

Data-Driven Marketing Strategies in Conventional and Online Retail for Customer Loyalty Enhancement

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ABSTRACT

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This study aims to analyze data-driven marketing strategies in conventional and online retail and their influence on customer loyalty, with retail type as a moderating variable. Using a quantitative approach, data was collected through surveys from 200 respondents across various regions in East Java (Surabaya, Malang, Blitar, Kediri, Probolinggo, and Jember) who are customers of Alfamart and Indomaret. Data analysis employed Structural Equation Modeling with PLS 3.0. Results show that personalization of promotion and communication ($\beta=0.279$, $p=0.002$), data-based segmentation and targeting ($\beta=0.262$, $p=0.002$), and digital channel utilization ($\beta=0.251$, $p=0.005$) significantly and positively affect customer loyalty. However, most moderating effects of retail type were not significant, except for the negative moderating effect of online retail on the relationship between personalization and loyalty ($\beta=-0.370$, $p=0.004$). The model explains 70.2% of loyalty variation. Companies should prioritize optimizing core data-driven marketing components rather than focusing excessively on retail channel expansion.

1. INTRODUCTION

Digital technology development has significantly transformed marketing patterns in the retail industry, creating two distinct business models: conventional retail and online retail (Mu dkk., 2026). Conventional retail, which has traditionally relied on direct customer interaction in physical stores, now faces significant challenges with the emergence of online retail offering convenience, personalization, and more efficient shopping experiences (Nakano, 2023). According to Shou dkk. (2024), global e-commerce sales are projected to reach \$6.7 trillion by 2025, with substantial growth in Southeast Asia, including Indonesia. In Indonesia itself, internet penetration reaching 77% of the total population in 2023 has driven online retail growth, while conventional retail struggles to remain relevant amid changing consumer behavior.

Modern consumers, particularly millennials and Gen Z, increasingly demand relevant, fast, and preference-aligned shopping experiences (Park dkk., 2023). They desire personalization in every brand interaction, from product recommendations to promotional offers tailored to their needs (Fillmann dkk., 2025). This drives retail companies to adopt data-driven marketing approach utilizing big data and data analytics to deeply understand consumer behavior (Tran, 2026). Changing consumer behavior, with Customer Relationship Management (CRM) approach, becomes the main driver of marketing evolution to provide consumer trust in authenticity, transparency, and product experience (Gazi dkk., 2024). This leads to unplanned and spontaneous purchases. Without CRM, companies struggle to retain customers and increase loyalty. Through data-driven marketing, companies can collect data from various sources such as online transactions, in-store shopping history, social media interactions, and customer preferences to create more targeted marketing strategies (Blömker & Albrecht, 2025).

The implementation of data-driven marketing in conventional retail faces challenges primarily in data integration between offline and online systems (Abid dkk., 2025). Many physical stores still use fragmented systems, making it difficult to combine customer data from offline transactions with online data (Kumar dkk., 2023). Conversely, online retail, despite technological advancement, often faces data quality and customer privacy issues. Retail companies encounter difficulties in ensuring accuracy and

consistency of collected data. Additionally, there are challenges regarding human resources and adequate technology infrastructure to effectively manage and analyze big data (Hosseini Dehshiri, 2025).

Customer loyalty has become a key factor in maintaining retail business competitiveness in this digital era (Khan & Sarkar, 2024). Strengthening digital strategies based on trust through Technology Acceptance Model and Trust-Based Relationship Theory builds loyalty toward service providers. Therefore, understanding how data-driven marketing strategies can enhance customer loyalty becomes crucial. This study aims to analyze data-driven marketing strategies implemented in conventional and online retail and their influence on customer loyalty.

2. THE PURPOSED METHOD

Problem-Solving Approach

The problem-solving approach was conducted through quantitative hypothesis testing on the relationship between data-driven marketing strategies and customer loyalty. This research formulates a model reflecting the main variables and statistically measures their influence on customer loyalty from the consumer perspective. These variables include:

1. Independent variables (X): data-driven marketing strategies
 - a. X1: Personalization of promotion and communication
 - b. X2: Data-based segmentation and targeting
 - c. X3: Digital channel utilization
2. Dependent variable (Y): customer loyalty
3. Moderating variables (M): retail type
 - a. M1: Conventional retail
 - b. M2: Online retail

Based on these variables, the conceptual framework and hypotheses of this research can be illustrated as follows:

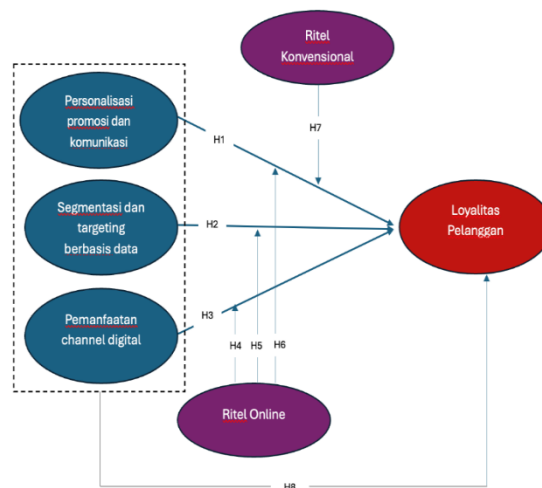


Figure 1. Research Conceptual Framework

1. H1: Personalization of promotion and communication significantly influences customer loyalty
2. H2: Data-based segmentation and targeting significantly influences customer loyalty
3. H3: Digital channel utilization significantly influences customer loyalty
4. H4: Online retail as a moderator of digital channel utilization significantly influences customer loyalty
5. H5: Online retail as a moderator of data-based segmentation and targeting significantly influences customer loyalty

6. H6: Online retail as a moderator of personalization of promotion and communication significantly influences customer loyalty
7. H7: Conventional retail as a moderator of personalization of promotion and communication significantly influences customer loyalty
8. H8: Data-driven marketing significantly influences customer loyalty

Previous Research

Previous supporting research is presented in the following table:

No	Authors	Title	Research Results
1	Yang et al.	Personalized Promotion Decision Making Based on Direct and Enduring Effect Predictions	This study developed a framework for personalized promotional decision-making by predicting direct and long-term effects on customers. Results showed this approach increased customer retention and loyalty through more effective incentive allocation.
2	Equihua et al.	Modelling Customer Churn for the Retail Industry in a Deep Learning Based Sequential Framework	This research introduced a deep learning-based survival model to predict customers at risk of discontinuing transactions with retail companies. This model helps identify customers requiring marketing intervention to enhance loyalty.
3	Arab	Providing an Approach to Predicting Customer Quality in E-Commerce Social Networks Based on Big Data and Unsupervised Learning Method	This study proposed a big data and unsupervised learning-based approach to predict customer quality in e-commerce social networks. Results demonstrated that big data analysis can improve marketing strategies focused on enhancing customer loyalty.
4	Saroyini et al.	Data-Driven Marketing Strategy to Reach Millennial Consumers	This research explored the effectiveness of data-driven marketing strategies in reaching millennial consumers. Through comprehensive literature review, it highlighted the importance of customer segmentation, content personalization, and omnichannel integration in enhancing millennial customer loyalty.
5	Loo	Transformation of Traditional Marketing Strategy to Digital; Challenges	Limited digital skills and financial constraints are major barriers to adopting digital marketing.
6	Taghikhah et al.	Shifts in consumer behavior towards organic products: theory-driven data analytics	The gap between intention and behavior, with emphasis on cognitive factors using TPB, TIB, IBT, AT, GFT approaches.

The novelty of this research, based on a summary of previous studies, lies in examining and comparing strategy implementation in conventional and online retail, the role of retail type as a moderating variable, and the use of consumer perspective in evaluating data-driven marketing.

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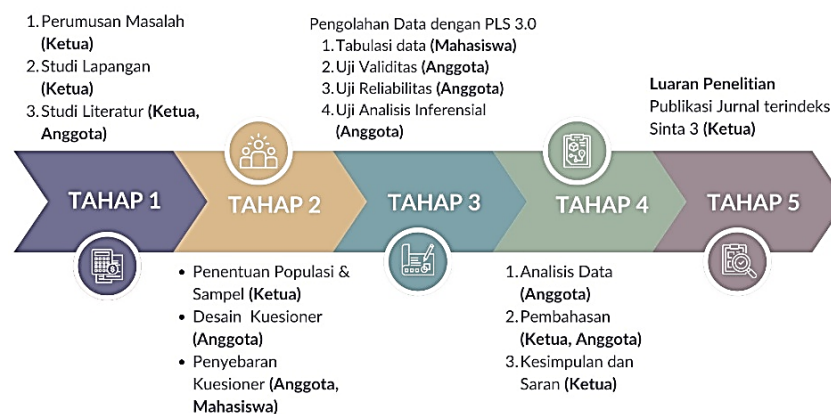


Figure 2. Research Flow Diagram

This study employs a quantitative descriptive method with survey techniques through questionnaire completion using a 1-5 Likert scale for Alfamart and Indomaret customers in East Java. The population in this research consists of all Alfamart and Indomaret customers in East Java. The sampling technique used is probability sampling with a random sampling approach. Locations will be divided into three regions: major cities (Surabaya, Malang), small cities (Blitar, Kediri), and peripheral regencies (Probolinggo, Jember). The specific number of Indomaret and Alfamart outlets in East Java is unknown; therefore, each city will randomly represent 2 Indomaret outlets and 2 Alfamart outlets. Since customer lists are unavailable (transactions are anonymous), the random walk approach is used, giving every customer entering the outlet an equal chance of becoming a respondent.

The sample in this research must meet predetermined population criteria. Sample size refers to Hair's statement where the minimum sample size in SEM research is 10 times the number of indicators (20), so the sample size is determined based on 10 times the number of research indicators (10×20). Thus, the research sample consists of 200 respondents. The obtained data is analyzed using Structural Equation Modeling (SEM) with PLS 3.0 analysis.

Table 2. Research Variables and Indicators

Variable	Indicators
Personalization of promotion and communication	Promotions received align with individual needs
	Special offers relevant to customer preferences
	Promotions consider previous customer interests
Data-based segmentation and targeting	Offers differentiated based on shopping habits
	Retailers can accurately identify market segments
	Promotions delivered based on relevant time or season
Digital channel utilization	Promotions delivered through digital media (email, social media, applications)
	Customer interaction with retailers facilitated through digital channels
	Product and promotion information easily accessible through digital platforms
Customer Loyalty	Tendency to make repeat purchases
	Likelihood of recommending the retailer to others
	Loyalty to the retailer despite competitor offers
	Level of satisfaction and trust in retailer services
Conventional Retail	Emotional bond with the brand or retailer
	Preference for shopping in physical stores
	Higher trust when seeing products directly
Online Retail	Shopping experience enhanced by store staff service
	Preference for shopping through digital platforms
	Payment and delivery convenience as determining factors
	Time efficiency in online purchasing process

1. RESULT AND DICUSSION

Respondents

This research involved 200 respondents residing in East Java. Respondent characteristics encompass two main aspects: age and residence. These characteristics are essential for understanding the profile of conventional and online retail consumers that serve as the foundation for formulating data-driven marketing strategies. The age distribution shows that the majority of respondents are from the productive age group:

Table 3. Age Distribution of Respondents

No	Age	Number
1	<17 years	7
2	17-25 years	74
3	26-35 years	63
4	36-45 years	33
5	46-55 years	15
6	>55 years	8
Total		200

The 17-25 age group (37%) dominates the respondents. This indicates that digitally active young generations are highly involved in interactions with retail, particularly online. The 26-35 age group (31.5%) ranks second, representing young professionals with strong loyalty potential when data-based marketing strategies are properly implemented. Other age distributions show diverse conventional and online retail consumers, requiring marketing strategies to consider cross-generational needs. Respondents came from various cities in East Java representing tapal kuda, mataraman, and gerbangkertosusila regions:

Table 4. Respondent Distribution by Residence

No	Residence	Number
1	Blitar, Kediri	60
2	Probolinggo, Jember	56
3	Surabaya, Malang	84
Total		200

The largest residence group comes from Surabaya and Malang (42%), the two largest economic centers in East Java with the most rapid development of conventional and online retail. Blitar and Kediri regions (30%) and Probolinggo and Jember (28%) also show significant contributions, providing consumer behavior insights from major to medium-sized cities. This regional diversity reflects that data-driven marketing strategies need to consider differences in preferences, digitalization levels, and shopping habits across regions. This demographic combination supports relevant analysis for formulating data-driven marketing strategies for both conventional and online retail in enhancing customer loyalty.

Measurement Model Assessment

Outer Loading

Table 5. Outer Loading Results

	M1.	M2.	X1.	X2.	X3.	Y1.
M1.1	0.851					
M1.2	0.813					
M1.3	0.834					
M2.1		0.808				
M2.2		0.784				
M2.3		0.827				
X1.1			0.803			
X1.2			0.809			
X1.3			0.842			
X2.1				0.868		
X2.2				0.838		
X2.3				0.830		
X3.1					0.871	

X3.2	0.817
X3.3	0.833
Y1.1	0.810
Y1.2	0.734
Y1.3	0.749
Y1.4	0.729
Y1.5	0.794

Based on outer loading test results, all indicators on constructs M1, M2, X1, X2, X3, and Y1 show loading values above 0.70. This indicates that each indicator has strong contribution in reflecting the measured construct. Therefore, all indicators are valid and meet convergent validity criteria as recommended by Hair et al. (2019). No indicators with loading values below the threshold exist, eliminating the need for indicator elimination in this measurement model.

Average Variance Extracted (AVE)

Table 6. AVE Results

Variable	Average Variance Extracted (AVE)
M1	0.694
M2	0.650
X1	0.669
X2	0.715
X3	0.706
Y1	0.583

Based on AVE calculation results, all constructs in this research show AVE values above the minimum threshold of 0.50. Construct M1 has an AVE value of 0.694, M2 at 0.650, X1 at 0.669, X2 at 0.715, X3 at 0.706, and Y1 at 0.583. These values indicate that more than 50% of indicator variance can be explained by their respective constructs. With all AVE values exceeding 0.50, it can be concluded that all constructs in the model meet convergent validity. This means the indicators forming each construct have adequate internal consistency and substantially represent their latent variables.

Reliability

Table 7. Reliability Test Results

Variable	Cronbach's Alpha	Composite Reliability (pc)
M1	0.780	0.872
M2	0.733	0.848
X1	0.754	0.858
X2	0.802	0.883
X3	0.794	0.878
Y1	0.822	0.875

Reliability test results show that all variables in the research model have Cronbach's Alpha and Composite Reliability values above the threshold of 0.70. Construct M1 has a Cronbach's Alpha of 0.780 and Composite Reliability of 0.872, while construct M2 shows Cronbach's Alpha of 0.733 and Composite Reliability of 0.848. Construct X1 has Cronbach's Alpha of 0.754 and Composite Reliability of 0.858. For construct X2, the obtained Cronbach's Alpha is 0.802 with Composite Reliability of 0.883, while construct X3 has values of 0.794 and 0.878 respectively. Finally, construct Y1 shows excellent reliability with Cronbach's Alpha of 0.822 and Composite Reliability of 0.875.

These values indicate that all constructs meet good internal reliability criteria. Composite Reliability above 0.70 shows that indicators within each construct have high internal consistency, while Cronbach's Alpha above the minimum threshold reinforces that constructs in this research are reliable. Therefore, all constructs are deemed suitable for further analysis.

Discriminant Validity Assessment

Cross Loading Results

All indicators have the highest loading values on their respective constructs compared to other constructs, confirming discriminant validity through cross loading.

Fornell-Larcker Criterion

Table 8. Fornell-Larcker Results

	M1.	M2.	X1.	X2.	X3.	Y1.
M1.	0.833					
M2.	0.647	0.806				
X1.	0.534	0.621	0.818			
X2.	0.634	0.597	0.547	0.846		
X3.	0.552	0.563	0.593	0.708	0.840	
Y1.	0.565	0.552	0.639	0.726	0.737	0.764

Fornell-Larcker discriminant validity test results show that the square root of AVE for each construct has higher values than its correlations with other constructs. For example, construct M1 has a square root AVE of 0.833, higher than its correlations with M2, X1, X2, X3, and Y1. Similar patterns appear in other constructs such as M2 (0.806), X1 (0.818), X2 (0.846), X3 (0.840), and Y1 (0.764). Since all constructs have diagonal values (square root AVE) greater than inter-construct correlations, it can be concluded that discriminant validity meets Fornell-Larcker criteria.

HTMT Ratio

Table 9. HTMT Results

	M1.	M2.	X1.	X2.	X3.	Y1.
M1.						
M2.	0.857					
X1.	0.690	0.830				
X2.	0.809	0.784	0.705			
X3.	0.699	0.731	0.756	0.865		
Y1.	0.703	0.700	0.807	0.873	0.888	

Discriminant validity testing using Heterotrait-Monotrait ratio (HTMT) shows all HTMT values below the threshold of 0.90. HTMT values between constructs, such as M1-M2 (0.857), M2-X1 (0.830), X1-X2 (0.705), X2-X3 (0.865), and others, are all <0.90. Therefore, all construct pairs meet discriminant validity criteria based on HTMT.

Structural Model Assessment

Coefficient of Determination (R²)

Table 10. R² Results

R Square		
	R-square	R-square adjusted
Y1.	0.702	0.688

Coefficient of determination testing results show construct Y1 has an R-square value of 0.702 and adjusted R-square of 0.688. This value indicates that 70.2% of variation in Y1 can be explained by its influencing constructs, while the remainder is explained by factors outside the model.

Predictive Relevance (Q²)

Table 11. Q² Results

	Q ² predict	RMSE	MAE
Y1.	0.634	0.612	0.446

Predictive relevance test (Q²) results show construct Y1 has a Q² value of 0.634, above 0.00. This value indicates the model has strong predictive relevance. Supporting values such as RMSE (0.612) and MAE (0.446) show prediction errors at low levels. Thus, the model has good predictive ability for construct Y1.

Path Coefficient Analysis

Table 12. Path Coefficient Results

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
M1. -> Y1.	-0.021	-0.001	0.097	0.218	0.827
M2. -> Y1.	0.023	0.009	0.077	0.294	0.769
X1. -> Y1.	0.279	0.282	0.091	3.047	0.002
X2. -> Y1.	0.262	0.270	0.084	3.131	0.002
X3. -> Y1.	0.251	0.249	0.089	2.834	0.005
M2. x X3. -> Y1.	0.094	0.102	0.152	0.618	0.537
M2. x X2. -> Y1.	0.091	0.093	0.078	1.161	0.246
M1. x X1. -> Y1.	0.086	0.071	0.081	1.062	0.288
M2. x X1. -> Y1.	-0.370	-0.354	0.129	2.863	0.004

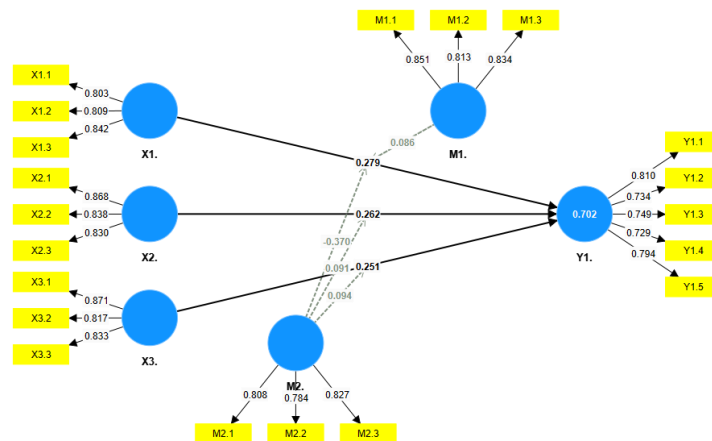


Figure 3. Path Analysis Diagram

H1: Influence of personalization of promotion and communication (X1) on customer loyalty (Y1)

Testing results show that personalization of promotion and communication significantly influences customer loyalty with a p-value of 0.002 (< 0.05). This indicates that better personalization of promotion and communication leads to higher customer loyalty levels. Retailer offers (Indomaret or Alfamart) focusing on individual customer needs can build long-term mutually beneficial relationships. Implementation of personalization strategies in Taiwan's business sector demonstrates that responsive customer service and tailored offers significantly increase customer satisfaction and loyalty (Fei dkk., 2025).

H2: Influence of data-based segmentation and targeting (X2) on customer loyalty (Y1)

Analysis results show that data-based segmentation and targeting have significant influence on customer loyalty with p-value 0.002 (< 0.05). These findings indicate that using data for segmentation can substantially increase customer loyalty levels. Understanding different customer group characteristics and behaviors enhances more effective marketing strategies. Successful Customer Segmentation effectively groups customers into homogeneous clusters, reflecting different purchasing patterns. This supports identification of customer groups such as loyal, passive, and potential customers (Berndt & Tierney, 2026).

H3: Influence of digital channel utilization (X3) on customer loyalty (Y1)

Research results show that digital channel utilization significantly influences customer loyalty, evidenced by p-value 0.005 (< 0.05). This means more optimal digital channel utilization increases customer loyalty. Literature synthesis by Ngo dkk. (2025) shows that social media helps increase Purchase Intention and Consumer Engagement, building customer trust in product purchases. This effort can encourage retailers to integrate digital marketing strategies with customer relationship management and improve service quality to create memorable customer experiences that drive repeat purchases (Chen, 2025).

H4: Moderation of online retail ($M2 \times X3$) on the relationship between digital channel utilization (X3) $\rightarrow$ customer loyalty (Y1)

Results show that online retail moderation does not significantly influence with p-value 0.537 (> 0.05). This means online retail cannot strengthen the relationship between digital channel utilization and customer loyalty. Moderation testing results show that interaction between online retail ($M2$) and digital channel utilization ($X3$) does not significantly influence customer loyalty ($Y1$), with p-value of 0.537 above the significance threshold of 0.05. These findings indicate that online retail does not have meaningful moderating role in strengthening or weakening the relationship between digital channel utilization and customer loyalty. Thus, high online retail activity does not necessarily enhance the positive impact of digital channel utilization on customer loyalty.

This condition may be caused by several factors. First, customers may already consider digital channels as primary means for brand interaction and transactions, regardless of whether transactions occur online or through specific online retail channels. Second, customer loyalty appears more influenced by consistent digital experience, service convenience, and interaction quality obtained rather than the existence or intensity of online retail usage. These findings also indicate that customer loyalty enhancement strategies through digital channels should not depend on strengthening online retail aspects. This means that even if companies expand their presence on various online retail platforms, this may not directly impact customer loyalty improvement if not accompanied by enhanced digital experience quality and customer satisfaction. These results can provide important input for management in directing more effective digital marketing strategies focused on customer experience management rather than merely expanding online sales channels.

H5: Moderation of online retail ($M2 \times X2$) on the relationship between data-based segmentation and targeting ($X2$) $\rightarrow$ customer loyalty (Y1)

Analysis results show that online retail moderation does not significantly influence with p-value 0.246 (> 0.05). Therefore, online retail presence does not strengthen the influence of data-based segmentation on customer loyalty. These findings indicate that the effectiveness of data-based segmentation and targeting strategies in building customer loyalty operates independently, unaffected by online retail intensity. Other research also shows that factors such as personalized customer experience, attractive loyalty programs, and interaction quality play more significant roles in building customer loyalty than merely multiplying online retail channels. When customers feel relevant and valued through targeted offers, loyalty can grow naturally without excessive dependence on online retail presence as intermediary. Practical implications of these findings suggest companies should focus on continuously improving data-based segmentation and targeting quality, and strengthening individual customer experience, rather than relying solely on online sales channel expansion. Data-based recommendations, personal communication, and adaptive service become key factors for creating sustainable customer loyalty in the digital business era.

H6: Moderation of online retail ($M2 \times X1$) on the relationship between personalization of promotion and communication ($X1$) $\rightarrow$ customer loyalty ($Y1$)

Research results show that interaction between online retail and personalization of promotion & communication has p-value 0.004 (< 0.05), but the coefficient is negative (-0.370). This means that although significant, the influence direction weakens the relationship between personalization and customer loyalty—thus rejecting the hypothesis expecting positive influence. This research shows that when personalization is overly associated with online retail channel intensity, the impact can be counterproductive—some customers may feel interactions are too massive, invasive, or even violate their privacy. Factors such as privacy perception, excessive promotion frequency, and communication approaches appearing generic due to automation on online platforms can cause loyalty decline, as customers feel overloaded with messages and offers that are no longer authentically personal. These findings serve as a reminder for company management that successful personalized promotion based on online channels requires balance between relevance, frequency, and interaction authenticity—not merely increasing promotion intensity through digital retail. Practically, digital marketing strategies in the omnichannel era should not only focus on expanding communication and promotion channels, but also on designing more empathetic and private customer experiences. Companies should restructure personalization frequency and methods to prioritize comfort, privacy, and customer trust, so that built loyalty results from truly personal and meaningful relationships, not from mass communication repression that can weaken customer attachment.

H7: Moderation of conventional retail ($M1 \times X1$) on the relationship between personalization of promotion & communication $\rightarrow$ customer loyalty

Results show that conventional retail moderation does not significantly influence this relationship, with p-value 0.288 (> 0.05). Thus, conventional retail does not strengthen the relationship between personalization of promotion and customer loyalty. Customer loyalty in conventional retail tends to be more influenced by service quality, store atmosphere, and product quality rather than the personalization of promotions commonly applied on digital channels. In physical store contexts, emotional relationships formed between customers and staff, along with direct shopping comfort, often become primary loyalty factors, rather than personalized promotion and communication messages. Personalized promotion strategies may not significantly impact because physical store customer preferences are more based on actual in-store experiences than data-based promotions. Service quality, transaction reliability, and physical store image play more direct roles in building loyalty than personalization approaches used in online retail. Implications of these results suggest companies should understand that customer loyalty enhancement strategies in conventional retail should focus on service and shopping experience aspects, not merely on intensifying personal promotions. In other words, effective personalization for conventional retail customers remains important, but may not be the primary loyalty-strengthening factor unless combined with superior service and store atmosphere.

H8: Influence of data-driven marketing on customer loyalty

Overall, data-driven marketing components ($X1, X2, X3$) significantly influence customer loyalty as all three have p-values 0.002, 0.002, and 0.005, all < 0.05 . Thus, the hypothesis that data-driven marketing significantly influences customer loyalty is accepted. Digital services play important roles in enhancing customer loyalty (Santoso et al., 2025); 90% of respondents acknowledged receiving product recommendations based on their purchase history, ultimately increasing comfort and satisfaction. Product recommendations based on interests and promotions based on shopping habits are considered forms of platform attention toward customers to create emotional customer attachment to the platform. Proper and intelligent social media usage, relevant and attractive content creation, customer experience personalization, and good customer data utilization can all contribute to building strong relationships between retail companies and their customers.

2. CONCLUSION

This research provides comprehensive insights into data-driven marketing strategies in both conventional and online retail contexts and their impact on customer loyalty. The findings reveal that core components of data-driven marketing personalization of promotion and communication, data-

based segmentation and targeting, and digital channel utilization—significantly and positively influence customer loyalty. However, the moderating role of retail type shows unexpected results, with most interactions being non-significant except for the negative moderation effect of online retail on personalization strategies.

The study demonstrates that personalization of promotion and communication significantly enhances customer loyalty ($\beta=0.279$, $p=0.002$), indicating that tailored marketing messages aligned with individual customer needs and preferences effectively build stronger customer relationships. Similarly, data-based segmentation and targeting significantly contributes to loyalty development ($\beta=0.262$, $p=0.002$), showing that understanding customer segments through data analytics enables more relevant and effective marketing approaches. Digital channel utilization also shows significant positive impact ($\beta=0.251$, $p=0.005$), confirming that leveraging digital platforms for customer engagement strengthens loyalty bonds.

Contrary to expectations, the moderating effects of retail type reveal important nuances. The negative moderating effect of online retail on personalization strategies ($\beta=-0.370$, $p=0.004$) suggests that excessive personalization in digital environments may trigger privacy concerns and communication fatigue among customers. This finding challenges conventional wisdom about digital marketing and highlights the importance of balanced personalization approaches that respect customer boundaries.

The non-significant moderating effects of both conventional and online retail on other relationships indicate that core data-driven marketing components retain their effectiveness regardless of retail format. This suggests that companies should prioritize optimizing fundamental data-driven marketing capabilities rather than focusing excessively on channel-specific strategies.

The model explains 70.2% of loyalty variation, indicating strong explanatory power. These findings have significant practical implications for retail managers: they should invest in building robust data analytics capabilities, focus on meaningful personalization that respects customer privacy, and develop integrated approaches that leverage data insights across all customer touchpoints regardless of channel format.

Future research could explore these relationships in different retail contexts, examine the long-term effects of data-driven marketing strategies, and investigate how emerging technologies like artificial intelligence might enhance or complicate these dynamics. Additionally, research incorporating actual purchase behavior data alongside survey responses could provide more objective validation of these findings.

REFERENCES

- Abid, M. F., Shamim, A., Thaichon, P., Quach, S., & Siddique, J. (2025). Designing an information technology-enabled framework in the retail service ecosystem. *Technological Forecasting and Social Change*, 215, 124078. <https://doi.org/10.1016/j.techfore.2025.124078>
- Berndt, A. D., & Tierney, K. D. (2026). Understanding customer grief in brand relationships. *Journal of Business Research*, 202, 115758. <https://doi.org/10.1016/j.jbusres.2025.115758>
- Blömker, J., & Albrecht, C.-M. (2025). A path from multichannel customer data to real-time personalization: Predicting customers' psychological traits through machine learning. *Journal of Retailing and Consumer Services*, 87, 104349. <https://doi.org/10.1016/j.jretconser.2025.104349>
- Chen, C.-T. (2025). Decoding the environmental information pathway: Wayfinding, crowding, and customer loyalty in transit-oriented shopping malls. *Sustainable Futures*, 10, 101088. <https://doi.org/10.1016/j.sftr.2025.101088>
- Fei, Y.-M., Liou, J.-C., & Sun, P. J. (2025). Evaluating the dual impact of AI and RPA on sustainability and brand equity: A case study of digital transformation in Taiwan's service sector. *Cleaner Engineering and Technology*, 29, 101106. <https://doi.org/10.1016/j.clet.2025.101106>

- Fillmann, J., Völckner, F., Imschloss, M., & Schulz, M. (2025). Transforming trash into treasure: Why consumers like personalized upcycling. *International Journal of Research in Marketing*. <https://doi.org/10.1016/j.ijresmar.2025.09.005>
- Gazi, Md. A. I., Mamun, A. A., Masud, A. A., Senathirajah, A. R. bin S., & Rahman, T. (2024). The relationship between CRM, knowledge management, organization commitment, customer profitability and customer loyalty in telecommunication industry: The mediating role of customer satisfaction and the moderating role of brand image. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(1), 100227. <https://doi.org/10.1016/j.joitmc.2024.100227>
- Hosseini Dehshiri, S. J. (2025). Big data adoption in smart renewable energy networks toward sustainability through decision-making methods under uncertainty. *Results in Engineering*, 28, 107887. <https://doi.org/10.1016/j.rineng.2025.107887>
- Khan, Md. R., & Sarkar, U. (2024). Business leadership in the digital age: IKEA's story in the retail and consumer sector. *Green Technologies and Sustainability*, 2(2), 100081. <https://doi.org/10.1016/j.grets.2024.100081>
- Kumar, M., Raj, H., Chaurasia, N., & Gill, S. S. (2023). Blockchain inspired secure and reliable data exchange architecture for cyber-physical healthcare system 4.0. *Internet of Things and Cyber-Physical Systems*, 3, 309–322. <https://doi.org/10.1016/j.iotcps.2023.05.006>
- Mu, T. tian, Shan, Q., Zhu, G., Xu, Y., Agag, G., & Alipour, O. (2026). Beyond technology: The dual role of AI and narratives in driving ESG performance in China's retail industry. *Journal of Retailing and Consumer Services*, 90, 104675. <https://doi.org/10.1016/j.jretconser.2025.104675>
- Nakano, S. (2023). Customer demand concentration in online grocery retailing: Differences between online and physical store shopping baskets. *Electronic Commerce Research and Applications*, 62, 101336. <https://doi.org/10.1016/j.elerap.2023.101336>
- Ngo, T. T. A., An, G. K., Dao, D. K., Nguyen, N. Q. N., Phong, B. H., Nguyen, N. Y. V., & Nguyen, T. B. N. (2025). Leveraging social media marketing activities (SMMAs) to enhance consumer satisfaction and purchase intention for bio-cosmetics. *Acta Psychologica*, 261, 105768. <https://doi.org/10.1016/j.actpsy.2025.105768>
- Park, S. Y., Yourell, J., McAlister, K. L., & Huberty, J. (2023). Exploring Generation Z and Young Millennials' Perspectives of a Spiritual Self-Care App and Their Spiritual Identity (Skylight): Qualitative Semistructured Interview Study. *JMIR Formative Research*, 7. <https://doi.org/10.2196/54284>
- Shou, X., Shi, Q., & Zhang, X. (2024). The adaptation and transformation of Yiwu's foreign trade enterprises amid major changes unseen in a century (2001–2021). *Transnational Corporations Review*, 16(4), 200080. <https://doi.org/10.1016/j.tncr.2024.200080>
- Tran, M. T. (2026). Advancing retail and service strategies: AI-driven consumer behavior prediction, gamification, and ethical marketing. *Journal of Retailing and Consumer Services*, 88, 104558. <https://doi.org/10.1016/j.jretconser.2025.104558>