Tamilmani et al., 2025). Prior studies have also found direct effects on perceived value and customer satisfaction, which, in turn, reinforce the influence of AI-based personalization on loyalty (Akdim & Casaló, 2023; Chotisarn & Phuthong, 2025; Hariguna & Ruangkanjanases, 2024; Hussain, 2025; Maroufkhani, Asadi, Ghobakhloo, Jannesari, & Ismail, 2022; Shahzad et al., 2024; Singh & Singh, 2024; Sucidha, 2025; Teepapal, 2025). In summary, AI-based personalization not only exerts a direct impact on loyalty but also amplifies it through the mediating roles of perceived value and satisfaction, positioning personalization as a strategic foundation for building long-term customer relationships in the digital era.

H_{1a}: AI-based personalization influences perceived value
H_{1b}: AI-based personalization influences customer satisfaction
H_{1c}: AI-based personalization influences customer loyalty

2.2 Marketing Analytical Capability

Marketing analytics capability refers to a firm's integrated ability to transform customer and market data into actionable insights that improve the speed and accuracy of marketing decision-making. Although this capability is internally embedded, it can become visible to consumers through customer-facing manifestations, such as the relevance of offers, timeliness of responses, consistency across touchpoints, and overall quality of the service experience on digital platforms. This logic is consistent with the resource-based view and dynamic capability perspective, which argue that superior firm capabilities create competitive advantages when they are deployed to reconfigure and execute market-facing activities that customers can experience (Barney, 2000; Teece, 2007; Teece, Pisano, & Shuen, 1997).

In other words, consumers do not perceive the capability itself; instead, they infer it from the quality and coherence of the outcomes it enables. Strategically, marketing analytics capabilities enhance decision precision, campaign effectiveness, and budget efficiency (Basu & Lim, 2023). From the consumer perspective, it allows brands to understand needs more accurately and deliver more relevant experiences, which can elevate perceived value and trust (Agag et al., 2024; Basal & Moulai, 2025; Sáenz et al., 2022; Zanon et al., 2025). Prior studies have also indicated that analytics capabilities can improve customer satisfaction and, through satisfaction, strengthen loyalty (Agag et al., 2024; Alfadhel, 2025; Fetais et al., 2023; Jabado & Jallaoli, 2024). Building on this theoretical bridge, the present study tests whether marketing analytics capability influences perceived value, customer satisfaction, and customer loyalty in AI-enabled marketing.

H_{2a}: Marketing analytics capability influences perceived value

H_{2b}: Marketing analytics capability influences customer satisfaction

H_{2c}: Marketing analytics capability influences customer loyalty

2.3. Perceived Privacy Assurance

Perceived privacy assurance refers to individuals' belief that a platform's privacy practices are transparent and trustworthy and that they have adequate control over how their personal data are collected and used (Hsu et al., 2022). In marketing contexts, the growing number of AI-enabled interactions that require personal data disclosure makes perceived privacy assurance a critical construct for understanding consumer behavior in the digital age. Perceived privacy assurance is important because it can shape consumer trust, willingness to share data, and purchase or usage intentions toward digital services (Irgui & Qmichchou, 2024). Privacy calculus theory posits that consumers weigh the benefits of personalization against the perceived privacy costs and risks; when privacy assurance is high, perceived risks tend to diminish, thereby strengthening perceived value, attitudes, and engagement (Dienlin, 2023).

Therefore, perceived privacy assurance can facilitate the adoption of digital and e-commerce services, as consumers feel safer when the expected benefits outweigh the perceived privacy risks (Yao & Tarofder, 2024). Prior studies also document that perceived privacy assurance enhances perceived value and satisfaction, which ultimately translates into stronger customer loyalty (Alhitmi, Mardiah, Al-sulaiti, & Abbas, 2024; Hendriana, Anjani, Dennison, & Subhan, 2023; Irgui & Qmichchou, 2024; Riaz, Ahmed, & Jibril, 2024; Teepapal, 2025; Yulianti, Taryana, & Anggriani, 2024). Accordingly, perceived privacy assurance operates not only as a key driver supporting technology adoption but also as an important variable in the customer value chain, with the potential to strengthen perceived value, satisfaction, and loyalty within AI-enabled marketing ecosystems.

H_{3a}: Perceived privacy assurance influences perceived PV

H_{3b}: Perceived privacy assurance influences customer satisfaction

H_{3c}: Perceived privacy assurance influences customer loyalty

2.4 Customer Satisfaction

Customer satisfaction refers to consumers affective evaluation of their experience with a product or service, in which perceived performance meets or exceeds expectations (Haseeb, Adnan, & Saeed, 2024). As a core indicator of customer experience, satisfaction matters because when it is consistently achieved, customers are more likely to develop loyalty, recommend the brand, and repurchase (Jasin & Firmansyah, 2023; Mittal et al., 2023). In marketing research, satisfaction functions as a psychological conduit through which perceived value and service quality translate into downstream behaviors such as retention and loyalty (Croitoru et al., 2024; Rosário & Casaca, 2023; Yum & Kim, 2024). Recent studies have highlighted the role of technology personalization, digital services, social media marketing, and predictive solutions in strengthening satisfaction (Chotisarn & Phuthong, 2025; Hossain et al., 2020; Kim et al., 2024; Misidawati, Devi, & Fatimah, 2023; Teepapal, 2025). Accordingly, satisfaction plays a crucial mediating role in converting perceived value into loyalty, making consistency across all touchpoints a key determinant of long-term loyalty.

H_{4a}: Customer satisfaction affects customer loyalty

2.5 Perceived Value

Perceived value is the customer's subjective evaluation of the total benefits received relative to the total costs incurred in a transaction or consumption experience (Zeithaml, 1988). The concept has evolved from a simple utilitarian trade-off to a multidimensional framework encompassing functional, emotional, social, and epistemic value (Sweeney & Soutar, 2001). In the digital era, perceived value is increasingly shaped by personalization, ease of access, interactivity, and data security, making it central to predicting consumer satisfaction, loyalty, and repurchase intentions. Emerging evidence underscores the role of technology in enhancing perceived value and, in turn, customer loyalty (Blut, Chaney, Lunardo, Mencarelli, & Grewal, 2024; Chandrakumar, 2024; Shahzad et al., 2024; Sucidha, 2025; Teepapal, 2025). Thus, perceived value functions as a strategic compass that guides firms in transforming data into meaningful experiences, thereby elevating satisfaction, reinforcing loyalty, and supporting business sustainability in the face of intensifying digital competition.

H_{4b}: Perceived value influences customer loyalty

2.6 Costumer Loyality

Customer loyalty is a commitment encompassing attitudinal and behavioral dimensions, whereby customers continue to choose a brand, shaped by repeated satisfying experiences and consistently perceived value (Kotler et al., 2022). Loyalty is pivotal because loyal customers generate recurring revenue, lower acquisition costs, and positive advocacy that strengthens a firm's competitive position (Mittal et al. 2023). From the consumer's perspective, loyalty arises from a stable perception of value coupled with satisfying experiences.

Theoretically, loyalty formation follows a cognitive–affective pathway: consumers first perceive value such as functional, emotional, or social, which elevates satisfaction and, in turn, influences loyalty (Chi & Phan, 2025; Croitoru et al., 2024). Recent research highlights AI-based personalization and marketing analytics as mechanisms that reinforce loyalty formation (Chotisarn & Phuthong, 2025; Hossain et al., 2020; Kim et al., 2024; Teepapal, 2025). Accordingly, customer loyalty is the cumulative outcome of ongoing value creation and satisfaction, which is increasingly strengthened by digital technologies and artificial intelligence in modern marketing strategies.

H_{5a}: AI-based personalization affects customer loyalty through satisfaction
H_{5b}: AI-based personalization affects customer loyalty through perceived value
H_{5c}: Marketing analytics capability affects customer loyalty through satisfaction
H_{5d}: Marketing analytics capability affects customer loyalty through perceived value
H_{5e}: Perceived privacy assurance affects customer loyalty through satisfaction
H_{5f}: Perceived privacy assurance affects customer loyalty through perceived value

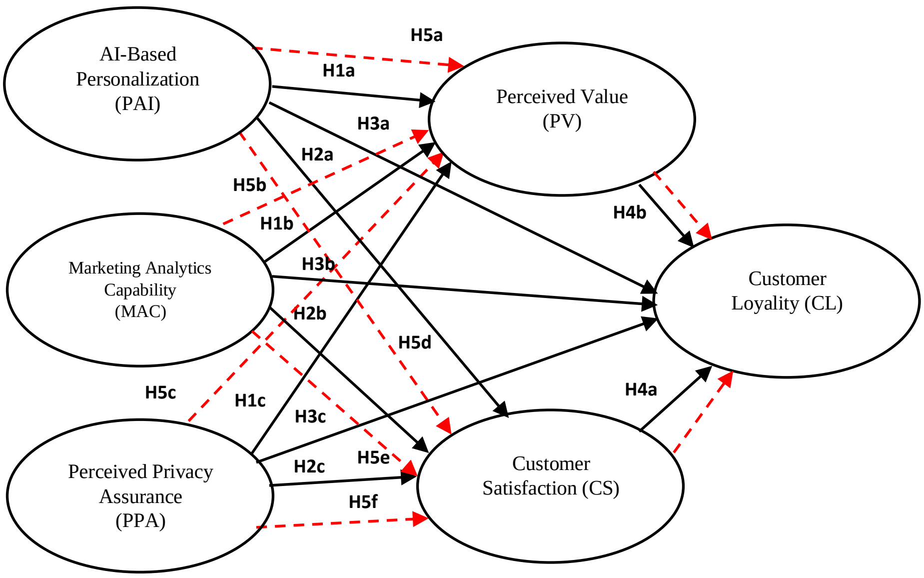

Figure 1. Conceptual framework

3. Methodology

This study adopts an explanatory quantitative design using a cross-sectional survey to test the effects of AI-based personalization, marketing analytics capability, and perceived privacy concerns on perceived value, customer satisfaction, and customer loyalty. It also examines whether perceived value and customer satisfaction mediate the relationship between these antecedents and customer loyalty. This study focuses on active e-commerce or social commerce users residing in South Sulawesi Province, Indonesia. The target population comprised consumers aged 17 years and above who had made at least one purchase on an e-commerce or social commerce platform within the past three months. The sample

size was determined using power-based sampling with an a priori power analysis to ensure an adequate probability of detecting the expected effects (Cohen, 1988; Faul, Erdfelder, Lang, & Buchner, 2007). For linear multiple regression with $f^2 = 0.10$, $\alpha = 0.05$, power = 0.80, and five predictors, the minimum required sample size was 138 respondents. However, given that the structural model will be estimated using PLS-SEM with serial mediation, the target sample is increased in line with recommendations to at least 400 respondents (J. Hair & Alamer, 2022). Allowing for a 20% buffer for attrition and invalid responses, the final target was 510 respondents.
The inclusion criteria were as follows: (1) residence in South Sulawesi Province, Indonesia; (2) at least one transaction on an e-commerce or social-commerce platform in the past three months; and (3) prior exposure to AI-based features (e.g., product recommendations or chatbots). Data were collected using an online questionnaire administered through Google Forms. The measurement of variables in this study included AI-based personalization, marketing analytics capabilities, perceived privacy concerns, perceived value, customer satisfaction, and loyalty based on question items or statements referred to from previous research. All variables were assessed on a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree) reflecting consumer perceptions. Fieldwork was conducted over two months (September–October 2025). The resulting data will be analyzed using SmartPLS 4. This study employed Partial Least Squares Structural Equation Modelling (PLS-SEM) to estimate both direct and indirect relationships between variables.

The analysis proceeds in three stages: the measurement model, structural model, and other additional analyses. First, the measurement model was assessed to verify that the indicators adequately represented their latent constructs. We examined indicator convergent validity, discriminant validity, composite reliability, and construct reliability. Only after the measures meet the accepted quality criteria do we proceed to the structural stage. Second, the structural model was evaluated by estimating path coefficients for the hypothesized relationships and specific indirect effects, including serial paths, with statistical significance established via bootstrapping and confidence intervals. We reported the R2, f2, approximate model fit, indirect effects, and predictive relevance. Third, to address potential common method bias and strengthen measurement quality, this study conducted Harman's single factor test and assessed full collinearity VIFs in SmartPLS. It will refine the perceived privacy assurance measurement by evaluating indicator loadings, reliability, and validity, and removing any weak items, where necessary. All analyses were performed using SmartPLS 4.

Table 1. Operational definition of variable

No	Variables	Statement Items	Source
1	PAI	1. I find that the recommendations I receive on this platform are relevant to my interests. 2. The content or offers I see are tailored to my previous activity. 3. I feel that the system learns my preferences over time. 4. AI-based personalization makes the shopping experience more convenient. 5. The timing of the recommendations or offers is usually correct for me. 6. The products displayed tend to be what I need at that time. 7. The level of personalization on this platform increased my engagement.	Bleier and Eisenbeiss (2015, 2019)
2	MAC	1. I feel that this platform is adept at using my data to improve the relevance of its offers. 2. In my view, the platform integrates data from multiple sources to serve me better than ChatGPT. 3. I can see analytics insights being translated into campaigns/features that benefit me in the future.	Akter, Wamba, Gunasekaran, Dubey, and Childe (2016); Hossain, Akter, Yanamandram,

No	Variables	Statement Items	Source
		4. This platform quickly responds to changes in my preferences. 5. I believe that this platform has advanced analytical technology. 6. The recommendation decisions I receive are based on in-depth data analysis. 7. The platform’s data-driven efforts increased the value of my experience.	and Strong (2024)
3	PPA	1. I find this platform’s privacy practices to be clear and easy to understand. 2. I feel that I have adequate control over the personal data I provide. 3. I believe that this platform uses my data responsibly. 4. I am confident that my data are protected from unauthorized access. 5. I trust that this platform will not share my data without my consent. 6. I feel comfortable sharing the data required for seamless service. 7. I believe that this platform is transparent when it comes to changes in privacy policies.	Malhotra, Kim, and Agarwal (2004); Smith, Milberg, and Burke (1996)
4	PV	1. Overall, this platform is a good value for the money I spend. 2. The quality of service I experience matches or exceeds the price of the service. 3. I enjoy using this platform. 4. This platform makes me feel more confident while shopping. 5. Using this platform enhances my image in the eyes of others. 6. The benefits I receive outweigh the costs (time, money, and effort) I incur. 7. The prices/fees charged feel fair relative to the benefits I perceive.	Sweeney and Soutar (2001)
5	CS	1. I am satisfied with my experience on this platform. 2. My experience meets or exceeds my expectations. 3. Compared with an ideal experience, the service of this platform is close to what I expect. 4. I feel happy using this platform. 5. Choosing this platform was the correct decision for me. 6. After using it, the platform’s performance confirmed my expectations. 7. I intend to keep using this platform because I am satisfied.	Fornell, Johnson, Anderson, Cha, and Bryant (1996); Morgeson, Hult, Sharma, and Fornell (2023)
6	CL	1. I intend to use this platform again in the future. 2. I recommend this platform to others. 3. I will speak positively about this platform. 4. I am willing to continue using this platform even when alternatives are available. 5. If necessary, I am willing to pay a little more to continue using this platform. 6. If a problem arises, I will first attempt to resolve it using this platform.	Zeithaml, Berry, and Parasuraman (1996)

No	Variables	Statement Items	Source
		7. I am likely to increase my purchase frequency or spending on this platform.	

4. Results and Discussions

4.1 Descriptive Analysis

Based on Table 2, respondents are profiled by gender, age, residence, highest education, and the most-used e-commerce or social-commerce platform. First, by gender, there were more female respondents (n = 361; 71%) than male respondents (n = 149; 29%). Second, by age, 22% are 17–25 years old (n = 109), 30% are 26–35 (n = 147), 31% are 36–45 (n = 155), and 17% are 46–55 (n = 86). Third, by residence, the majority lived in Makassar (n = 342; 67%), followed by Maros (n = 66; 13%), Pare-Pare (n = 51; 10%), and Palopo (n = 51; 10%). Fourth, regarding the highest level of education attained, 49% held a bachelor's degree (n = 251), 26% held a master's degree (n = 130), and 25% held a doctoral degree (n = 129). Fifth, regarding the platform used most frequently, the distribution was dominated by Shopee (n = 189; 37%), followed by TikTok Shop (n = 143; 28%), Tokopedia (n = 112; 22%), and Instagram Shop (n = 66; 13%).

Table 2. Respondent characteristics

No.	Characteristics	Aspect	Frequency	Percentage (%)
1	Gender	Woman	361	71
		Man	149	29
2	Age	17 – 25 years	109	22
		26 – 35 years	147	30
		36 – 45 years	155	31
		46 – 55 years	86	17
3	Domicile	Makassar	342	67
		Maros	66	13
		Pare-Pare	51	10
		Palopo	51	10
4	Education	Bachelor	251	49
		Master	130	26
		Doctoral	129	25
5	Social Commerce	Shopee	189	37
		TikTok Shop	143	28
		Tokopedia	112	22
		Instagram Shop	66	13

4.2 Measurement Model

The measurement model was assessed to ensure that the indicators appropriately reflected their intended constructs, thereby establishing validity and reliability. At this stage, we examined convergent validity, discriminant validity, composite reliability, and construct reliability. The initial convergent validity results showed that AI-based Personalization and Marketing Analytics Capability had standardized loadings ranging from 0.766 to 0.900. For Perceived Privacy Assurance, Perceived Value, Customer Satisfaction, and Customer Loyalty, the loadings ranged from 0.662 to 0.862.

The criterion for convergent validity is ≥ 0.70; accordingly, several indicators were removed to meet this threshold, and the model was re-estimated (Morgeson et al., 2023). The results indicate that AI-based Personalization, Marketing Analytics Capability, Perceived Privacy Assurance, Perceived Value, Customer Satisfaction, and Customer Loyalty exhibit loadings between 0.729 and 0.900 as shown in Table 3 and Figure 2. In addition, Table 3 reports Average Variance Extracted (AVE) values exceeding 0.50 for all constructs, indicating that the convergent validity requirement is satisfied.

Table 3. Convergent validity test

Variables	Items	Loading Factor (1)	Loading Factor (2)	Collinearity (VIF)	Cronbach's Alpha	Rho_C	AVE
PAI	PAI1	0,847	0,848	2,544	0,913	0,931	0,659
	PAI2	0,846	0,846	2,557			
	PAI3	0,841	0,842	2,506			
	PAI4	0,807	0,807	2,202			
	PAI5	0,766	0,766	1,893			
	PAI6	0,794	0,794	2,118			
	PAI7	0,775	0,773	1,887			
MAC	MAC1	0,900	0,900	3,771	0,928	0,942	0,699
	MAC2	0,846	0,846	2,624			
	MAC3	0,857	0,856	2,815			
	MAC4	0,839	0,840	2,585			
	MAC5	0,811	0,811	2,210			
	MAC6	0,809	0,809	2,273			
	MAC7	0,785	0,785	2,050			
PPA	PPA1	0,859	0,862	2,665	0,899	0,922	0,664
	PPA2	0,840	0,841	2,396			
	PPA3	0,805	0,805	2,089			
	PPA4	0,807	0,812	2,105			
	PPA5	0,807	0,820	2,133			
	PPA6	0,739	0,744	1,732			
	PPA7	0,697	-	-			
PV	PV1	0,846	0,849	2,415	0,881	0,910	0,627
	PV2	0,800	0,805	2,031			
	PV3	0,792	0,805	2,013			
	PV4	0,763	0,766	1,783			
	PV5	0,764	0,778	1,859			
	PV6	0,686	-	-			
	PV7	0,739	0,745	1,664			
CS	CS1	0,780	0,793	1,932	0,865	0,899	0,598
	CS2	0,817	0,823	2,047			
	CS3	0,786	0,803	2,009			
	CS4	0,747	0,749	1,723			
	CS5	0,718	0,729	1,604			
	CS6	0,732	0,736	1,590			
	CS7	0,699	-	-			
CL	CL1	0,862	0,867	2,675	0,893	0,919	0,654
	CL2	0,815	0,825	2,206			
	CL3	0,791	0,796	2,053			
	CL4	0,816	0,826	2,323			
	CL5	0,770	0,768	1,832			
	CL6	0,755	0,764	1,860			
	CL7	0,662	-	-			

Discriminant validity was assessed to determine the extent to which each construct was empirically distinct from the others. Discriminant validity was assessed using The Heterotrait–Monotrait Ratio (HTMT). The HTMT values ranged from 0.159 to 0.677. All values were below the conservative threshold of 0.85, indicating that each construct shared more variance with its indicators than with the indicators of other constructs. This pattern suggests that the latent variables are empirically distinct and that conceptual overlap is unlikely to bias structural relationships.

Table 4. Discriminant validity test with the Heterotrait–Monotrait Ratio (HTMT)

	MAC	CS	CL	PPA	PV	PAI
MAC						
CS	0,159					
CL	0,422	0,657				
PPA	0,192	0,441	0,544			
PV	0,677	0,221	0,611	0,484		
PAI	0,227	0,459	0,502	0,183	0,161	

Table 3 also shows the results of the reliability test using two indicators: composite reliability and construct reliability. The results of this test aim to assess the level of internal consistency of each variable, where a variable is categorized as reliable if it obtains a value higher than 0.70 (J. F. Hair, Hult, Ringle, & Sarstedt, 2017). The test results show a composite reliability value for the AI Personalization variable of 0.931; Marketing Analytics Capability of 0.942; Perceived Privacy Assurance of 0.922; Perceived Value of 0.910; Satisfaction of 0.899; and Customer Loyalty of 0.919.

On the other hand, the results of the construct reliability test for the AI Personalization, Marketing Analytics Capability, Perceived Privacy Assurance, Perceived Value, Satisfaction, and Customer Loyalty variables with reference to the Cronbach's Alpha value ranged from 0.865 to 0.928. Thus, it can be concluded that all variables met the criteria for composite and construct reliability because the Cronbach's alpha value was greater than 0.70. Common method bias was assessed to ensure that the observed relationships among constructs were not spuriously inflated using a single-source, self-reported, cross-sectional survey and a common measurement procedure (Spector & Brannick, 2009). In addition, outer model collinearity was examined using Variance Inflation Factors (VIF). suggest that VIF values of 5 or higher indicate potential collinearity concerns, particularly for formative indicators, whereas VIF values below 5 are generally viewed as not reaching a critical level (J. F. Hair et al., 2017). The indicator VIF values ranged from 1.59 to 3.77, remaining below the recommended threshold of 5, indicating the absence of critical multicollinearity among indicators.

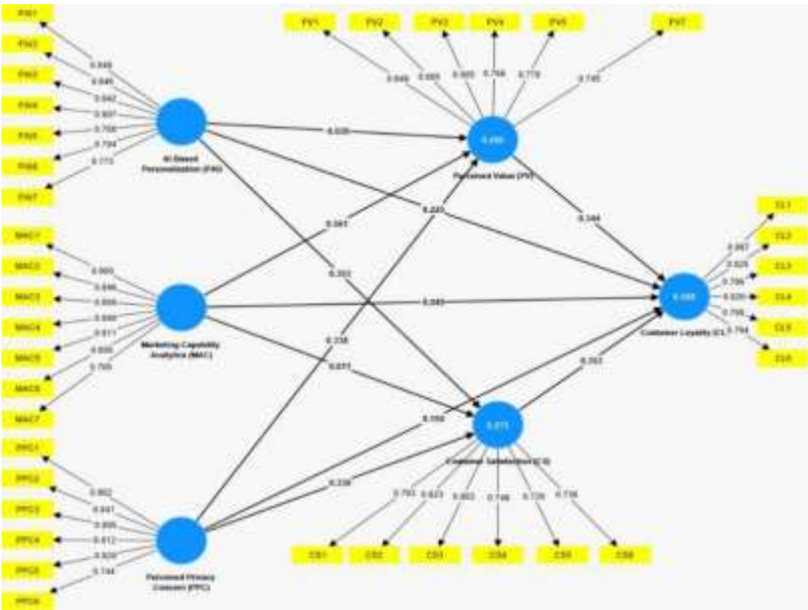

Figure 2. Measurement model test

4.3 Structural Model

The model fit was evaluated to gauge the extent to which the estimated structural model aligned with the empirical data and to provide additional evidence that the hypothesized inter-construct relationships were well represented (J. F. Hair et al., 2017). The Standardized Root Mean Square Residual (SRMR) was 0.037, which meets the conventional criterion of < 0.10. The discrepancy measures d_ULS = 1.025 and d_G = 0.357 satisfy the stated threshold (> 0.05), and the very small differences between the saturated and estimated models indicate no substantive discrepancy between the empirical and theoretical structures. The Chi-square value of 1029.921 remains acceptable for a PLS context, acknowledging the statistic's sensitivity to large samples. The NFI of 0.915 exceeds the minimum benchmark of 0.90, signaling an adequate fit relative to the baseline model (J. F. Hair et al., 2017). Collectively, these indices suggest that the model exhibits a good overall fit and appropriately represents the hypothesized structural relationships.

R-squared was used to evaluate the model's predictive power, with the following interpretation: strong if ≥ 0.67, moderate if ≥ 0.33, and weak if ≥ 0.19 (J. F. Hair et al., 2017). The results show that Perceived Value has R^2=0.486, indicating that 48.6% of its variance is explained by AI-based personalization, marketing analytics capability, and perceived privacy assurance. This indicates a moderate level of predictive ability. Customer Satisfaction has R^2=0.275, meaning that 27.5% of its variance is explained by the same antecedents, which reflects a weak level under the stated criteria. Customer Loyalty has R^2=0.588, indicating that 58.8% of its variance is explained by perceived value and customer satisfaction. This indicates a moderate level of model predictive ability. Overall, these R^2 values indicate that the model attains moderate explanatory power for perceived value and customer loyalty but only a weak level for customer satisfaction, suggesting that the specification is adequate for explaining loyalty-related outcomes, while additional antecedents may be needed to better account for variance in satisfaction.

The F-square test was used to gauge the magnitude of each predictor's effect on the dependent variables in the structural model. Following a previous study, the interpretive guidelines were as follows: small if $f^2 \geq 0.02$, medium if $f^2 \geq 0.15$, and large if $f^2 \geq 0.35$ (J. F. Hair et al., 2017). Based on the results, the effects of AI-based personalization on perceived value, customer satisfaction, and customer loyalty were 0.002 (small), 0.161 (medium), and 0.099 (small), respectively. The effects of marketing analytics capability on perceived value, customer satisfaction, and customer loyalty were f^2 = 0.571 (high), 0.000 (no effect), and 0.003 (small), respectively. Perceived privacy assurance affects perceived value, customer satisfaction, and customer loyalty with f^2 = 0.211 (medium), 0.143 (small), and 0.041 (small), respectively. Finally, the effects of perceived value on customer loyalty and customer satisfaction on customer loyalty were f^2 = 0.150 (medium) and 0.220 (medium), respectively. Taken together, the f^2 results indicate that loyalty is explained primarily through mediated pathways, with a large effect of marketing analytics capability on perceived value and a medium effect of AI-based personalization on satisfaction, whereas privacy assurance exerts only small-to-medium effects, and most direct antecedent effects are small or negligible.

The Q-squared test was used to assess the predictive relevance of the model. Using PLSpredict, all endogenous constructs exhibited positive Q^2_predict values, indicating out-of-sample predictive capability. Specifically, perceived value showed the highest predictive relevance (Q^2_predict = 0.478), followed by customer loyalty (Q^2_predict = 0.429), and customer satisfaction (Q^2_predict = 0.263). The prediction errors were lowest for perceived value (RMSE = 0.725; MAE = 0.585) and highest for customer satisfaction (RMSE = 0.861; MAE = 0.703), suggesting a stronger predictive performance for perceived value and loyalty than for satisfaction. At the indicator level, all manifest variables produced positive Q^2_predict values, and the PLS-SEM model generally outperformed the linear model benchmark, as reflected by lower RMSE values across all indicators and lower MAE values for nearly all indicators, with only one item showing a marginally higher MAE under the PLS-SEM. Overall, these results provide evidence of meaningful out-of-sample predictive power for the proposed model.

The statistical method used in this study is SEM with a PLS approach, which is employed to test the research hypotheses by evaluating the adequacy of the structural model. The analysis examined the direct and indirect effects of AI-based personalization, marketing analytics capability, perceived privacy assurance, perceived value, and customer satisfaction on customer loyalty. The objective of this study is to empirically explain the interrelationships among the variables. Two types of analyses were conducted: tests of direct effects and tests of indirect effects. For hypothesis testing, path coefficients were estimated and their significance assessed; a relationship is deemed significant when the t-statistic exceeds 1.96 and the p-value is below 0.05 (J. F. Hair et al., 2017). Overall, the results indicate that the model adequately explains the causal links among AI-based personalization, marketing analytics capability, perceived privacy assurance, perceived value, customer satisfaction, and customer loyalty, with most paths being statistically significant as shown in Table 5.

Table 5. Hypothesis test results

Hypothesis	Model	β	Standard Deviation	T-Statistic	P Values	Result
H_{1a}	PAI → PV	-0,030	0,033	0,923	0,356	Not Sig
H_{1b}	PAI → CS	0,353	0,040	8,791	0,000	Sig
H_{1c}	PAI → CL	0,225	0,034	6,649	0,000	Sig
H_{2a}	MAC → PV	0,561	0,029	19,104	0,000	Sig
H_{2b}	MAC → CS	0,011	0,040	0,277	0,782	Not Sig
H_{2c}	MAC → CL	0,049	0,039	1,247	0,213	Not Sig
H_{3a}	PPA → PV	0,338	0,033	10,220	0,000	Sig
H_{3b}	PPA → CS	0,330	0,040	8,327	0,000	Sig
H_{3c}	PPA → CL	0,156	0,037	4,206	0,000	Sig
H_{4a}	CS → CL	0,353	0,035	10,043	0,000	Sig
H_{4b}	PV→ CL	0,344	0,043	7,954	0,000	Sig
H_{5a}	PAI → PV → CL	-0,010	0,011	0,914	0,361	Not Sig
H_{5b}	MAC → PV → CL	0,193	0,027	7,201	0,000	Sig
H_{5c}	PPA → PV → CL	0,116	0,019	6,045	0,000	Sig
H_{5d}	PAI → CS → CL	0,125	0,019	6,560	0,000	Sig
H_{5e}	MAC → CS → CL	0,004	0,014	0,275	0,783	Not Sig
H_{5f}	PPA → CS → CL	0,116	0,019	6,045	0,000	Sig

4.4 Discussion

Currently, AI-based technologies have become central to firms' customer strategies, providing powerful tools for marketing analytics and AI-driven personalization that can enhance perceived value and customer satisfaction. In this study, we measured the direct effects of AI-driven personalization and marketing analytics capabilities on perceived value, customer satisfaction, and customer loyalty. Grounded in the privacy calculus and cognition–affect perspectives, we also examine a model in which AI-driven personalization and marketing analytics capabilities foster loyalty through two pathways: a cognitive pathway (perceived value) and an affective pathway (customer satisfaction), while acknowledging the pivotal role of perceived privacy assurance in data-driven personalization. Specifically, we tested the mediating roles of perceived value and customer satisfaction in the relationships between AI-driven personalization and marketing analytics capabilities and customer loyalty, and we assessed how PPA relates to these outcomes in the context of social commerce in Indonesia. We evaluated these propositions using survey data and employed SEM based on PLS as the data-analysis approach.

Building on these premises, the findings indicate that personalization influences customers more through experiential and relational evaluations than through value-based cost-benefit calculations. Personalization significantly improves customer satisfaction and loyalty, but its effect on perceived value was not supported. This pattern is theoretically consistent with the distinction between perceived value as an explicit trade-off assessment and satisfaction as a broader affective evaluation shaped by convenience, enjoyment, and interaction quality.

In the present context, personalization may make the platform feel smoother and more responsive, which raises satisfaction and encourages repeat patronage, in line with prior evidence that personalization strengthens satisfaction and loyalty (Hassan, Abdelraouf, & El-Shihy, 2025; Khelil, 2025; Teepapal, 2025). In contrast, perceived value may remain stable when personalization provides only marginal improvements in relevance that are not salient enough to be interpreted as a meaningful functional or economic gain, or when perceived benefits are offset by psychological costs such as intrusiveness, reduced autonomy, or privacy concerns. Previous studies have similarly shown that perceived value increases mainly when personalization delivers substantial benefits and is not perceived as intrusive (Akdim & Casaló, 2023; Teepapal, 2025). Taken together, the nonsignificant personalization-to-perceived-value path suggests a boundary condition: personalization can enhance how customers feel about the service and strengthen loyalty; however, it may not shift value perceptions unless the benefits are strong enough to change customers' trade-off judgments.

Marketing analytics capability has a significant effect on perceived value but does not have a significant direct effect on customer satisfaction or loyalty. This pattern suggests that analytics primarily shape customers' cognitive evaluations by improving the clarity and credibility of the offer, for example, through more relevant recommendations, clearer value signals, and perceptions of more appropriate pricing. As a result, customers report higher perceived value, which is consistent with prior studies linking analytics-driven marketing and data-enabled personalization to stronger value perceptions (Akdim & Casaló, 2023; Basu & Lim, 2023; Maroufkhani et al., 2022; Sáenz et al., 2022; Teepapal, 2025).

In contrast, satisfaction and loyalty appear to depend more on how well the platform delivers after the decision to purchase, including the smoothness of checkout, usability of the interface, fulfillment reliability, and quality of after-sales support. From this perspective, analytics functions mainly as a backstage capability that influences what customers see and decide before purchase, but it affects satisfaction and loyalty only when its insights are translated into consistent execution across the customer journey. When these downstream elements are not equally strong, the influence of analytics tends to remain confined to perceived value, which helps explain the nonsignificant direct effects on satisfaction and loyalty observed in this study's results.

In this study, Perceived Privacy Assurance (PPA) is operationalized using assurance-oriented items that captured customers' perceptions of control, transparency, and data protection. Conceptually, PPA serves as a risk-mitigating signal that can strengthen customers' evaluations of the platform and support relationship outcomes; therefore, it is expected to influence perceived value, customer satisfaction, and customer loyalty (Alhitmi et al., 2024; Dienlin, 2023; Irgui & Qmichchou, 2024; Martin & Murphy, 2017; Riaz et al., 2024; Yao & Tarofder, 2024). Prior evidence indicates that stronger protection and security can increase perceived value, which encourages continued use intentions (Anshori et al., 2022).

This suggests that customers interpret robust safeguards as an added benefit rather than a mere compliance feature. Privacy and security features have also been shown to reduce privacy-related anxiety, thereby improving satisfaction (Ruslim & Aurellia, 2025). Over time, transparent communication and consistent protection can reinforce trust, which helps convert favorable evaluations into loyal behavior. Customer satisfaction and perceived value significantly affect customer loyalty.

This finding is consistent with prior research, indicating that increases in perceived value and user satisfaction strengthen loyalty (Arabella et al., 2025; Blut et al., 2024; Haseeb et al., 2024; Mittal et al., 2023; Sirdeshmukh et al., 2002; Zeithaml, 1988; Zeithaml et al., 1996). In this study, we also tested the mediating roles of perceived value and satisfaction in the relationships between AI-driven personalization, marketing analytics capabilities, perceived privacy assurance, and customer loyalty. The results show that perceived value amplifies the effects of marketing analytics capabilities and perceived privacy assurance on customer loyalty (Agag et al., 2024; Blut et al., 2024; Tjahjana et al., 2024). Satisfaction amplifies the effects of AI-driven personalization and perceived privacy assurance on customer loyalty (Khelil, 2025; Teepapal, 2025; Tjahjana et al., 2024).

5. Conclusions

5.1 Conclusion

This study achieved its objectives of examining the influence of AI-based personalization, marketing analytics capability, and perceived privacy assurance on customer loyalty in the context of social commerce, both directly and indirectly through perceived value and customer satisfaction. The main findings show that AI-based personalization significantly increases customer satisfaction and loyalty but has no significant effect on perceived value. Furthermore, marketing analytics capability has a significant effect on perceived value but does not have a significant direct effect on customer satisfaction or loyalty. Perceived privacy assurance positively affects perceived value, customer satisfaction, and customer loyalty. The roles of perceived value and customer satisfaction are also crucial because both significantly increase customer loyalty, confirming that customer loyalty is formed through cognitive (perceived value) and affective (satisfaction) pathways. Overall, this study confirms that loyalty in AI-enabled commerce is strengthened through two complementary channels: cognitive and affective. Its important contribution is to clarify the different roles and indirect mechanisms of personalization, analytical capabilities, and privacy perceptions in shaping loyalty in social commerce.

The findings indicate that loyalty develops through two complementary routes: cognitive and affective. Marketing analytics capability primarily supports the cognitive route by strengthening perceived value, which suggests that analytics investments need to be translated into clear customer-facing value signals, such as relevant recommendations and fair pricing, particularly in price-sensitive settings. Personalization primarily supports the affective route by improving satisfaction, which then drives loyalty, implying that personalization should be managed as part of experience design rather than treated as a purely functional add-on. These results also align with privacy calculus, as perceived privacy assurance appears to reduce perceived risks and strengthen both perceived value and satisfaction, thereby reinforcing loyalty. Practitioners should therefore pursue technology-enabled innovation alongside transparent privacy practices and meaningful user control, while future studies may examine boundary conditions such as product type, privacy sensitivity, and explainability.

Methodologically, this study contributes by combining a theory-driven serial mediation design with a rigorous PLS-SEM evaluation strategy to explain how technology-related antecedents translate into loyalty through cognitive and affective mechanisms. The model was estimated using SmartPLS with bootstrapping to test specific indirect effects, including serial mediation paths, while reporting effect sizes and predictive relevance to complement statistical significance. The measurement model assessment followed established guidelines by verifying internal consistency and convergent validity, establishing discriminant validity using HTMT, and checking collinearity diagnostics to reduce the risk of inflated estimates. In addition, potential common method bias was addressed through procedural remedies and statistical checks, including Harman's single factor test and full collinearity VIF assessment. Finally, this study extends methodological practice by reporting PLSpredict results, allowing the model to be evaluated not only for explanatory power but also for out-of-sample predictive performance.

5.2 Research Limitations

This study has several limitations that should be considered when interpreting the findings. First, the cross-sectional design limits the study's ability to make strong causal inferences and capture changes in customer loyalty over time, meaning that the observed relationships should be interpreted as associations rather than definitive causal effects. Second, although SEM-PLS is suitable for prediction-oriented modeling, the study may still face endogeneity concerns that could bias the estimated path coefficients and inflate or deflate the observed effects among AI-driven personalization, marketing analytics capabilities, perceived value, satisfaction, and loyalty. Third, the use of self-reported data may introduce bias because all variables were measured based on respondents' perceptions simultaneously and with the same instrument. Fourth, the research sample was limited to one region, namely South Sulawesi, which means that the results should be interpreted cautiously when generalizing to a national or cross-cultural context in Indonesia. In addition, the privacy-related construct in this study is conceptualized as perceived privacy assurance, which reflects customers' perceptions of security, transparency, and control over their personal data rather than privacy anxiety. Therefore, the findings should be interpreted as indicating that stronger perceived privacy assurance is associated with higher perceived value, satisfaction, and loyalty.

5.3 Suggestions and Directions for Future Research

Based on the findings and limitations above, the recommended direction for further research is to expand the sample and research context by involving respondents from across provinces or on a national scale. In addition, conducting cross-platform comparisons (e.g., Shopee, TikTok Shop, and Tokopedia) to test whether the cognitive-affective pathway pattern remains consistent in different contexts is recommended. Additionally, future research could use a longitudinal or panel design to observe changes in perceived value, customer satisfaction, and customer loyalty over time, so that causal inferences become stronger. Data enrichment is also important for combining surveys with actual behavioral data, such as purchase frequency, repeat purchases, and referrals. A mixed-method approach, such as interviews or forum group discussions, can be used to explain in more depth the reasons why AI-based personalization does not increase perceived value. On the other hand, the measurement of privacy variables needs to be refined by clearly separating privacy anxiety and privacy assurance or perceived control as two different constructs and then testing the influence of each on perceived value, customer satisfaction, and customer loyalty. Finally, subsequent research could add moderator variables or other factors, such as trust, perceived intrusiveness, AI literacy, and service quality, to enrich the model and improve its predictive power.

Author Contributions

All authors contributed to the study and approved the final manuscript. The specific roles and responsibilities are as follows: VA, conceptualization, study design, manuscript drafting, revision, and final approval. BS contributed to supervision, study design, and final approval. HM contributed to the methodology and final approval. AR contributed to data collection, investigation, validation, and final approval. ALA contributed to data collection, analysis, manuscript drafting, revision, and final approval.

References

Agag, G., Moustafa, Y., Almoraish, A., Eid, R., Chaib, H., Gherissi, T., & Shabban, S. (2024). Journal of retailing and consumer services understanding the relationship between marketing analytics, customer agility, and customer satisfaction: A longitudinal perspective. *Journal of Retailing and Consumer Services, 77*(May 2023), 103663-103663. doi:https://doi.org/10.1016/j.jretconser.2023.103663

Akdim, K., & Casaló, L. V. (2023). Perceived value of AI-based recommendations service: the case of voice assistants. *Service Business, 17*(1), 81-112. doi:https://doi.org/10.1007/s11628-023-00527-x

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics, 182*, 113-131. doi:https://doi.org/10.1016/j.ijpe.2016.08.018

Alfadhel, M. (2025). Unpacking when and how business analytics affect firm performance and customer satisfaction: A longitudinal examination. *Journal of Retailing and Consumer Services, 84*, 104219-104219. doi:https://doi.org/10.1016/j.jretconser.2024.104219

Alhitmi, H. K., Mardiah, A., Al-sulaiti, K. I., & Abbas, J. (2024). Data security and privacy concerns of AI-driven marketing in the context of economics and business field : an exploration into possible solutions. *Cogent Business & Management, 11*(1), ---. doi:https://doi.org/10.1080/23311975.2024.2393743

Amazon Web, S. (2025). [New AWS Research Shows Strong AI Adoption Momentum in Indonesia].

Anshori, M. Y., Karya, D. F., & Gita, M. N. (2022). Study on the Reuse Intention of E-Commerce Platform Applications: Security, Privacy, Perceived Value, and Trust. *Jurnal Manajemen Teori dan Terapan | Journal of Theory and Applied Management, 15*(1), 13-24. doi:https://doi.org/10.20473/jmtt.v15i1.34923

Aqabneh, M. I. (2025). The Influence of Customer Perceived Value, Satisfaction, and Trust on Loyalty among E-Shoppers in Palestine's E-Commerce Platforms. *Journal of Management World, 2025*(1), 546-557. doi:https://doi.org/10.53935/jomw.v2024i4.734

Arabella, C., Mani, L., Sahabu, F. C., & Aras, M. (2025). Customer satisfaction and loyalty in the digital era: a survey on a leading travel startup application in Indonesia. *Multidisciplinary Science Journal, 7*(9). doi:https://doi.org/10.31893/multiscience.2025446

Barney, J. B. (2000). Firm resources and sustained competitive advantage. In J. A. C. Baum & F. Dobbin (Eds.), *Economics Meets Sociology in Strategic Management* (Vol. 17, pp. 0): Emerald Group Publishing Limited. https://doi.org/10.1016/S0742-3322(00)17018-4

Basal, M., & Moulai, K. (2025). Predictive Analytics for Customer Behavior Prediction in Artificial Intelligence. *Economics World, 12*(2), 142-154. doi:https://doi.org/10.17265/2328-7144/2025.02.006

Basrowi, B., Ali, J., & Suryanto, T. (2023). Unpacking the Impact of Customer Perceived Value and Competitive Advantage on Customer Loyalty: The Mediating Role of Trust. *Shirkah: Journal of Economics and Business, 8*(1), 60-77. doi:https://doi.org/10.22515/shirkah.v8i1.540

Basu, R., & Lim, W. M. (2023). Marketing analytics : The bridge between customer psychology and marketing decision-making. *Psychology and Marketing, 40*(12), 2588-2611. doi:https://doi.org/10.1002/mar.21908

Bleier, A., & Eisenbeiss, M. (2015). The Importance of Trust for Personalized Online Advertising. *Journal of Retailing, 91*(3), 390-409. doi:https://doi.org/10.1016/j.jretai.2015.04.001

Bleier, A., & Eisenbeiss, M. (2019). *Personalized Online Advertising Effectiveness : The Interplay of What , When , Personalized Online Advertising Effectiveness : The Interplay of What , When , and Where*. https://doi.org/10.1287/mksc.2015.0930

Blut, M., Chaney, D., Lunardo, R., Mencarelli, R., & Grewal, D. (2024). Customer Perceived Value : A Comprehensive. *Journal of Service Research, 27*(4), 501-524. doi:https://doi.org/10.1177/10946705231222

Chandrakumar, H. (2024). The Use of AI-Driven Personalization for Enhancing the Customer Experience for Gen-Z. *Open Journal of Business and Management, 12*(06), 4472-4481. doi:https://doi.org/10.4236/ojbm.2024.126225

Chi, H.-k., & Phan, H.-t. (2025). Revealing the role of corporate social responsibility , service quality , and perceived value in determining customer loyalty : A Meta-Analysis Study. *Susta, 17*(10), 1-30. doi:https://doi.org/10.3390/su17104304

Chotisarn, N., & Phuthong, T. (2025). Impact of artificial intelligence-enabled service attributes on customer satisfaction and loyalty in chain hotels: Evidence from coastal tourism destinations in western Thailand. *Social Sciences and Humanities Open, 11*(November 2024), 101306-101306. doi:https://doi.org/10.1016/j.ssaho.2025.101306

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Science: Second Edition*: Lawrence Erlbaum Associates.

Croitoru, G., Capatina, A., Florea, N. V., Codignola, F., & Sokolic, D. (2024). A cross-cultural analysis of perceived value and customer loyalty in restaurants. *European Research on Management and Business Economics, 30*(3), 100265-100265. doi:https://doi.org/10.1016/j.iedeen.2024.100265

Dienlin, T. (2023). Privacy Calculus (pp. 70-79).

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*(2), 175-191. doi:https://doi.org/10.3758/BF03193146

Fetais, A. H., Algharabat, R. S., Aljafari, A., & Rana, N. P. (2023). Do Social Media Marketing Activities Improve Brand Loyalty ? An Empirical Study on Luxury Fashion Brands. *Information Systems Frontiers, 25*, 795-817. doi:https://doi.org/10.1007/s10796-022-10264-7

Fornell, C., Johnson, M. D., Anderson, E. W., Cha, J., & Bryant, B. E. (1996). The American Customer Satisfaction Index : Nature , purpose , and findings. *Journal of Marketing, 60*(4), 7-18. https://doi.org/10.2307/1251898

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics, 1*(3), 100027-100027. doi:https://doi.org/10.1016/j.rmal.2022.100027

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2 ed.): Sage Publications.

Hariguna, T., & Ruangkanjanases, A. (2024). Assessing the impact of artificial intelligence on customer performance : a quantitative study using partial least squares methodology. *Data Science and Management, 7*(3), 155-163. doi:https://doi.org/10.1016/j.dsm.2024.01.001

Haseeb, A., Adnan, M., & Saeed, Z. (2024). The impact of brand image on customer satisfaction and brand loyalty : A systematic literature review. *Heliyon, 10*(16), 1-10. doi:https://doi.org/10.1016/j.heliyon.2024.e36254

Hassan, N., Abdelraouf, M., & El-Shihy, D. (2025). The moderating role of personalized recommendations in the trust–satisfaction–loyalty relationship: an empirical study of AI-driven e-commerce. *Future Business Journal, 11*(1). doi:https://doi.org/10.1186/s43093-025-00476-z

Hendriana, E., Anjani, S., Dennison, A., & Subhan, Z. N. (2023). A Mediation Analysis of cognitive and affective costumer trust in costumer loyality towards E-Marketplace. *Jurnal Aplikasi Manajemen, 20*(1), 181-195. doi:http://dx.doi.org/10.21776/ub.jam.2022.020.01.18

Hermann, E., & Puntoni, S. (2024). Artificial intelligence and consumer behavior: From predictive to generative AI. *Journal of Business Research, 180*, 114720-114720. doi:https://doi.org/10.1016/j.jbusres.2024.114720

Hossain, M. A., Akter, S., & Yanamandram, V. (2020). Revisiting customer analytics capability for data-driven retailing. *Journal of Retailing and Consumer Services, 56*, 102187-102187. doi:https://doi.org/10.1016/j.jretconser.2020.102187

Hossain, M. A., Akter, S., Yanamandram, V., & Strong, C. (2024). Navigating the platform economy: Crafting a customer analytics capability instrument. *Journal of Business Research, 170*, 114260-114260. doi:https://doi.org/10.1016/j.jbusres.2023.114260

Hsu, C.-l., Liao, Y.-c., Lee, C.-w., & Chan, L. K. (2022). Privacy concerns and information sharing : the perspective of the u-shaped curve. *Frontiers in Psychology, 13*, 1-11. doi:https://doi.org/10.3389/fpsyg.2022.771278

Hussain, Z. (2025). AI-driven personalization and purchase intention in modest fashion : Sharia compliance as moderator. *International Journal of Halal Industry, 1*(1), 33-45. doi:https://doi.org/10.20885/IJHI.vol1.iss1.art3

Irgui, A., & Qmichchou, M. (2024). Contextual marketing and information privacy concerns in m-commerce and their impact on consumer loyalty. *Arab Gulf Journal of Scientific Research, 42*(3), 1150-1170. doi:https://doi.org/10.1108/AGJSR-09-2022-0198

Jabado, R., & Jallaoli, R. (2024). Enhancing customer relationship management with data analytics: insights from retail survey. *Digital Economy & Society, 12*(2), 76-100. doi:https://doi.org/10.18080/jtde.v12n2.987

Jasin, M., & Firmansyah, A. (2023). The role of service quality and marketing mix on customer satisfaction and repurchase intention of SMEs products. *Uncertain Supply Chain Management, 11*, 383-390. doi:https://doi.org/10.5267/j.uscm.2022.9.004

Khelil, H. B. (2025). The Impact of AI-Driven Personalization on Costumer Loyality. *Academy of Marketing Studies Journal, 29*(4), 1-8.

Kim, L., Jindabot, T., & Yeo, S. F. (2024). Understanding customer loyalty in banking industry: A systematic review and meta analysis. *Heliyon, 10*(17), e36619-e36619. doi:https://doi.org/10.1016/j.heliyon.2024.e36619

Kotler, P., Keller, K. L., & Chernev, A. (2022). *Marketing Management*: Pearson.

Labib, E. (2024). Artificial intelligence in marketing: exploring current and future trends. *Cogent Business and Management, 11*(1), ---. doi:https://doi.org/10.1080/23311975.2024.2348728

Lin, M.-m., Jeong, Y.-m., Zhang, Y.-d., & Liu, Z.-y. (2024). Enhancing Customer Loyalty in E-Commerce: The Role of Personalization Recommendation Systems and Flow State. *Journal of The Korea Society of Computer and Information, 29*(6), 223-233. doi:https://doi.org/10.9708/jksci.2024.29.06.223

Magrizos, S., Campora, M., Lamprinakos, G., Giovanis, A., & Christofi, M. (2025). Transparency by design: the effect of privacy policies visualisation on brand trust and perceived intrusion. *Behaviour & Information Technology, 45*(3), 450-462. doi:https://doi.org/10.1080/0144929x.2025.2520594

Malhotra, N., Kim, S. S., & Agarwal, J. (2004). Internet Users' Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model. *Information Systems Research, 15*(4), 336-355. doi:https://doi.org/10.1287/isre.1040.0032

Maroufkhani, P., Asadi, S., Ghobakhloo, M., Jannesari, M. T., & Ismail, W. K. W. (2022). How do interactive voice assistants build brands' loyalty? *Technological Forecasting and Social Change, 183*, 121870-121870. doi:https://doi.org/10.1016/j.techfore.2022.121870

Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science, 45*(2), 135-155. doi:https://doi.org/10.1007/s11747-016-0495-4

Mehrabian, A., & Russell, J. A. (1974). *An Approach to Environmental Psychology*: M.I.T. Press.

Misidawati, D. N., Devi, E. K., & Fatimah, S. (2023). The Effect of Digital Marketing Strategy and Service Quality on Customer Satisfaction in the Indonesian E-Commerce Industry. *Sinergi International Journal of Management and Business, 1*(2), 160-171. doi:https://doi.org/10.61194/ijmb.v1i2.145

Mittal, V., Han, K., Frennea, C., Blut, M., Shaik, M., Bosukonda, N., & Sridhar, S. (2023). Customer satisfaction, loyalty behaviors, and firm financial performance: what 40 years of research tells us. *Marketing Letters, 34*(2), 171-187. doi:https://doi.org/10.1007/s11002-023-09671-w

Morgeson, F. V., Hult, G. T. M., Sharma, U., & Fornell, C. (2023). The American Customer Satisfaction Index (ACSI): A sample dataset and description. *Data in Brief, 48*, 109123-109123. doi:https://doi.org/10.1016/j.dib.2023.109123

Pavlou, P. A., & Gefen, D. (2004). Building Effective Online Marketplaces with Institution-Based Trust. *Information Systems Research, 15*(1), 37-59. doi:10.1287/isre.1040.0015

Reitsamer, B. F., & Becker, L. (2024). Customer journey partitioning: A customer-centric conceptualization beyond stages and touchpoints. *Journal of Business Research, 181*(April), 114745-114745. doi:https://doi.org/10.1016/j.jbusres.2024.114745

Riaz, H., Ahmed, H., & Jibril, A. B. (2024). Reassessing customer trust and privacy concerns in omnichannel customer experience. *Cogent Business & Management, 11*(1), 1-22. doi:https://doi.org/10.1080/23311975.2024.2410405

Rosário, A. T., & Casaca, J. A. (2023). Relational marketing and customer satisfaction : a systematic literature review. *Estudios Gerenciales, 39*(169), 516-532. doi:https://doi.org/10.18046/j.estger.2023.169.6218

Ruslim, T. S., & Aurellia, A. (2025). The Path to Loyality: Examining shopee's service attributes and customer satisfaction of customers in Jakarta. *Indonesian Journal of Business and Entrepreneurship, 11*(2), 505-517. doi:http://dx.doi.org/10.17358/IJBE.11.2.505

Sáenz, J., Ortiz de Guinea, A., & Peñalba-Aguirrezabalaga, C. (2022). Value creation through marketing data analytics: The distinct contribution of data analytics assets and capabilities to unit and firm performance. *Information & Management, 59*(8), 103724-103724. doi:https://doi.org/10.1016/j.im.2022.103724

Shahzad, M. F., Xu, S., An, X., & Javed, I. (2024). Assessing the impact of AI-chatbot service quality on user e-brand loyalty through chatbot user trust, experience and electronic word of mouth. *Journal of Retailing and Consumer Services, 79*, 103867-103867. doi:https://doi.org/10.1016/j.jretconser.2024.103867

Sherly Steffi, L., Subha, B., Kuriakose, A., Singh, J., Arunkumar, B., & Rajalakshmi, V. (2025). The impact of ai-driven personalization on consumer behavior and brand engagement in online marketing. In A. Hamdan & U. Braendle (Eds.), (pp. 485-492). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-67890-5_43

Singh, P., & Singh, V. (2024). The power of AI : enhancing customer loyalty through satisfaction and efficiency. *Cogent Business & Management, 11*(1), 1-14. doi:https://doi.org/10.1080/23311975.2024.2326107

Singla, A., Sukharevsky, A., Yee, L., Chui, M., & Hall, B. (2025). *The state of AI: How Organizations are Rewiring to Capture Value*. Retrieved from https://www.mckinsey.com/~/media/mckinsey/business functions/quantumblack/our insights/the state of ai/2025/the-state-of-ai-how-organizations-are-rewiring-to-capture-value_final.pdf

Sirdeshmukh, D., Singh, J., & Sabol, B. (2002). Consumer Trust, Value, and Loyalty in Relational Exchanges. *Journal of Marketing, 66*(1), 15-37. doi:https://doi.org/10.1509/jmkg.66.1.15.18449

Smith, H. J., Milberg, S. J., & Burke, S. J. (1996). Information Privacy: Measuring Individuals' Concerns about Organizational Practices. *MIS Quarterly*, *20*(2), 167-196. https://doi.org/10.2307/249477

Spector, P., & Brannick, M. (2009). *Common method variance or measurement bias? The problem and possible solutions*.

Sucidha, I. (2025). The Role of AI-Driven Personalization in Shaping Consumer Loyalty in E-Commerce. *Management Studies and Business Journal (PRODUCTIVITY)*, *2*(4), 2374-2388. https://doi.org/10.62207/xbvh6t64

Sweeney, J. C., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. *Journal of Retailing*, *77*(2), 203-220. doi:https://doi.org/10.1016/S0022-4359(01)00041-

Tamilmani, S., Archana, S., Mohan, T., Santhi, V., Kamalakannan, S., & Saikrishnan, S. (2025). Brand Loyalty in the Digital Age : The Role of Personalization and AI in Consumer Engagement. *Journal of Information Systems Engineering and Management*, *10*(32S), 716-721. doi:https://doi.org/10.52783/jisem.v10i32s.5404

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319-1350. doi:https://doi.org/10.1002/smj.640

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal*, *18*(7), 509-533.

Teepapal, T. (2025). AI-driven personalization: Unraveling consumer perceptions in social media engagement. *Computers in Human Behavior*, *165*, 108549-108549. doi:https://doi.org/10.1016/j.chb.2024.108549

Tjahjana, D., Dwidienawati, D., Hakim, A., Rivera, A., Tandiono, N., & Ardika, Y. (2024). The Influence of Security and Privacy on Gen Z Trust in Indonesian E-Commerce 2 Literature Review. *WSEAS Transactions on Business and Economics*, *21*, 775-785. doi:https://doi.org/10.37394/23207.2024.21.65

Vieira, V. A. (2013). Stimuli–organism-response framework: A meta-analytic review in the store environment. *Journal of Business Research*, *66*(9), 1420-1426. doi:https://doi.org/10.1016/j.jbusres.2012.05.009

Xu, H., Luo, X., Carroll, J. M., & Rosson, M. B. (2011). The personalization privacy paradox: An exploratory study of decision making process for location-aware marketing. *Decision Support Systems*, *51*(1), 42-52. doi:https://doi.org/10.1016/j.dss.2010.11.017

Yao, H., & Tarofder, A. K. (2024). Privacy Concerns in E-commerce Marketing: A Systematic Literature Review Study. *International Journal of Global Economics and Management*, *2*(3), 64-75. doi:https://doi.org/10.62051/IJGEM.v2n3.07

Yulianti, L. N., Taryana, A., & Anggriani, Z. D. (2024). The Influence of Perceived Quality, Value, Satisfaction, Trust, Commitment on Loyality and Strategies to Increase Loyality. *Jurnal Aplikasi Manajemen*, *22*(3), 749-766. doi:http://dx.doi.org/10.21776/ub.jam.2024.022.03.10

Yum, K., & Kim, J. (2024). The Influence of Perceived Value, Customer Satisfaction, and Trust on Loyalty in Entertainment Platforms. *Applied Sciences (Switzerland)*, *14*(13). doi:https://doi.org/10.3390/app14135763

Zanon, L. G., Arantes, R. F. M., Calache, L. D. D. R., Martins, R. A., & Carpinetti, L. C. R. (2025). Customer-Perceived Value and Social Media Analytics: How Supplier Evaluation Can Benefit from Aspect-Based Sentiment Analysis and Fuzzy Inference. *Cognitive Computation*, *17*(5), 144-144. doi:https://doi.org/10.1007/s12559-025-10495-1

Zauner, A., Koller, M., & Hatak, I. (2015). Customer perceived value—Conceptualization and avenues for future research. *Cogent Psychology*, *2*(1). doi:https://doi.org/10.1080/23311908.2015.1061782

Zeithaml, V. A. (1988). Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence. *Journal of Marketing*, *52*(3), 2-22. doi:https://doi.org/10.1177/002224298805200302

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The Behavioral Consequences of Service Quality. *Journal of Marketing*, *60*(2), 31-46. https://doi.org/10.2307/1251929