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Discount Framing, Live Commerce, and CRM Automation on Repurchase Intention through Perceived Value in Shopee and TikTok Shop Users

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Abstract

Background: E-commerce platforms increasingly rely on promotional strategies, interactive shopping experiences, and automation-based Customer Relationship Management (CRM) systems. Previous studies have examined *discount framing*, *live commerce*, and CRM automation separately, without addressing their simultaneous effects on repurchase intention through perceived value, a critical gap in the digital marketing literature.
Objective: Grounded in the Stimulus–Organism–Response (S-O-R) theory, this study examines the influence of *discount framing*, *live commerce*, and CRM automation on repurchase intention, with perceived value as a mediating variable, among Shopee and TikTok Shop users in Indonesia.
Methods: A quantitative cross-sectional survey was administered to 424 respondents selected using purposive sampling. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.
Results: The results indicate that *discount framing*, *live commerce*, and CRM automation have positive and significant effects on perceived value and repurchase intention. Furthermore, perceived value has a positive and significant effect on repurchase intention and partially mediates the relationships between *discount framing*, *live commerce*, and CRM automation and repurchase intention. Among the three stimulus variables, CRM automation demonstrated the strongest contribution to increasing perceived value, highlighting the importance of personalized communication, rapid automated responses, and relevant product recommendations in shaping positive consumer evaluations. These findings extend the application of the S-O-R theory by emphasizing that perceived value serves as an important psychological mechanism linking digital marketing stimuli to repurchase behavior.
Conclusion: E-commerce platforms should optimize promotional formats, enhance *live commerce* interactivity, and strengthen CRM automation capabilities to maximize perceived value and sustain repurchase behavior.

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INTRODUCTION

Currently, the exponential development of digital technology has encouraged structural transformation in the e-commerce industry on a global scale, including in Indonesia. E-commerce platforms are no longer positioned solely as mediums for online transactions but have developed into integrated and technology-based digital marketing ecosystems. These ecosystems combine the use of social media, interactive content, and data-driven customer relationship management (CRM) to create more dynamic interactions, personalize services, and optimize digital marketing strategies through consumer analytics. These rapid transformations have generated a critical scientific problem: although promotional stimuli, interactive commerce features, and AI-driven CRM systems are now integral components of platform strategies, their combined psychological impacts on consumer repurchase decisions, through the lens of perceived value, remain insufficiently theorized and empirically tested.

These developments have also significantly accelerated Indonesia's digital economy growth. The e-Conomy SEA 2024 report indicates that the Gross Merchandise Value (GMV) of Indonesia's digital economy is estimated to reach approximately US$90 billion by 2024, representing an increase of around 13% compared with the previous year and positioning Indonesia as the largest digital economy market in Southeast Asia. Within the digital economy structure, the e-commerce sector remains the largest contributor, with a value of approximately US$65 billion in 2024. This growth is supported by various digital platform innovations, including the development of video commerce features that enhance consumer shopping experiences. Therefore, digital marketing strategies have become important instruments for e-commerce companies to attract, engage, and retain consumers amid increasingly competitive market dynamics.

In Indonesia, competition within the e-commerce industry demonstrates market concentration among several major platforms, particularly Shopee and TikTok Shop. Based on the 2025 Indonesian Internet Profile survey released by the Indonesian Internet Service Providers Association (APJII), Shopee became the e-commerce platform with the highest internet user access rate at 53.22%, while TikTok Shop recorded an access percentage of 27.37%. These data demonstrate the strong dominance of both platforms in Indonesian consumers' online shopping activities. This phenomenon also reflects a shift in consumer behavior from conventional e-commerce patterns toward social commerce, which is more integrated with social content and interactive experiences (Zhang et al., 2017).

The social commerce model develops through the integration of video-based entertainment content, social media interactions, and live commerce features within digital transaction processes (Sun et al., 2019; Wongkitrungrueng & Assarut, 2020). Shopee and TikTok Shop were selected not only because of their market dominance but also because they represent fundamentally different commerce models: Shopee operates as a marketplace platform that integrates discount-driven promotions and CRM automation, whereas TikTok Shop functions as a social commerce platform that leverages live streaming as its primary sales driver. This structural distinction provides an ideal comparative context for examining how multiple digital marketing stimuli simultaneously influence perceived value and repurchase behavior.

As competition among platforms intensifies, e-commerce companies are increasingly implementing various digital marketing strategies, particularly discount framing, live commerce, and CRM automation. Discount framing is recognized as a factor influencing consumers' perceived value and purchase intention in online shopping contexts (Chen & Cheng, 2019). Furthermore, live commerce, which combines live broadcasting with real-time interactions, can enhance hedonic experiences, trust, and consumer engagement, thereby influencing purchase intentions (Sun et al., 2019; Wongkitrungrueng & Assarut, 2020). Meanwhile, CRM automation supported by artificial intelligence and data personalization enables companies to manage customer interactions more responsively, personally, and efficiently through chatbots, algorithm-based recommendations, and automated service features (Grewal et al., 2020; Huang & Rust, 2021). The impleme ntation of automated systems also supports improvements in customer experience and the sustainable management of data-driven customer relationships.

These findings indicate that digital marketing strategies influence not only initial purchase decisions but also have the potential to generate repurchase intentions through enhanced perceived value and consumer experiences. In digital commerce contexts, repurchase decisions are no longer determined solely by functional factors such as price but are also influenced by interactive experiences, emotional engagement, and consumer trust in digital platforms. This condition is increasingly relevant considering that contemporary digital consumers, particularly Generation Z and Millennials, demonstrate high levels of digital engagement in social media usage and online shopping activities (Munsch, 2021).

Previous studies have examined the individual contributions of discount framing, live commerce, and CRM automation to consumer decision-making; however, critical inconsistencies and contextual gaps remain. Regarding discount framing, Wei (2025) found that its effectiveness depends on product heterogeneity, while Pasek (2021) demonstrated the superiority of nominal formats over percentage-based formats, suggesting that framing effects are highly context-dependent and may not be universally applicable across platforms. Regarding live commerce, Sun (2019) and Wongkitrungrueng (2020) confirmed its positive role in enhancing consumer engagement; however, most studies have focused on single-platform contexts, limiting cross-platform generalizability.

Regarding CRM automation, Grewal (2020) and Huang (2021) emphasized the transformative role of artificial intelligence in improving customer interaction quality, yet limited empirical studies have examined the contribution of automation within a comprehensive consumer value pathway. Most importantly, existing research has not integrated all three stimuli into a unified theoretical model that explains the psychological pathway from digital marketing inputs to repurchase outcomes through perceived value.

Three specific gaps justify this study. First, from an empirical perspective, existing research has not examined the simultaneous effects of discount framing, live commerce, and CRM automation on repurchase intention within a single structural model, leaving their relative contributions and potential interaction effects insufficiently understood. Second, theoretically, previous applications of the Stimulus–Organism–Response (S-O-R) theory in e-commerce research have primarily emphasized atmospheric or hedonic stimuli without adequately positioning perceived value as an organism-level mechanism that connects multiple technological marketing stimuli with behavioral outcomes. Third, contextually, digital marketing studies in Indonesian e-commerce have generally examined platforms independently rather than comparatively, limiting understanding of how marketplace environments (Shopee) and social commerce environments (TikTok Shop) differently shape consumer behavior.

Generation Z and Millennials were selected as the research population because they represent dominant user segments in e-commerce and social commerce activities. Both generations demonstrate high levels of digital engagement and tend to actively respond to digital platform-based marketing strategies. Based on these considerations, this study aims to examine the influence of discount framing, live commerce, and CRM automation on repurchase intention through perceived value among Shopee and TikTok Shop users in Indonesia.

This study provides three distinct contributions. Theoretically, it extends S-O-R theory by positioning perceived value as an organism-level cognitive mediator that connects three distinct digital marketing stimuli (discount framing, live commerce, and CRM automation) to repurchase intention, demonstrating that the S-O-R mechanism operates through value appraisal rather than direct attitude formation in social commerce contexts. Empirically, this study provides an integrated examination of these three stimuli within a single Partial Least Squares Structural Equation Modeling (PLS-SEM) framework using a large Indonesian sample (n = 424), establishing comparative effect sizes that enable platform managers to prioritize strategic investments. Practically, the findings provide differentiated strategic recommendations for Shopee and TikTok Shop by recognizing their distinct commercial architectures. These contributions advance digital marketing and social commerce literature beyond previous single-stimulus investigations.

METHOD

This study employed a quantitative approach with an explanatory research design to examine the structural and predictive relationships among discount framing, live commerce, CRM automation, perceived value, and repurchase intention among Shopee and TikTok Shop users in Indonesia. Given the cross-sectional nature of the data, this study did not claim causal inference;

instead, it tested theoretically grounded structural pathways consistent with an explanatory (predictive-structural) research paradigm (Hair et al., 2017).

The Stimulus–Organism–Response (S-O-R) framework was selected over alternative theories (Technology Acceptance Model and Theory of Planned Behavior) because it explicitly accounts for environmental stimuli, rather than individual attitudes or cognitive ease, as primary drivers of consumer responses, making it directly applicable to the multi-stimulus digital commerce environment. Within this framework, discount framing, live commerce, and CRM automation were conceptualized as platform-level stimuli (S), perceived value was conceptualized as the consumer's internal evaluative organism (O), and repurchase intention was conceptualized as the behavioral response (R) (Eroglu et al., 2001; Wongkitrungrueng & Assarut, 2020).

The research population consisted of users of the Shopee and TikTok Shop e-commerce platforms in Indonesia, particularly Generation Z and Millennials who were active in online shopping transactions. These two generational groups were selected because they demonstrate high levels of digital engagement and represent dominant segments in social commerce and live commerce activities (Munsch, 2021). The unit of analysis in this study was individual consumers, while the observation unit consisted of Shopee and TikTok Shop users who had experience using digital promotion features, live commerce, and data-based personalization services.

The sampling technique used was purposive sampling because the study required respondents with specific characteristics relevant to the research objectives. Respondents were selected through several screening questions to ensure alignment with the research criteria, including having shopping experience through Shopee or TikTok Shop within the previous six months, making online purchases at least twice, experiencing digital promotions such as discounts, live commerce, or automated notifications, and being within the age range of 17–40 years representing Generation Z and Millennials.

Data collection was conducted online using Google Forms, which were distributed through WhatsApp, Instagram, Telegram, and relevant digital communities. Based on the screening process, this study obtained 424 respondents who met the research criteria. This number exceeded the minimum recommendations for Structural Equation Modeling–Partial Least Squares (SEM-PLS) analysis involving multiple latent constructs and mediating relationships (Hair et al., 2019). The final sample of 424 respondents provided sufficient statistical power for PLS-SEM analysis. Using G*Power 3.1 analysis with an effect size of $f^2 = 0.15$, $\alpha = 0.05$, and statistical power of 0.80 for a model with five predictors, the minimum required sample size was 92 respondents (Cohen, 1977). Additionally, based on the 10-times rule recommended by Hair (2017), the minimum sample size for a construct receiving five structural paths was 50 respondents. Therefore, the sample size of 424 respondents provided substantial statistical power. Of the initial respondents contacted, 487 responses were received, of which 63 responses were excluded because they failed to meet the screening criteria (inactive users or respondents outside the target age range), resulting in 424 valid responses for analysis.

The research instrument used was a structured questionnaire employing a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. The Likert scale was considered effective for measuring consumer perceptions, attitudes, and evaluations of digital experiences in e-commerce contexts. All variable indicators were adapted from previous studies that had been validated and tested for reliability. The discount framing variable was measured through consumer perceptions of price promotion presentations, including nominal discounts, discount percentages, flash sales, and promotional deadlines (Chen & Cheng, 2019; Pasek & Kasih, 2021; Wei et al., 2025).

The live commerce variable was measured based on interactivity, product demonstrations, host communication, social presence, and the ability to respond to consumer questions in real time during live broadcasts (Sun et al., 2019: Wongkitrungrueng & Assarut, 2020). The CRM automation variable was measured through service personalization, automated recommendations, chatbot services, cart reminders, and digital responsiveness indicators (Adam et al., 2021; Grewal et al., 2020; Huang & Rust, 2021). Furthermore, perceived value was measured based on consumers' evaluations of economic benefits, convenience, time efficiency, and emotional benefits experienced during the online shopping process (Chen & Cheng, 2019;

Zeithaml, 1988). Meanwhile, repurchase intention was measured through consumers' tendencies to repurchase, consider the platform as their preferred choice, and recommend the platform to others (Hellier et al., 2003).

Data analysis was performed using Structural Equation Modeling based on Partial Least Squares (SEM-PLS) with the assistance of SmartPLS 4 software. The SEM-PLS technique was selected because it is appropriate for predictive research, enables the simultaneous testing of complex models involving multiple mediated relationships, and is relatively robust against non-normal data distributions and moderate sample sizes (Henseler et al., 2015).

The analysis was conducted through two main stages: measurement model evaluation and structural model evaluation. At the measurement model stage, convergent validity was assessed through outer loading values (>0.70) and Average Variance Extracted (AVE >0.50). Furthermore, discriminant validity was evaluated using the Fornell–Larcker Criterion and the Heterotrait–Monotrait Ratio (HTMT <0.85) (Fornell & Larcker, 1981; Henseler et al., 2015). Construct reliability was evaluated using Cronbach's Alpha and Composite Reliability, with a minimum acceptable value of 0.70 (Hair et al., 2017).

Before SEM-PLS analysis was conducted, data screening was performed to identify missing values and outliers. Missing data inspection revealed no missing values because all questionnaire items were mandatory in the Google Forms survey design. Multivariate outliers were assessed using Mahalanobis distance ($p < 0.001$), and no observations exceeded the threshold for a model containing 26 indicators. Univariate outliers were examined through boxplot analysis, and no extreme values were identified that could distort distributional assumptions. Common method bias was assessed using Harman's single-factor test, which produced a single-factor variance of 28.3%, well below the 50% threshold, indicating that common method bias did not represent a significant threat to the validity of the findings (Podsakoff et al., 2003).

In the structural model stage, path coefficients, R^2 values, effect sizes (f^2), and predictive relevance (Q^2) were evaluated to assess the predictive capability of the research model. The significance of relationships among variables was tested using bootstrapping with 5,000 resamples (Hair et al., 2017). In addition, this study examined the direct effect, indirect effect, and mediating effect of perceived value on the relationship between discount framing, live commerce, CRM automation, and repurchase intention through bias-corrected bootstrapping to determine the type of mediation, including partial or full mediation (Preacher & Hayes, 2008).

Mediation effects were assessed using bias-corrected bootstrapping with 5,000 resamples at a 95% confidence interval. The mediation type was classified according to (Zhao et al., 2010): when both the direct effect (c′) and indirect effect (a×b) were significant and moved in the same direction, mediation was classified as complementary (partial mediation); when only the indirect effect was significant, mediation was classified as indirect-only (full mediation); and when the direct and indirect effects moved in opposite directions, mediation was classified as competitive mediation. The decision to retain measurement indicators followed the criterion of outer loadings >0.70 recommended by (Hair et al., 2017).

This research also adhered to research ethics principles throughout the data collection process. Respondents participated voluntarily, and all respondents received explanations regarding the research objectives before completing the questionnaire. Respondents' identities were kept confidential, and no personal information that could directly identify participants was collected. All collected data were used exclusively for academic purposes and analyzed in aggregate form to maintain respondent anonymity in accordance with ethical principles of social research. Furthermore, the collected data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with SmartPLS 4 software through measurement model and structural model evaluations. This study did not require formal institutional ethics review board (IRB) approval under applicable national guidelines because it involved anonymous and voluntary survey data without sensitive personal information. The research was conducted in accordance with the ethical principles of the Declaration of Helsinki as adapted for social science research.

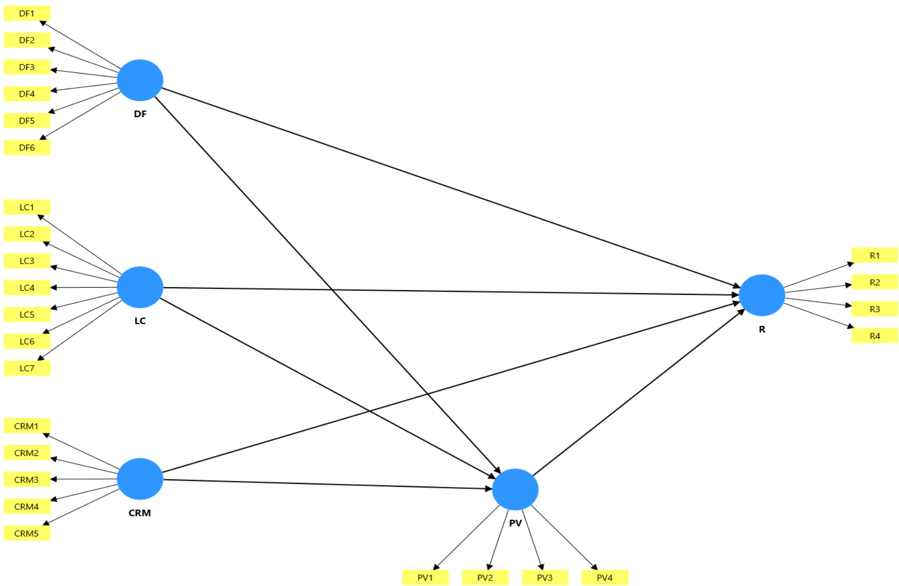

Figure 1. Conceptual Research Framework

RESULTS AND DISCUSSION

Results

Table 1. Respondents Characteristics

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	134	31.6
	Female	290	68.4
Generation	Gen Z (17–29 years)	300	70.8
	Millennial (30–45 years)	124	29.2
Occupation	Student	158	37.3
	Employee	91	21.5
	Civil Servant (ASN/PNS)	64	15.1
	Entrepreneur	57	13.4
	Housewife	33	7.8
	Freelancer	15	3.5
	Others	6	1.4
Region of Residence	DKI Jakarta	148	34.9
	East Java	115	27.1
	Central Java	41	9.7
	Bali	17	4.0
	West Java	16	3.8
	Banten	14	3.3
	South Sumatra	13	3.1
	Others	60	14.1
Online Shopping Frequency	1–2 times/month	153	36.1
	3–5 times/month	204	48.1
	>5 times/month	67	15.8
Preferred Platform	Shopee	212	50.0
	TikTok Shop	212	50.0

Based on Table 1, most respondents in this study were female. These findings indicate that women represent one of the active consumer segments in online shopping activities and interactions with e-commerce platforms, particularly in searching for product information, evaluating alternatives, and making purchase decisions.

In terms of generation, most respondents belonged to the Generation Z category, followed by the millennial generation. The dominance of younger age groups indicates that the use of digital platforms has become an integral part of daily activities among consumers who have grown up in a technology- and internet-oriented environment. This generation tends to demonstrate a high level of technology acceptance and is more responsive to various forms of digital marketing strategies (Priporas et al., 2020).

Based on age distribution, most respondents were within the 21–25-year age range. This age group represents digital consumers who actively utilize social media and e-commerce platforms to obtain product information and conduct online transactions. The high involvement of younger consumers in online shopping activities also reflects a shift in consumer behavior toward greater reliance on digital technology in the purchase decision-making process.

Regarding educational background, most respondents held a bachelor's degree. A relatively high level of education may influence consumers' ability to evaluate product information, compare alternatives, and assess the perceived benefits before making purchasing decisions.

In terms of occupation, respondents were predominantly students and private-sector employees. These groups generally have high internet usage intensity and demonstrate greater openness to digital innovations in their daily consumption activities. Meanwhile, based on domicile, most respondents were from East Java, which is one of the provinces in Indonesia with significant internet penetration and e-commerce activity.

Based on online shopping frequency, most respondents made transactions 3–5 times per month. These findings indicate that most respondents were active users of e-commerce platforms. Furthermore, Shopee was the most frequently used platform compared with TikTok Shop and other platforms. This condition suggests that Shopee continues to maintain strong consumer appeal through various promotional features, transaction convenience, and an integrated shopping experience.

Measurement Model Assessment

Convergent Validity and Reliability

Evaluation of the measurement model was conducted to ensure that all indicators accurately and consistently measured the latent constructs. In the SEM-PLS approach, convergent validity testing is performed by examining the outer loading and Average Variance Extracted (AVE) values, while construct reliability is evaluated using Cronbach's Alpha and Composite Reliability (CR). An indicator is considered to have good convergent validity if its outer loading value exceeds 0.70. Furthermore, an AVE value greater than 0.50 indicates that the construct is able to explain more than 50% of the variance in its indicators. Construct reliability is considered adequate when the Cronbach's Alpha and Composite Reliability values exceed 0.70 (Hair et al., 2017). The results of the convergent validity and reliability testing for all research constructs are presented in Table 2.

Table 2. Measurement Model Assessment: Descriptive Statistics, Reliability, and Validity

Construct		Other Loading	CA	CR (rho_a)	CR (rho_c)	AVE
	Discount Framing		0.908	0.913	0.928	0.684
DF1	I'm more interested in buying when the discount is shown in the form of a percentage (e.g. 50% OFF).	0.773				
DF2	I am more interested in buying when the discount is shown in the form of a nominal discount (for example: IDR 50,000 OFF).	0.796				
DF3	Percentage discounts look more	0.845				

	appealing to me than other forms.					
DF4	Discounts in the form of nominal rupiah are easier for me to understand.	0.831				
DF5	The presentation of the discount view helps me compare product offers.	0.849				
DF6	The display of discounts on promotional events (e.g. flash sale or 12.12) attracted my interest in the product.	0.865				
			0.909	0.912	0.928	0.647
LC1	Live streaming helped me see the product more realistically than just through photos.	0.827				
LC2	Live streaming made me more confident in the condition of the products offered.	0.772				
LC3	I can see the details of the product clearly through live streaming.	0.828				
LC4	The seller responded quickly to my question during the live stream.	0.788				
LC5	I get complete product information through live streaming.	0.818				
LC6	Live streaming makes it easier for me to make purchasing decisions.	0.778				
LC7	The interaction during the live stream helped reduce my doubts about the product.	0.819				
			0.867	0.867	0.904	0.653
CRM1	The platform has an automated system that sends regular updates to information or promotions	0.793				
CRM2	The help feature (chatbot) on the live platform provides automatic answers immediately after the message is sent	0.822				
CRM3	The platform displays product recommendations that are specifically customized based on the last search activity	0.804				
CRM4	The platform systematically displays transaction history and account preferences clearly on the user interface.	0.794				
CRM5	The platform provides an interactive chatbot feature that is active for 24 hours to guide the shopping process	0.829				
			0.844	0.846	0.895	0.681
PV1	Shopping through this platform provides value that is worth the cost I incur.	0.852				

PV2	Overall, the experience of shopping through this platform provided good value for me	0.831				
PV3	The benefits I get from this platform are greater than the sacrifices I make	0.831				
PV4	Overall, the platform provides me with decent benefits	0.785				
			0.861	0.862	0.906	0.706
R1	I intend to make a repurchase through this platform in the future	0.829				
R2	I will most likely make a repurchase through this platform	0.866				
R3	I prefer to buy back from this platform than any other	0.835				
R4	I will continue to use this platform for future purchases	0.830				

Source: Data processing results using SmartPLS 4 (2026)

Based on Table 2, all indicators show outer loading values above the minimum threshold of 0.70, indicating that they meet the criteria for convergent validity. The AVE values of each construct are also above 0.50, demonstrating that each construct can adequately explain the variance of its indicators. In terms of reliability, all constructs have Cronbach's Alpha and Composite Reliability values exceeding 0.70. These findings indicate that the research instrument has a good level of internal consistency and that all constructs are suitable for structural model analysis in the subsequent stage (Hair et al., 2017).

Discriminant Validity

After confirming convergent validity and reliability, discriminant validity was assessed using two complementary approaches: the Fornell–Larcker Criterion and the Heterotrait–Monotrait Ratio (HTMT). The Fornell–Larcker Criterion requires that the square root of each construct's AVE be greater than its correlations with other constructs (Fornell & Larcker, 1981). In addition, the HTMT approach was employed as a more sensitive method for assessing discriminant validity, in which HTMT values below 0.90 indicate acceptable discriminant validity (Henseler et al., 2015). Table 3 presents the results of the Fornell–Larcker Criterion, where the diagonal values represent the square root of the AVE values.

According to Henseler (2015), a construct demonstrates adequate discriminant validity when its HTMT value is below 0.90. Values below this threshold indicate that each construct has sufficient distinctiveness and can be considered a separate concept within the research model. The results of discriminant validity testing using the HTMT approach are presented in Table 3.

Table 3. Discriminant Validity – Fornell–Larcker Criterion and HTMT (SmartPLS 4, 2026)

	Red	**SD**	**CRM**	**DF**	**LC**	**PV**	**R**
CRM Automation	4.334	0.753	0.808				
Discount Framing	4.397	0.773	0.451	0.827			
Live Commerce	4.442	0.718	0.502	0.553	0.805		
Perceived Value	4.310	0.756	0.630	0.601	0.603	0.825	
Repurchase Intention	4.323	0.812	0.572	0.559	0.670	0.605	0.840

Source: Data processing results using SmartPLS 4 (2026)

Based on Table 3, the Fornell–Larcker criterion is satisfied for all constructs: the square root of each AVE value (diagonal values) exceeds the inter-construct correlations in the corresponding rows and columns. The highest inter-construct correlation is 0.670 (Live Commerce–Repurchase Intention), which is below the square roots of their respective AVE values

(0.805 and 0.840). In addition, the HTMT analysis confirmed that all ratios fell below the conservative threshold of 0.85 recommended by Henseler (2009), further supporting discriminant validity. These results confirm that each construct is empirically distinct and measures a unique conceptual domain.

Structural Model Evaluation

Once the measurement model meets the criteria for validity and reliability, structural model evaluation is conducted to assess the predictive capability of the proposed model. This evaluation is performed through the Coefficient of Determination (R^2) and Predictive Relevance (Q^2) values. The R^2 value indicates the extent to which exogenous constructs explain the variance of endogenous constructs, while the Q^2 value is used to evaluate the predictive relevance of the model based on observational data (Hair et al., 2017).

Coefficient of Determination (R^2) and Predictive Relevance (Q^2)

Table 4. Structural Model Assessment & Construct Cross-validated Redundancy

	R-square	R-square adjusted	Q^2predict	RMSE	MAE
PV	0.562	0.559	0.551	0.683	0.477
R	0.473	0.470	0.440	0.757	0.471

Based on Table 4, the R^2 value indicates that the model has an adequate ability to explain the endogenous variables. an R^2 value of 0.75 is categorized as strong, 0.50 as moderate, and 0.25 as weak. In addition, all Q^2 values are greater than zero, indicating that the model has good predictive relevance for the observed data.

Effect Size (f^2)

In addition to evaluating the predictive ability of the model, this study also measured the contribution of each exogenous variable to the endogenous variable using the effect size (f^2) analysis. The f^2 value indicates the change in the R^2 value when a particular construct is excluded from the model. According to Cohen (1977), an f^2 value of 0.02 indicates a small effect, 0.15 indicates a moderate effect, and 0.35 indicates a large effect.

Table 5. Effect Size f Square

Relationships Between Constructs	f^2	Categories
CRM Automation → Perceived Value	0.220	Medium
Discount Framing → Perceived Value	0.129	Small
Live Commerce → Perceived Value	0.091	Small
CRM Automation → Repurchase Intention	0.062	Small
Discount Framing → Repurchase Intention	0.035	Small
Live Commerce → Repurchase Intention	0.196	Medium
Perceived Value → Repurchase Intention	0.018	Very Small (below 0.02)

Based on Table 5, the effect size value (f^2) demonstrates the contribution of each exogenous construct to improving the model's predictive ability. The greater the f^2 value, the greater the role of a variable in explaining the endogenous variable it influences. The results of the analysis show that CRM Automation has the strongest influence on Perceived Value compared with other relationships (f^2 = 0.220), followed by Live Commerce on Repurchase Intention (f^2 = 0.196). Meanwhile, the other relationships show relatively small effect sizes, although they still contribute to the formation of Perceived Value and Repurchase Intention.

These findings indicate that not all variables have the same level of explanatory power within the model; therefore, identifying effect sizes is important for understanding the relative contribution of each construct in explaining consumer repurchase behavior on the Shopee and TikTok Shop platforms. Notably, the effect size of Perceived Value on Repurchase Intention is very small (f^2 = 0.018, below the 0.02 threshold for a small effect according to (Cohen, 1977). However, this finding does not imply that the relationship is negligible. In the context of SEM-PLS, effect size (f^2) measures the incremental contribution to R^2, whereas statistical significance is determined through the bootstrapped t-statistic ($t = 3.109$; $p = 0.002$). A significant but small f^2 value indicates that, although Perceived Value explains only a marginal additional variance in Repurchase Intention beyond the direct effects of the stimulus variables, the relationship itself remains statistically significant and theoretically meaningful.

This pattern is consistent with a partial mediation scenario in which stimuli (Discount Framing, Live Commerce, and CRM Automation) exert strong direct effects that reduce the marginal contribution of the organism variable (Zhao et al., 2010). Academically, this finding aligns with recent research on digital consumer behavior, which suggests that behavioral intentions in high-stimulus environments are primarily driven by experiential stimuli rather than cognitive value appraisal alone.

Hypothesis Testing

Hypothesis testing was conducted using a bootstrapping procedure in SmartPLS 4 with 5,000 subsamples to evaluate the significance of relationships between constructs in the research model. The decision to accept or reject hypotheses was based on a t-statistic value greater than 1.96 and a p-value lower than 0.05 at a 5% significance level. This analysis aimed to examine the direct effects among the research variables, which include Discount Framing, Live Commerce, CRM Automation, Perceived Value, and Repurchase Intention.

Table 6. Hypothesis testing of direct and indirect relationship

Hypothesis	Relationships Between Constructs	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics	P Values	Verdict
Direct Effect							
H1	Discount Framing → Perceived Value	0.294	0.292	0.058	5.093	0.000	Accepted
H2	Live Commerce → Perceived Value	0.254	0.248	0.064	3.965	0.000	Accepted
H3	CRM Automation → Perceived Value	0.369	0.371	0.068	5.403	0.000	Accepted
H4	Discount Framing → Repurchase Intention	0.307	0.300	0.092	3.326	0.001	Accepted
H5	Live Commerce → Repurchase Intention	0.170	0.179	0.055	3.104	0.002	Accepted
H6	CRM Automation → Repurchase Intention	0.394	0.380	0.087	4.515	0.000	Accepted
H7	Perceived Value → Repurchase Intention	0.165	0.170	0.053	3.109	0.002	Accepted
Indirect Effect							
H8	Discount Framing → Perceived Value → Repurchase Intention	0.048	0.049	0.017	2.811	0.005	Accepted
H9	Live Commerce → Perceived Value → Repurchase Intention	0.042	0.042	0.016	2.586	0.010	Accepted
H10	CRM Automation → Perceived Value → Repurchase Intention	0.061	0.064	0.025	2.406	0.016	Accepted

Hypothesis testing was conducted using a bootstrapping procedure in SmartPLS 4 with a significance level of 5%. A hypothesis was considered supported if it had a t-statistic value of >1.96 and a p-value of <0.05. Zhao (2010), the type of mediation was classified based on the pattern of direct and indirect effects. Since both the direct effects (c′) and indirect effects (a × b) were statistically significant and operated in the same positive direction for all three pathways (H8, H9, and H10), the mediation was classified as complementary partial mediation. This indicates that Perceived Value enhances, rather than fully explains, the influence of digital marketing stimuli on Repurchase Intention. The complementary nature of this mediation suggests that these stimuli activate both cognitive value-based evaluation and direct behavioral motivation simultaneously, which is consistent with dual-process perspectives on consumer decision-making.

Based on Table 6, all hypotheses proposed in this study were supported. Regarding the direct relationships, Discount Framing had a positive and significant effect on Perceived Value (β = 0.294; t = 5.093; p = 0.000), supporting H1. Live Commerce also had a positive and significant effect on Perceived Value (β = 0.254; t = 3.965; p = 0.000), supporting H2. Furthermore, CRM Automation had a positive and significant effect on Perceived Value (β = 0.369; t = 5.403; p = 0.000), supporting H3.

Regarding the dependent variable, Repurchase Intention, Discount Framing demonstrated a positive and significant effect (β = 0.307; t = 3.326; p = 0.001), supporting H4. Live Commerce also had a positive and significant effect on Repurchase Intention (β = 0.170; t = 3.104; p = 0.002), supporting H5. Similarly, CRM Automation showed a positive and significant effect on Repurchase Intention (β = 0.394; t = 4.515; p = 0.000), supporting H6. In addition, Perceived Value had a positive and significant effect on Repurchase Intention (β = 0.165; t = 3.109; p = 0.002), supporting H7.

Regarding the indirect effects, Perceived Value was found to mediate the relationship between Discount Framing and Repurchase Intention (β = 0.048; t = 2.811; p = 0.005), supporting H8. Perceived Value also mediated the relationship between Live Commerce and Repurchase Intention (β = 0.042; t = 2.586; p = 0.010), supporting H9. Furthermore, Perceived Value mediated the relationship between CRM Automation and Repurchase Intention (β = 0.061; t = 2.406; p = 0.016), supporting H10.

Discussion

The results of the study show that Discount Framing, Live Commerce, and CRM Automation function as digital marketing stimuli that significantly increase consumers' Perceived Value on the Shopee and TikTok Shop platforms. These findings support the Stimulus-Organism-Response (S-O-R) framework, which explains that external stimuli influence consumers' internal states before generating specific behavioral responses (Mehrabian & Russell, 1974). In this study, Perceived Value serves as an internal evaluation mechanism formed when consumers assess the benefits obtained from their digital shopping experiences.

Discount Framing has been shown to increase Perceived Value, indicating that the way platforms present promotional information plays an important role in shaping consumers' evaluations of transactions. These findings are consistent with Chen (2019), who explained that the format of discount presentation can influence consumers' perceptions of benefits.

The findings of Wei (2024) also demonstrate that the effectiveness of price promotions is determined not only by the discount magnitude but also by how promotional messages are communicated to consumers. In the context of Shopee and TikTok Shop, various promotional formats, such as flash sales, vouchers, cashback programs, and double-date campaigns, provide savings signals that can enhance perceived transaction value. For digital consumers, particularly Generation Z and Millennials, promotional information that is easy to understand and perceived as beneficial tends to generate more positive evaluations of e-commerce platforms.

In addition to Discount Framing, Live Commerce has also been proven to increase Perceived Value. These findings indicate that real-time interactions during live streaming sessions help consumers obtain more comprehensive information, reduce product uncertainty, and increase confidence in purchasing decisions. These results are consistent with Wongkitrungrueng (2020) and Sun (2019), who found that live streaming can enhance social presence, consumer engagement, and shopping experiences. In an e-commerce environment characterized by limited direct physical interaction with products, live commerce functions as a risk-reduction mechanism that enables consumers to evaluate products more comprehensively. Therefore, the informational benefits and interactive experiences provided during live streaming sessions contribute to increased Perceived Value.

CRM Automation demonstrates the strongest influence on Perceived Value among all stimuli ($\beta = 0.369$; $f^2 = 0.220$) and produces the highest direct effect on Repurchase Intention ($\beta = 0.394$). This finding represents one of the most important empirical contributions of this study and requires deeper theoretical interpretation. The relative superiority of CRM Automation compared with Discount Framing and Live Commerce can be explained through the perspective of service personalization theory and AI-mediated value co-creation (Huang & Rust, 2021). While promotional discounts and live streaming create temporary value experiences, CRM automation (through continuous chatbot interactions, behavioral recommendation algorithms, and proactive cart-reminder notifications) generates a sustained value stream throughout the customer journey (Grewal et al., 2020).

This continuous personalization reduces consumers' cognitive search costs and creates relational value that extends beyond individual transactions. Furthermore, from an S-O-R perspective, CRM automation uniquely combines utilitarian stimuli (efficiency and relevance) with relational stimuli (responsiveness and perceived care), resulting in a stronger organism-level evaluation that more effectively translates into repurchase motivation. This finding challenges the conventional emphasis on promotional tactics as the primary driver of e-commerce loyalty and suggests that investment in AI-driven service personalization may generate greater returns in consumer retention compared with purely price-based stimulation strategies.

This study also demonstrates that Perceived Value has a positive effect on Repurchase Intention. These findings support the concept of value-based consumer behavior, which explains that consumers tend to maintain relationships with platforms when the benefits obtained are perceived to outweigh the sacrifices made (Zeithaml, 1988). When consumers perceive that a platform provides a combination of economic benefits, convenience, and satisfying shopping experiences, they demonstrate a stronger tendency to make repeat purchases. Thus, Perceived Value serves as an important factor connecting digital shopping experiences with consumer loyalty behavior.

In addition to the indirect influence through Perceived Value, all digital marketing stimuli are also shown to have direct effects on Repurchase Intention. These findings indicate that Discount Framing, Live Commerce, and CRM Automation not only shape consumers' internal evaluations but also directly encourage repurchase decisions. Discount Framing provides attractive economic incentives, Live Commerce creates engagement and interactive experiences, while CRM Automation improves convenience and service efficiency. These results demonstrate that digital consumers' repurchase behavior is influenced by a combination of functional, economic, and experiential benefits obtained while using e-commerce platforms.

The mediation analysis confirms that Perceived Value acts as a complementary partial mediator in all three stimulus-to-response relationships (Zhao et al., 2010). The psychological mechanism underlying this mediation can be understood through the organism stage of S-O-R theory. When consumers encounter discount promotions, live streaming sessions, or automated service interactions, they do not immediately translate these stimuli into behavioral decisions. Instead, they engage in a cognitive appraisal process in which perceived benefits (economic savings, informational completeness, and service efficiency) are evaluated against perceived sacrifices (time, effort, and uncertainty), resulting in an overall Perceived Value judgment (Zeithaml, 1988).

This evaluated value, rather than the stimulus itself, subsequently drives Repurchase Intention. The complementary mediation effect further indicates that stimuli also influence repurchase intention through a more automatic affective pathway that may occur beyond deliberate value assessment. This dual-pathway interpretation is consistent with elaboration likelihood and dual-process perspectives on consumer decision-making, where highly involved digital consumers may process marketing stimuli through both central (value evaluation) and peripheral (habitual engagement) routes simultaneously (Petty & Cacioppo, 1986).

The findings of this study should also be interpreted within the context of respondent characteristics, which are dominated by Generation Z (70.8%) and Millennials (29.2%). Both generations are recognized as consumer groups with high levels of digital literacy, intensive social media usage, and active participation in e-commerce activities (Djafarova & Bowes, 2021; Priporas et al., 2020). These characteristics may explain why all digital marketing stimuli demonstrate significant influences in this study. Generation Z tends to respond positively to interactive content and real-time experiences such as live commerce, whereas Millennials often emphasize efficiency, convenience, and practical benefits derived from digital technologies. Therefore, digital marketing strategies that integrate attractive promotions, interactive experiences, and personalized services represent important factors in increasing perceived value and encouraging repurchase behavior among modern digital consumers.

Specific Managerial Implications: For Shopee, the findings suggest prioritizing the optimization of CRM automation through enhanced AI-driven product recommendation algorithms and proactive re-engagement notifications, as this stimulus demonstrates the strongest effects on both perceived value and repurchase intention. Discount framing should be redesigned beyond isolated promotional events toward sequential voucher strategies that maintain perceptions of savings throughout the customer journey. For TikTok Shop, investment in live commerce infrastructure (particularly host training, real-time question-and-answer optimization, and post-live replay features) is likely to generate substantial incremental returns given the platform's social commerce architecture, where live commerce demonstrates a medium effect on repurchase intention ($f^2 = 0.196$).

For SMEs and independent sellers on both platforms, the results indicate that even without large advertising budgets, the strategic use of CRM chatbot features and algorithm-optimized product listings can substantially enhance consumer perceived value and retention. Platform developers should integrate A/B testing frameworks that enable sellers to experimentally compare discount framing formats (nominal versus percentage discounts) and CRM automation configurations to continuously optimize repurchase conversion rates.

CONCLUSION

This study analyzed the influence of discount framing, live commerce, and CRM automation on repurchase intention through perceived value among Shopee and TikTok Shop users in Indonesia. The empirical results confirm that all three stimuli positively and significantly enhance perceived value, which subsequently mediates the relationship with repurchase intention through complementary partial mediation. The most influential stimulus is CRM automation ($\beta = 0.369$ on perceived value; $\beta = 0.394$ on repurchase intention), highlighting that AI-driven personalization and automated service interactions have surpassed traditional price-based promotions as primary mechanisms for consumer value creation and loyalty formation in Indonesian social commerce. These findings validate the applicability of the Stimulus–Organism–Response (S-O-R) theory in digital commerce by confirming perceived value as the cognitive organism mechanism that translates marketing stimuli into behavioral responses.

Theoretically, this study makes three contributions to the S-O-R theory and digital commerce literature. First, it confirms perceived value as an organism-level cognitive mediator connecting platform-level marketing stimuli to repurchase behavior, a role that remains underexplored in previous S-O-R applications, which have primarily focused on emotional or atmospheric responses. Second, by demonstrating that CRM automation generates a significantly stronger effect on perceived value ($\beta = 0.369$) than both discount framing ($\beta = 0.294$) and live commerce ($\beta = 0.254$), this study challenges the assumption that price incentives are the dominant drivers of online repurchase decisions. Instead, the findings suggest that AI-mediated relational personalization has emerged as a powerful value-creation mechanism in contemporary social commerce. Third, the complementary partial mediation pattern reveals that digital marketing stimuli operate through dual behavioral pathways, both cognitive (value appraisal) and affective (direct engagement motivation), which has important implications for how future S-O-R research conceptualizes organism constructs in technology-mediated consumption environments.

The principal scientific contribution of this study is the empirical demonstration that CRM automation, not promotional discounting or live commerce, constitutes the most influential digital marketing stimulus for both perceived value formation and repurchase intention in Indonesian social commerce. This finding challenges the conventional marketing assumption that price-based stimuli dominate online consumer behavior and provides a theoretically grounded, empirically validated framework, namely the Integrated Digital Marketing Stimulus–Perceived Value–Repurchase Intention (IDMS-PV-RI) model, which can be adapted and tested across different e-commerce contexts, populations, and cultural settings. Future research should apply this framework longitudinally across additional platforms (Tokopedia, Lazada, Instagram Shop), incorporate multi-group moderation analyses to examine generational, cultural, and product category differences, and utilize actual behavioral data (click-through rates and purchase transaction logs) to address the limitations associated with self-reported measurements.

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AUTHOR CONTRIBUTION STATEMENT

The author contributes to all stages of research, starting from the preparation of Stimulus-Organism–Response-based research concepts and frameworks (S-O-R), the development of research instruments, data collection, data analysis using SmartPLS 4, the interpretation of research results, to the preparation of the overall manuscript. The author is fully responsible for the entire content of the article, including literature review, hypothesis development, research methodology, analysis results, discussion, and conclusion.

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