Proceeding of International Conference on Business Management and Accounting (ICOBIMA)
Volume 4, No. 1, November 2025, page 41-52
Online ISSN: 2988-5590 | Print ISSN: 3021-7563

Beyond The Algorithm: The Mediating Role of Perceived Value in Driving Customer Loyalty

Julina Julina [1*], Nurlasera Nurlasera [2], Desrir Miftah [3], Qonitah Rifda Zahirah [4]

[1,2,3] Universitas Islam Negeri Sultan Syarif Kasim Riau, Indonesia

[4] Universitas Islam Negeri Sunan Kalijaga Yogyakarta, Indonesia

Email: julina@uin-suska.ac.id [1], nurlasera@uin-suska.ac.id [2], desrir.miftah@uin-suska.ac.id [3], 24208012001@student.uin-suka.ac.id [4]

*Corresponding Author

ABSTRACT

In the era of rapid digital commerce, understanding the factors that drive customer loyalty in online shopping is crucial for retailers seeking to maintain a competitive advantage. This study examines the impact of Product Recommendation Relevance, Content and Promotion Personalization, and Adaptive Navigation Ease on Perceived Value and Customer Loyalty, considering both direct and indirect effects through perceived value. Data from 162 respondents were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that Product Recommendation Relevance significantly influences Perceived Value and has a significant indirect effect on loyalty, though its direct effect on loyalty is not significant. In contrast, Content and Promotion Personalization does not significantly affect either perceived value or loyalty, directly or indirectly. Adaptive Navigation Ease has a significant positive effect on both Perceived Value and Customer Loyalty, and also exhibits a significant indirect effect on loyalty through perceived value. Moreover, Perceived Value plays a strong mediating role, significantly influencing customer loyalty. These findings highlight that improving navigation ease and delivering relevant product recommendations are key strategies to enhance perceived value and foster customer loyalty. From a managerial perspective, online retailers should prioritize optimizing website or app navigation and curating product recommendations, while personalization efforts should be carefully aligned with consumer preferences to effectively impact loyalty.

Keywords: Adaptive Navigation Ease; Content and Promotion Personalization; Customer Loyalty; Perceived Value; Product Recommendation Relevance

DOI: https://doi.org/10.35145/icobima.v4i1.5300

SDGs: Decent Work and Economic Growth (8); Industry, Innovation, and Infrastructure (9); Responsible Consumption and Production (12); Peace, Justice, and Strong Institutions (16)

INTRODUCTION

Digital and e-commerce platforms are increasingly relying on algorithm-based mechanisms to improve the customer experience. The product recommendation system suggests items based on user behavior, content personalization tailors offer to preferences, and adaptive navigation ensures a seamless user journey. A 2018 study by Barilliance revealed that product recommendations contributed to as much as 31% of total e-commerce revenue, with 12% of purchases on average coming from recommended items. Similarly, Salesforce found that while only 7% of site traffic involves clicks on recommendations, those clicks generate 24% of total orders and 26% of revenue. In fact, shoppers who engage with product recommendations convert at a rate 5.5 times higher than those who don't. As consumers increasingly expect personalized experiences, personalization is now seen as a sign of professionalism in online retail. Supporting this, an Accenture report highlighted that personalization raises the likelihood of a purchase by 75% (MacDonald, 2025). Awad & Krishnan (2006) examined the relationship between information transparency features on online websites/services and consumers' willingness to be profiled for personalization. Based on a survey of >400 online consumers, they found a paradox: consumers who value information transparency the most tend to be the most reluctant to be profiled. These results have strategic implications: companies must balance the benefits of personalization with the privacy sensitivities of different consumer segments.

Although these technological innovations attract the attention of customers, they do not automatically guarantee loyalty. Customer loyalty is often influenced by how customers perceive the value of their interactions with the platform. In addition to algorithm performance, the truly perceived benefits, such as convenience,

relevance, time savings, or emotional satisfaction, determine whether customers remain loyal. The right product recommendations can increase conversion rates, extend the duration of shopping sessions, and encourage repeat purchases. A study by MyBuys showed that recommended products in the shopping cart had a 915% higher conversion rate than the overall site average. Additionally, 56% of consumers stated that they are more likely to return to sites that offer relevant product recommendations. This shows that a personalized shopping experience not only increases customer satisfaction but also strengthens an emotional connection with the brand, which in turn increases customer loyalty. Thus, understanding and optimizing the relevance of product recommendations is an important strategy for online retailers in building sustainable customer loyalty (Imran, 2024).

In an increasingly competitive e-commerce industry, content personalization and promotions have become a key strategy to increase customer loyalty. Research shows that 80% of consumers are more likely to make a purchase when a brand offers a personalized experience. Additionally, 62% of consumers are willing to spend more money if their shopping experience is tailored to personal preferences (iagloyalty.com). Personalization allows brands to remember customer preferences, provide relevant product recommendations, and recall previous interactions, all of which contribute to increased loyalty (attentive.com). However, meeting the demands of personalization is not as easy as expected, especially with the recent generational shift. 85% of businesses are adjusting their marketing strategies to accommodate Gen Z's high expectations of digital experience quality and individualization (Keating, 2024). Another thing that's also important to note is that improper or excessive personalization can cause customers to feel annoyed or uncomfortable, potentially damaging relationships and lowering loyalty. Therefore, this study aims to explore how content personalization and promotions can affect customer loyalty in the context of online shopping.

Previous research has highlighted perceived value as a central factor linking digital strategy and loyalty outcomes. Therefore, this study aims to examine the influence of the relevance of product recommendations, content personalization and promotion, and adaptive navigation ease on customer loyalty, with perceived value as a mediating variable.

LITERATURE REVIEW

Customer Loyalty

Customer loyalty refers to the sustained favorable relationship between consumers and a company, reflected in their repeated preference for a particular brand instead of its rivals. This loyalty is shaped by positive experiences, trust, satisfaction, and an emotional attachment to the brand. Customers who are loyal typically repurchase, support the brand in competitive situations, interact across multiple channels, and frequently recommend it to others. Many empirical studies have identified factors that influence loyalty, including customer satisfaction, trust, perceived value, product/service quality, brand image & brand equity, loyalty programs & incentives, switching costs & barriers, personal & situational factors. This research will test some of these factors, namely product recommendation relevance, content and promotion personalization, adaptive navigation ease, and perceived value.

Product Recommendation Relevance

Product recommendation relevance refers to how well product suggestions align with a user's preferences, behaviors, and needs, thereby increasing the likelihood of a purchase. It involves displaying the items that a user is most likely interested in, which enhances user experience, boosts conversion rates, increases average order value, and fosters customer loyalty. An e-commerce product recommendation engine is a technology designed to suggest relevant products to shoppers as they browse an online store. Powered by machine learning, it continually improves its accuracy by analyzing customer interests and past browsing behavior. Although basic customers also liked the suggestion that can be added manually, best practices in e-commerce emphasize the use of a dedicated recommendation engine. The needs and preferences of the audience can be effectively accommodated through the provision of appropriate product recommendations. The primary task is to identify the type of recommendations most suitable and to determine the points within the customer journey at which they should be integrated. Research by Oestreicher-Singer & Sundararajan (2012) indicates that explicitly displaying copurchase relationships can, on average, amplify the influence of complementary products on one another’s demand by as much as threefold. Moreover, newer and more popular products appear to leverage the attention generated by their network position more effectively, while greater diversity in spillover sources further strengthens the demand impact of the recommendation network. Another previous study provides fresh empirical evidence on the significance of network position in electronic markets and underscores the advantages of aligning (virtual) shelf placement with consumer preferences revealed through shared purchasing behavior. This study investigated how norm-based versus comparison-based recommendation framings influence consumers’ intention to click on products

suggested by online retailers. Across four empirical studies, the hypotheses were tested, and the results showed that norm-based framing outperformed comparison-based framing. The findings further suggest that perceived recommendation value serves as the mediating mechanism driving this effect. Additionally, the advantage of norm-based framing was evident only when a limited number of products were recommended and when those products were highly substitutable for the focal item (Zhang et al, 2022). Based on the discussion, the hypothesis in this study is as follows:

H1a: The relevance of product recommendations has a positive effect on perceived value.

H1b: The relevance of product recommendations has a positive effect on customer loyalty.

Content and Promotion Personalization

Personalization is a marketing strategy that tailors content, offers, and promotions based on customer preferences, behaviors, and personal data. The theoretical basis includes the Personalization–Privacy Paradox (Awad & Krishnan, 2006). According to this theory, customers love personalization because it increases relevance, but at the same time, they are concerned about privacy. The more relevant a message or content is, the higher the consumer attention and engagement. According to the Stimulus–Organism–Response (SOR) Model, personalized content and promotions act as stimuli that influence the perception and emotions of consumers (organisms) and ultimately generate responses in the form of satisfaction, repurchase intent, and loyalty. Other theories, such as Relationship Marketing Theory, state that personalization strengthens the emotional and relational relationship between the company and the consumer, which is the basis of loyalty. Personalized content (e.g., product recommendations based on interests) makes consumers feel the product is more relevant, resulting in increased functional value. Personalized promotions (e.g., special discounts or exclusive offers) increase economic value because consumers feel they have a greater financial benefit. From the perspective of Equity Theory, consumers will judge whether the treatment received is fair and beneficial. Personalization increases the perception that they are receiving special treatment, so that the perceived value increases.

Preferential content and promotions create an emotional bond, thereby increasing *attitudinal loyalty*. Personalization makes it more difficult for consumers to move to competitors because they feel that the experience at the brand is unique. Relevant and consistent experiences build trust, satisfaction, and ultimately *behavioral loyalty* (repeat purchase). Furthermore, loyal customers who are satisfied with personalization often become brand advocates, recommending to others. Based on the discussion, the hypothesis in this study is as follows:

H2a: Personalized content and promotions have a positive effect on perceived value.

H2b: Personalized content and promotions have a positive effect on customer loyalty.

Adaptive Navigation Ease

In the competitive digital era, the *ease of use* of an e-commerce platform has become a determining factor for success. Traditional concepts such as *usability* and *navigation* are now evolving with the presence of personalization technology. Adaptive Navigation Ease (ANE) emerged as a development of this concept. ANE refers to the ability of a system (such as a website or application) to dynamically adjust its structure, layout, and navigation recommendations based on specific user behaviors, history, preferences, and contexts (Zhou, 2021). It is no longer static and equal navigation for everyone, but "smart" and adaptable navigation, which aims to make it easier and faster for users to find the desired product or information. Although the term "adaptive navigation ease" is not used explicitly in all studies, related concepts such as ease of navigation, perceived ease of use, and usability are often discussed and can provide useful insights. The studies show that ease of navigation and user perception of ease of use have a positive impact on customer satisfaction, which in turn affects customer loyalty.

Adaptive Navigation Ease can be seen as a combination of ease of navigation and adaptive capabilities. Navigation Ease is the extent to which users can move from one part of a system to another without excessive cognitive effort. This includes menu clarity, layout consistency, and efficiency in finding goals. Adaptive Capability is features such as saved search history, recommendations of products that may be preferred, intelligent filtering, and interfaces that change based on user habits (e.g., displaying favorite categories on the main page). ANE effectively reduces non-monetary costs incurred by customers, such as time and effort, which is a key component of Perceived Value theory. Adaptive Navigation Ease is a modern and superior manifestation of Perceived Ease of Use. When a site is easy to navigate and personally understands the needs of the user, the perceived ease of use will increase significantly, ultimately driving continued acceptance and use. State flow is a psychological state in which a person is completely immersed and enjoying an activity. Complicated navigation can disrupt flow. Instead, Adaptive Navigation Ease facilitates flow by removing barriers, making the search and

search process smooth and enjoyable. This flow experience is strongly related to increased Perceived Value and intention to return (Loyalty). Based on the discussion, the hypothesis in this study is as follows:

H3a: The ease of adaptive navigation has a positive effect on perceived value.

H3b: The ease of adaptive navigation has a positive effect on perceived value.

Perceived Value

Perceived value acts as a mediator by personalizing and increasing perceived value, and it is this value that drives loyalty. Research by Eggert & Ulaga (2002) in the context of B2B shows that perceived value is a more direct and stronger antecedent to repurchase intent compared to satisfaction. Consumers who feel they get high value from a transaction will tend to feel satisfied, and this satisfaction becomes a stepping stone to loyalty. Customers who are loyal because of perceived value (not just because of low prices) show lower price sensitivity. They understand and appreciate the "value for money" they receive, so they are more tolerant of price increases as long as the core value they get is maintained. Research by Tsiotsou (2006) on the service industry shows that perceived value significantly moderates the relationship between service quality and loyalty. Based on the discussion, the hypothesis in this study is as follows:

H4: Perceived value has a positive effect on customer loyalty.

H5a–c: Perceived value mediates the relationship between the relevance of product recommendations, personalized content and promotions, and the ease of adaptive navigation on customer loyalty.

Based on the previous discussion, this study builds a research model as shown in Figure 1.

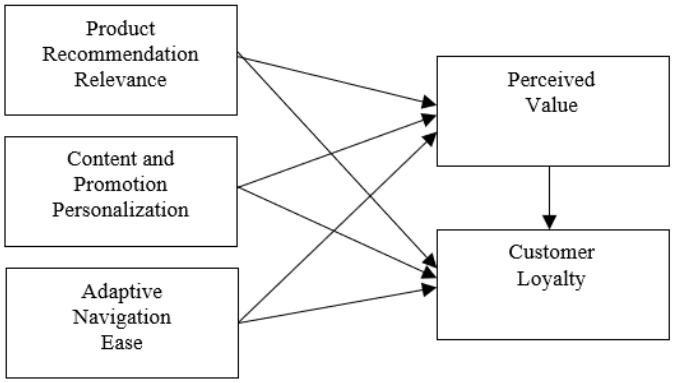

Figure 1. Proposed Model

METHOD

Data collection in this study was carried out by distributing questionnaires online using a digital survey platform. The *purposive sampling* technique is applied with certain criteria to ensure that respondents are a representation of the target population. A total of 150 respondents who met the criteria participated and provided complete responses, so that all data could be used for further analysis. The data from the questionnaire were then processed and analyzed using *Structural Equation Modeling* (SEM) with the help of SmartPLS 3 software. The selection of SmartPLS was considered appropriate because of its ability to build and test complex models, as well as its robustness in handling small sample sizes and data that is not always normally distributed. Data analysis is carried out in two main stages: first, evaluating *the outer model* (measurement model) to ensure the validity and reliability of the indicator in constructing variables; and second, testing *the inner model* (structural model) to evaluate the causal relationship between latent variables and their statistical significance through *the bootstrapping* procedure.

RESULT

Respondent Identities

The characteristics of the respondents in this study are as follows. Based on gender, the majority were female, with 117 respondents (72.2%), while male respondents numbered 45 (27.8%), out of a total of 162 participants. In terms of age distribution, most respondents were 20 years old, accounting for 88 individuals (54.3%). This was followed by 41 respondents (25.3%) aged 21, 24 respondents (14.8%) aged 19, 6 respondents (3.7%) aged 22, and only 3 respondents (1.9%) aged 18. Regarding monthly income, the largest proportion of respondents, 100 individuals (61.7%), reported earning less than IDR 1,000,000. Meanwhile, 59 respondents (36.4%) earned between IDR 1,000,000 and 3,000,000, and only 3 respondents (1.9%) had an income above IDR 3,000,000. When viewed from the perspective of online shopping platforms, the vast majority of respondents (154 individuals or 95.1%) used Shopee. Tokopedia was used by 6 respondents (3.7%), while only 2 respondents (1.2%) reported using Lazada.

Table 1. Descriptive Analysis of Respondents

Characteristics	Number of respondents	%
Gender		
Male	45	27,8
Female	117	72,2
Total	162	100
Age Range		
18	3	1,9
19	24	14,8
20	88	54,3
21	41	25,3
22	6	3,7
Total	162	100
Revenue Per Month		
< IDR 1,000,000	100	61,7
IDR 1,000,000 – 3,000,000	59	36,4
> IDR 3,000,000	3	1,9
Total	162	100
Platform for Online Shop		
Loop	2	1,2
Shopee	154	95,1
Tokopedia	6	3,7
Total	162	100

Source: Data processed (2025)

The descriptive statistical analysis of the research variables in Table 2 indicates varying perceptions among respondents. For Product Recommendation Relevance, the mean scores ranged from 3.704 to 3.920, suggesting that respondents generally perceived product recommendations as moderately relevant. The highest perception was observed for RRP2 (M = 3.920, SD = 0.929), while the lowest was for RRP1 (M = 3.704, SD = 0.981). In terms of Content and Promotion Personalization, the mean values ranged from 3.062 to 3.728. Items PKP1 (M = 3.062, SD = 0.986) and PKP2 (M = 3.105, SD = 0.953) recorded the lowest mean scores across all variables, indicating that respondents perceived a relatively weaker personalization in content and promotions. In contrast, PKP3 (M = 3.728, SD = 0.956) and PKP4 (M = 3.617, SD = 0.937) were rated higher, suggesting a more favorable perception of personalized promotional efforts. For Adaptive Navigation Ease, the means ranged from 3.562 to 3.784, reflecting that respondents found online platforms to be moderately easy to navigate. KNA3 (M = 3.784, SD = 0.901) obtained the highest mean, while KNA2 (M = 3.562, SD = 0.846) was rated the lowest. Overall, the relatively small variation in mean scores shows that navigation ease was consistently perceived at a moderate-to-high level. Regarding Perceived Value, the mean scores were between 3.512 and 3.889. Item I1 (M = 3.889, SD = 0.956) was rated the highest, indicating that respondents recognized significant value in their online shopping experience. Conversely, I3 (M = 3.512, SD = 0.925) was rated the lowest, suggesting some reservations in certain aspects of perceived value. Finally, for Customer Loyalty, the mean values ranged from 3.358 to 3.877. The highest score was for LP2 (M = 3.877, SD = 0.915), implying relatively strong intentions to repurchase or

remain loyal. However, LP3 (M = 3.358, SD = 1.046) had the lowest mean across all items, indicating that loyalty-related behaviors such as recommending to others may not be as strong as direct repurchase intentions.

Table 2. Descriptive Statistic

Variable	Item	Mean	Standard Deviation
Product Recommendation Relevance	RRP1	3.704	0.981
	RRP2	3.920	0.929
	RRP3	3.735	0.941
	RRP4	3.840	0.981
Content and Promotion Personalization	PKP1	3.062	0.986
	PKP2	3.105	0.953
	PKP3	3.728	0.956
	PKP4	3.617	0.937
Adaptive Navigation Ease	KNA1	3.605	0.819
	KNA2	3.562	0.846
	KNA3	3.784	0.901
	KNA4	3.716	0.864
Perceived Value	I1	3.889	0.956
	I2	3.722	0.848
	I3	3.512	0.925
	I4	3.636	0.967
Customer Loyalty	LP1	3.778	0.949
	LP2	3.877	0.915
	LP3	3.358	1.046
	LP4	3.821	0.936

Source: Data processed (2025)

Measurement Test (Outer Model)

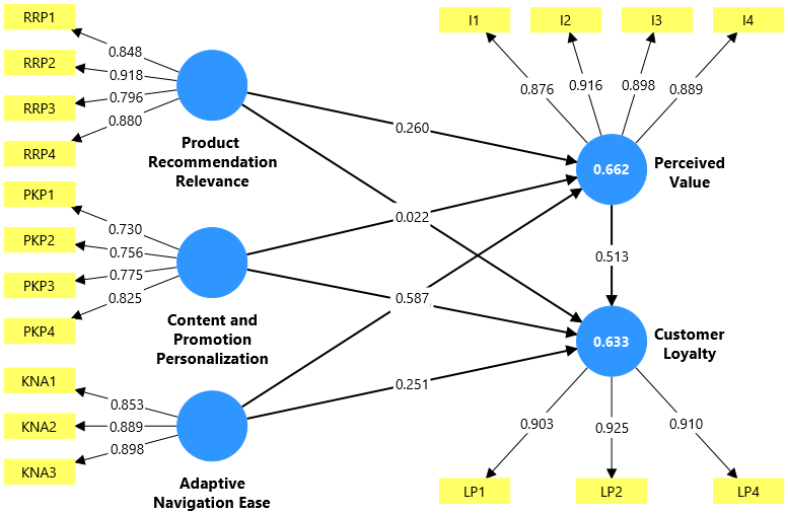

Figure 2. PLS-SEM Results

Convergent Validity Test

The validity of the convergence can be measured by checking the Loading factor value and the Average Variance Extracted (AVE) value. The indicator is considered valid if the loading factor value is greater than 0.7 in a confirmatory study, while for explanatory studies, a loading factor value between 0.6 to 0.7 is considered good (Ghozali & Latan, 2012). Then, to ensure that the Average Variance Extracted (AVE) value test has been met, a value above 0.5 is required.

Table 3. Average Variance Extracted

Variable	Average variance extracted (AVE)
Adaptive Navigation Ease (and)	0.775
Content and Promotion Personalization (CPP)	0.596
Customer Loyalty (CL)	0.834
Perceived Value (PV)	0.801
Product Recommendation Relevance (PRR)	0.742

Source: Data processed (2025)

Discriminant Validity Test

The validity of the discriminant can be assessed through two methods, namely by using the Cross Loading value and the Heterotrait-Monotrait ratio (HTMT) (Henseler et al., 2015). An indicator is considered discriminatively valid if its cross-loading value is higher than the construct that should reflect it compared to other constructs (Henseler et al., 2015).

Table 4. Heterotrait-Monotrait (HTMT)

	ANE	CPP	CL	PV	PRR
ANE					
CPP	0.895				
CL	0.810	0.625			
PV	0.886	0.715	0.849		
PRR	0.842	0.749	0.711	0.777	

Source: Data processed (2025)

Table 4 illustrates the average correlation rate between indicators in each latent variable. The limit of the average value of Heterotrait-Monotrait (HTMT) is 0.9, which means that the difference between the indicators in each variable can be identified when the value is below 0.9 (Henseler et al., 2015). In the context of this study, the HTMT ratio value obtained showed a number below 0.9. Therefore, it can be concluded that the model in this study meets the discriminant validity.

Reliability Test

Evaluation of variable reliability using reflective indicators can be carried out by two methods, namely through Composite Reliability (CR) and Cronbach's Alpha (CA) values (Hair et al., 2014). A variable is considered to have adequate reliability if its composite reliability value and Cronbach's Alpha exceed 0.7, although a value of 0.60 is still acceptable (Ghozali & Latan, 2012).

Table 5. Composite Reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
Adaptive Navigation Ease	0.855	0.870	0.912
Content and Promotion Personalization	0.777	0.789	0.855
Customer Loyalty	0.900	0.901	0.938
Perceived Value	0.917	0.918	0.941
Product Recommendation Relevance	0.884	0.896	0.920

Source: Data processed (2025)

Structural Test (Inner Model)

The structural model (Inner Model) is an overview of the cause-and-effect relationship or the estimation of strength between latent variables. Inner Model testing is carried out to ensure that the structural model that has been built has adequate stability and accuracy. This study evaluates it by assessing the path coefficient and evaluating the R-squared value.

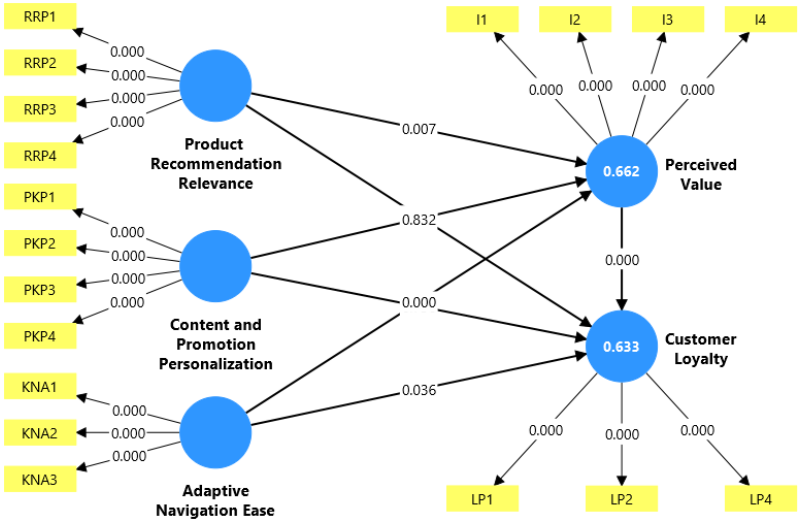

Figure 3. Bootstrapping

Table 6. R Square

	R-square	R-square adjusted
Customer_Loyalty (Y)	0.633	0.623
Perceived_Value (I)	0.662	0.656

Source: Data processed (2025)

The coefficient of determination (R^2) was used to assess the explanatory power of the structural model. The results indicate that Perceived Value (I) has an R^2 of 0.662, with an adjusted R^2 of 0.656, suggesting that approximately 66% of the variance in perceived value is explained by the predictors in the model (Product Recommendation Relevance, Content and Promotion Personalization, and Adaptive Navigation Ease). For Customer Loyalty (Y), the R^2 is 0.633 and the adjusted R^2 is 0.623, indicating that around 63% of the variance in customer loyalty is accounted for by the model, which includes Product Recommendation Relevance, Content and Promotion Personalization, Adaptive Navigation Ease, and Perceived Value as predictors. These values suggest that the model has a substantial explanatory power, with the majority of variance in both perceived value and customer loyalty being explained by the included constructs.

Table 7. Direct Effect

		Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
H1a	Product Recommendation Relevance -> Perceived Value	0.260	0.250	0.096	2.693	0.007
H1b	Product Recommendation Relevance -> Customer Loyalty	0.115	0.114	0.084	1.379	0.168
H2a	Content and Promotion Personalization -> Perceived Value	0.022	0.033	0.104	0.212	0.832
H2b	Content and Promotion Personalization -> Customer Loyalty	-0.033	-0.030	0.096	0.338	0.736
H3a	Adaptive Navigation Ease -> Perceived Value	0.587	0.589	0.075	7.778	0.000
H3b	Adaptive Navigation Ease -> Customer Loyalty	0.251	0.260	0.119	2.100	0.036
H4	Perceived Value -> Customer Loyalty	0.513	0.502	0.109	4.693	0.000

Source: Data processed (2025)

First, Product Recommendation Relevance demonstrated a significant positive effect on Perceived Value (O = 0.260, T = 2.693, p = 0.007). However, its direct effect on Customer Loyalty was positive but not statistically significant (O = 0.115, T = 1.379, p = 0.168). This indicates that relevant product recommendations improve consumers' perception of value but do not directly lead to stronger loyalty. The results of Nanda et al's (2024) research show that the automated product recommendation system developed for e-commerce websites significantly helps users improve their online shopping experience. The use of Lift Ratio parameters in validating association rules provides strong evidence of the relevance and accuracy of the resulting product recommendations, which can improve customer satisfaction and sales potential. Another study was conducted by Wattimena & Rofi'i (2023), where the results showed that the combined approach of CBR and K-Means Clustering can improve the performance of e-commerce product recommendations, ensure the accuracy of recommendations, and produce a more satisfying shopping experience for users. Nguyen (2021) stated that the online product recommendation system offered by E-commerce websites is essential in providing real-time product recommendations based on past customer behavior and references, having a significant impact on increasing buyer satisfaction, increasing website revenue through up-selling or cross-selling, and building long-term relationships between websites and customers. The research model developed found that customer loyalty is significantly influenced by the quality of decision-making, while the quality of decision-making is influenced by the relevance of content and clarity (consumers' awareness of the many representations of how recommended information is presented to them).

Second, Content and Promotion Personalization did not significantly influence either Perceived Value (O = 0.022, T = 0.212, p = 0.832) or Customer Loyalty (O = –0.033, T = 0.338, p = 0.736). These results suggest that personalization efforts in content and promotions were not perceived as meaningful drivers of value creation or loyalty among respondents. According to research by Bleier & Eisenbeiss (2015), personalization increases click-throughs, especially in the early stages of the purchase decision-making process. Here, banners with a high level of content personalization are most effective when consumers have just visited the advertiser's online store. Furthermore, Zhang & Wedel (2009) investigated the effectiveness of customized promotions at three levels of rigor (mass market, segment-specific, and individual-only) in online and offline stores. They found that (1) the optimization procedure resulted in a substantial increase in profits compared to current practice for all types of promotions (adjusted and undifferentiated); (2) Loyalty promotion is more profitable in online stores than in offline stores, while the opposite is true for competitive promotions. Ball et al (2006) wanted to determine whether, and how, personalization can add to the power of explanation. They tested two models, namely the basic model (from Ball et al, 2004) and the model with added personalization variables. The results are clear that the addition of personalization adds power when it comes to explaining satisfaction, loyalty, and trust, the most important variables for a marketer. Service personalization is an important antecedent of loyalty, satisfaction, and trust. These effects have long been assumed, but now have some empirical support. Personalized relationships, built on communication, are more trusting and more satisfying – in short, closer, and more likely to last. Personalization adds psychological comfort to relationships and increases psychological barriers to transition. AI-based personalization significantly increases satisfaction and affective loyalty, but the impact on contextual/complex behavioral loyalty depends on the situation (Zed et al, 2024). The results of Jimi's (2025) research found that ease of navigation has an indirect effect on consumer loyalty.

Third, Adaptive Navigation Ease showed strong and significant effects on both outcome variables. It had a substantial positive influence on Perceived Value (O = 0.587, T = 7.778, p = 0.000) and a significant direct effect on Customer Loyalty (O = 0.251, T = 2.100, p = 0.036). This implies that easier navigation not only enhances the perceived value of the online shopping experience but also contributes directly to customer loyalty. The influence of Adaptive Navigation Ease (ANE) on customer loyalty and perceived value is quite significant in the context of digital services and applications. Adaptive navigation improves the user experience by making interactions more intuitive, fast, and convenient, so that users feel more satisfied and the perceived value of the service increases. When users easily find what they're looking for and perform tasks seamlessly, they tend to show higher loyalty to the product or service. Customer loyalty is formed because the ease of navigation increases user satisfaction and trust, which ultimately affects their intention to continue using the service or recommend it to others. In summary, Adaptive Navigation Ease plays an important role in increasing perceived value by facilitating access and use of services, and driving customer loyalty through increased user satisfaction and repeated positive experiences. Furthermore, according to Wilson et al (2021), both customer satisfaction and trust were found to positively mediate the impact of perceived usability and perceived ease of use on customer loyalty; Trust serves as a better mediator as compared to satisfaction. The results of the study of Esmeli et al (2025) show that the integration of e-loyalty-related features significantly improves the performance of the recommendation system, with neural networks in sequence outperforming other algorithms. Their research contributes to the literature by highlighting the importance of utilizing customer loyalty data to improve the accuracy of recommendations. Its

theoretical implications include emphasizing the importance of using longitudinal user engagement data in recommendation systems to move from static personalization to behaviorally sensitive adaptive technologies. From a practical perspective, our findings suggest that the integration of e-loyalty features can improve recommendation accuracy, offering valuable insights for e-commerce businesses looking to personalize their services.

Finally, Perceived Value itself was found to be a critical determinant of Customer Loyalty, with a strong and significant effect (O = 0.513, T = 4.693, p = 0.000). This highlights that consumers who perceive higher value from their online shopping experiences are more likely to remain loyal. According to Andianto & Firdausy (2020), perceived value has a positive and significant effect on customer loyalty. Customers who feel good value from a product or service—whether in terms of benefits, reasonable prices, or ease of service—are more likely to remain loyal and recommend the product to others.

Table 8. Indirect Effect

		Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
H5a	Product Recommendation Relevance -> Customer Loyalty	0.133	0.127	0.059	2.238	0.025
H5b	Content and Promotion Personalization -> Customer Loyalty	0.011	0.016	0.053	0.214	0.830
H5c	Adaptive Navigation Ease -> Customer Loyalty	0.301	0.294	0.072	4.194	0.000

Source: Data processed (2025)

The analysis of indirect effects on Customer Loyalty through Perceived Value shows the following patterns:

1. Product Recommendation Relevance also shows a significant indirect effect on customer loyalty through Perceived Value. While its direct effect on loyalty is smaller (O = 0.115, T = 1.379, p = 0.168), its significant influence on perceived value (O = 0.260, T = 2.693, p = 0.007) indicates that relevant product recommendations improve loyalty indirectly by increasing perceived value.
2. Content and Promotion Personalization does not exhibit a meaningful indirect effect on customer loyalty. Since its impact on perceived value is not significant (O = 0.022, T = 0.212, p = 0.832), it also fails to generate a significant mediated effect on loyalty.
3. Adaptive Navigation Ease has a significant positive indirect effect on customer loyalty. This is supported by its strong impact on Perceived Value (O = 0.587, T = 7.778, p = 0.000), which in turn significantly influences customer loyalty (O = 0.513, T = 4.693, p = 0.000). This suggests that part of the effect of navigation ease on loyalty operates indirectly by enhancing perceived value.

In summary, Perceived Value acts as an important mediating variable for both Adaptive Navigation Ease and Product Recommendation Relevance, helping to translate these factors into higher customer loyalty, while Content and Promotion Personalization do not contribute significantly either directly or indirectly.

CONCLUSION

Personalized recommendations have changed the way users interact with digital platforms, making the experience more relevant, engaging, and enjoyable. By leveraging advanced data and algorithms, businesses can improve user satisfaction and drive growth. However, it's important to address challenges related to privacy, bias, and data quality to ensure recommendations remain effective and trustworthy. As technology advances, personalized recommendations are likely to increasingly become an integral part of our digital experience, offering solutions tailored to our unique needs and preferences.

Content personalization and promotion synergistically drive richer user experiences and better business outcomes in e-commerce. The cutting-edge system leverages deep learning, semantic frameworks, adaptive ranking models, and hybrid algorithms to provide relevant, diverse, and dynamically designed product recommendations and promotional offers. While challenges such as cold start, scalability, and ethical issues remain, new methods continue to push the boundaries of personalization. Future practical research and

implementation are expected to emphasize more nuanced semantic understanding, user-centric transparency, and multi-modal data integration to further enhance the relevance and effectiveness of personalized content and promotions.

Adaptive Navigation Ease has evolved from just a "nice-to-have" feature to a crucial competitive strategy in e-commerce. Empirical evidence consistently shows that investments in creating smart and adaptive navigation yield significant returns through increased Perceived Value and Customer Loyalty. For practitioners, the main implication is the need to allocate resources to develop sophisticated recommendation systems, personalized search algorithms, and dynamic user interfaces. For researchers, this area is still open to further exploration, for example, regarding the impact of ANE on specific customer segmentation or in the context of non-e-commerce platforms such as financial services or education.

Another important finding is that Perceived Value has a significant direct effect on Customer Loyalty. In other words, perceived value acts as a key mediator in explaining how Adaptive Navigation Ease and Product Recommendation Relevance can enhance customer loyalty. This underscores that customers tend to be more loyal when they perceive high value from an online shopping experience that is easy, efficient, and relevant to their needs. The managerial implication of this study is that online retailers should prioritize improving adaptive navigation ease and delivering relevant product recommendations to foster positive perceived value in the minds of customers. Consequently, customer loyalty can be strengthened not only through direct interactions but also by consistently creating perceived value.

REFERENCES

Andianto, K., & Firdausy, C. M. (2020). The Effect of Perceived Value, Perceived Quality, and Customer Satisfaction on Warunk Upnormal Customer Loyalty in Jakarta. *Journal of Managerial and Entrepreneurship*, *2*(3), 758-764.

Awad, N. F., & Krishnan, M. S. (2006). The personalization privacy paradox: an empirical evaluation of information transparency and the willingness to be profiled online for personalization. *MIS quarterly*, 13-28.

Ball, D., Coelho, P. S., & Vilares, M. J. (2006). Service personalization and loyalty. *Journal of Services Marketing*, *20*(6), 391-403.

Ball, D., Simões Coelho, P., & Machás, A. (2004). The role of communication and trust in explaining customer loyalty: An extension to the ECSI model. *European journal of marketing*, *38*(9-10), 1272-1293.

Bleier, A., & Eisenbeiss, M. (2015). Personalized online advertising effectiveness: The interplay of what, when, and where. *Marketing Science*, *34*(5), 669-688.

Eggert, A., & Ulaga, W. (2002). Customer perceived value: a substitute for satisfaction in business markets?. *Journal of Business & Industrial Marketing*, *17*(2/3), 107-118.

Esmeli, R., Can, A. S., Awad, A., & Bader-El-Den, M. (2025). Understanding customer loyalty-aware recommender systems in E-commerce: an analytical perspective. *Electronic Commerce Research*, 1-27.

https://www.attentive.com/press-releases/new-global-study-reveals-consumers-demand-more-personalization-in-marketing-81-ignore-irrelevant-messages-while-personalized-experiences-drive-loyalty-and-sales?

https://www.iagloyalty.com/news-insights/personalisation-boosts-customer-loyalty-heres-why?

Imran, I. (2024). 5 Benefits of Product Recommendations in E-commerce, https://www.addsearch.com/blog/product-recommendations-in-e-commerce/

Keating, G. (2024). Announcing the State of Personalization 2024, https://www.twilio.com/en-us/blog/insights/state-of-personalization-2024

MacDonald, J. (2025). 21 E-commerce Product Recommendation Tips (That Increase Conversions), https://thegood.com/insights/ecommerce-product recommendation/#:~:text=personalize%20product%20recommendations

Ghozali, I., & Lathan, H. (2012). Partial Least Squares: Concept and Application Path Modeling Using Program XLSTAT-PLS for Empirical Research. *BP UNDIP*.

Hair Jr., J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial Least Squares Structural Equation Modeling (PLS-SEM): An Emerging Tool in Business Research. *European Business Review*, *26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128

Hendra, H., Hermawan, A., & Edy, E. (2024). Smart Product Recommendations in Web E-Commerce: Leveraging Apriori Algorithm for Market Basket Analysis. *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, *18*(3).

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Jimi, J. (2025). The Effect of Ease of Navigation, Service Quality, and Consumer Experience on Consumer Loyalty on Food Delivery Platforms, *Journal of Management and Accounting Research,* 5 (2), 576-595

Nguyen, P. (2021). The Effect Of Online Product Recommendation Systems on Consumer Behavior: Vietnamese E-Commerce Websites. *Available at SSRN 3761654*.

Oestreicher-Singer, G., & Sundararajan, A. (2012). The visible hand? Demand effects of recommendation networks in electronic markets. *Management science*, *58*(11), 1963-1981.

Tsiotsou, R. (2006). The role of perceived product quality and overall satisfaction on purchase intentions. *International journal of consumer studies*, *30*(2), 207-217.

Wattimena, F. Y., & Rofi'i, Y. U. (2023). E-Commerce Product Recommendation System Using Case-Based Reasoning (CBR) and K-Means Clustering. *International Journal of Software Engineering and Computer Science (IJSECS)*, *3*(2), 162-173.

Wilson, N., Keni, K., & Tan, P. H. P. (2021). The role of perceived usefulness and perceived ease-of-use toward satisfaction and trust, which influence computer consumers' loyalty in China. *Gadjah Mada International Journal of Business*, *23*(3), 262-294.

Zed, E. Z., Kartini, T. M., & Purnamasari, P. (2024). The Power Of Personalization: Exploring The Impact Of AI-Driven Marketing Strategies On Consumer Loyalty In E-Commerce. *Jurnal Ekonomi*, *13*(04), 1303-1314.

Zhang, J., Balaji, M. S., Luo, J., & Jha, S. (2022). Effectiveness of product recommendation framing on online retail platforms. *Journal of Business Research*, *153*, 185-197.

Zhang, J., & Wedel, M. (2009). The effectiveness of customized promotions in online and offline stores. *Journal of Marketing Research*, *46*(2), 190-206.