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# The Effect of Recommendation Algorithms and Provision of Digital Facilities on Purchasing Patterns and Consumer Loyalty on E-Commerce Platforms in Jakarta

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## ABSTRACT

This study investigates the effect of recommendation algorithms and the provision of digital facilities on purchasing patterns and consumer loyalty in e-commerce platforms in Jakarta. Using a quantitative approach, data was collected from 180 respondents through a structured questionnaire utilizing a Likert scale (1-5). The data was analyzed using Structural Equation Modeling with Partial Least Squares (SEM-PLS 3). The results show that recommendation algorithms have a significant positive impact on both consumer loyalty and purchasing patterns, with path coefficients of 0.454 and 0.419, respectively. Additionally, the provision of digital facilities also influences consumer loyalty (0.360) and purchasing patterns (0.405). The study found that enhancing both personalized recommendations and digital infrastructure can significantly improve customer retention and sales, emphasizing the importance of these factors for e-commerce platforms in Jakarta. The model's $R^2$ values suggest that it explains a substantial portion of the variance in consumer loyalty (0.567) and purchasing patterns (0.580), with high predictive relevance. The findings provide practical insights for e-commerce businesses to optimize user experience and strengthen consumer relationships, contributing to improved competitive advantage in the digital market.

***Keywords:*** *Recommendation Algorithms, Digital Facilities, Consumer Loyalty, Purchasing Patterns, E-Commerce.*

## 1. INTRODUCTION

The rapid growth of e-commerce platforms in Jakarta has significantly transformed consumer purchasing behaviors, with recommendation algorithms and digital facilities playing pivotal roles. These elements enhance user experiences and drive sales by influencing consumer decisions and fostering loyalty. Personalized recommendations are a critical factor influencing consumer decisions, as they enhance the shopping experience by offering tailored product suggestions based on previous interactions and preferences [1]. These algorithms increase the likelihood of purchases by presenting consumers with relevant products, thereby improving satisfaction and fostering loyalty [2]. The ability to compare products easily through these recommendations also plays a significant role in consumer decision-making, as it simplifies the shopping process and enhances trust in the platform [1]. Similarly, the convenience and accessibility provided by digital facilities are major drivers of the shift towards online shopping, as they allow consumers to shop without time and space constraints [3]. E-commerce platforms that offer a user-friendly interface and seamless transaction processes are more likely to gain consumer trust and satisfaction, which are essential for building long-term loyalty [2], [4]. Additionally, the variety of products available online, coupled with competitive pricing, further enhances the appeal of e-commerce platforms, encouraging more frequent purchases [5].

Recommendation algorithms have become integral to e-commerce strategies by analyzing consumer data to predict preferences and offer personalized product suggestions. These systems enhance user engagement, satisfaction, and conversion rates, making them a cornerstone of modern e-commerce platforms. Recommendation systems, utilizing techniques like collaborative filtering and content-based approaches, provide personalized product suggestions that enhance user engagement and satisfaction [6], [7]. The integration of deep learning and context-aware models in recommendation systems addresses challenges like data sparsity and evolving user preferences, improving the precision of recommendations [6], [8]. Real-time adaptation mechanisms and user feedback loops are crucial for optimizing recommendations, ensuring they remain relevant and effective [8], [9]. However, other digital facilities such as seamless website navigation, secure payment systems, and mobile-friendly interfaces also significantly influence consumer interactions. User-friendly interfaces and intuitive navigation are essential for retaining users and facilitating smooth interactions on e-commerce platforms [10]. Ensuring secure and efficient payment processes builds consumer trust and encourages repeat purchases [10]. With the rise of mobile commerce, responsive and mobile-optimized websites are critical for capturing a broader audience and enhancing accessibility [10]. The interplay between these elements creates a comprehensive user experience that drives business success.

Understanding how these factors impact consumer purchasing patterns and loyalty is essential for businesses seeking a competitive edge in Jakarta's bustling e-commerce market. As online shopping continues to grow, consumers are increasingly influenced by the convenience, personalization, and technological innovations offered by these platforms. Thus, investigating the relationship between recommendation algorithms, digital facilities, purchasing behavior, and consumer loyalty is vital for both academic research and practical business applications. This study seeks to explore the effects of recommendation algorithms and the provision of digital facilities on purchasing patterns and consumer loyalty on e-commerce platforms in Jakarta. By focusing on these elements, this research aims to provide valuable insights into how these technological features contribute to shaping consumer behavior.

## 2. LITERATURE REVIEW

### *2.1 Recommendation Algorithms in E-Commerce*

Recommendation algorithms play a crucial role in modern e-commerce by analyzing consumer data to predict preferences and provide personalized product suggestions, thereby enhancing engagement and conversion rates. The main types include collaborative filtering, content-based filtering, and hybrid models. Collaborative filtering identifies user behavior patterns but faces challenges like data sparsity and evolving preferences, requiring innovative approaches [11]. Advanced models integrate collaborative and content-based filtering to improve precision for both new and existing users [11]. Content-based filtering matches products with users' past interactions, making it effective in cases with limited data [6]. Hybrid models combine both techniques to enhance accuracy and address individual limitations [6], [10]. Machine learning advancements, including deep learning and attention mechanisms, further optimize these systems by improving prediction accuracy and user satisfaction [12]. Additionally, algorithms like Random Forest and Support Vector Machines refine recommendation performance and adapt to complex user behavior [12], [13].

### *2.2 Digital Facilities in E-Commerce*

Digital facilities on e-commerce platforms play a crucial role in shaping consumer behavior by enhancing user experience and convenience through intuitive design, easy navigation, secure payment systems, mobile compatibility, and customer support. Usability is key to consumer satisfaction, as seamless navigation and user-friendly interfaces boost loyalty [14]. Well-designed platforms that facilitate smooth transactions and product discovery foster trust and repeat purchases, with intelligent customer service systems positively influencing purchase intentions [15]. Security features, including secure payment gateways and data protection, are essential for consumer confidence, as concerns about fraud can deter purchases [16]. Trust and information quality further mediate purchase intentions [15]. Mobile compatibility is increasingly vital, with seamless mobile experiences expanding market reach [17]. Additionally, intelligent customer service systems, such as chatbots and 24/7 support, enhance satisfaction and loyalty by providing timely assistance [15]. Reliable customer support remains highly valued by consumers [14]. These digital facilities collectively enhance accessibility, security, and engagement on e-commerce platforms.

### *2.3 Purchasing Patterns in E-Commerce*

The shift from in-store to online shopping has transformed consumer purchasing patterns, driven by convenience, personalized recommendations, and competitive pricing. E-commerce platforms use advanced algorithms to analyze user behavior, delivering tailored recommendations that enhance satisfaction and drive sales [7]. Personalized recommender systems leverage purchase history and browsing patterns to improve engagement and conversions [7]. The ability to compare products and prices empowers consumers to make informed decisions [1]. Online shopping's accessibility, along with mobile commerce and social media, further influences consumer choices [1]. Promotions like discounts, free shipping, and product quality significantly impact purchasing behavior, while reviews and ratings serve as crucial social proof [18], [19]. Generational differences also shape online shopping trends, with millennials favoring digital convenience, Generation X valuing reviews and brand reputation, and Baby Boomers adopting online shopping with concerns about data security and a preference for traditional payment methods [20].

### *2.4 Consumer Loyalty in E-Commerce*

Consumer loyalty in e-commerce extends beyond transactions to encompass emotional connections and trust, with personalized experiences, high-quality service, and consistent value delivery playing crucial roles in fostering repeat purchases and ongoing engagement. E-commerce platforms that prioritize consumer protection can enhance brand loyalty by influencing trust and satisfaction, as shown in research conducted in Nigeria [21]. E-service quality is another critical determinant of loyalty, directly affecting customer satisfaction and trust, while promotions and advertisements further contribute to loyalty, though e-word of mouth has a minimal impact [22]. Emotional connections through personalized experiences strengthen brand equity and customer trust by aligning with individual preferences and maintaining service consistency [23]. Additionally, service quality and customer satisfaction are pivotal in driving loyalty, particularly for MSMEs, where customer-oriented and sustainable strategies are recommended [24], [25]. The integration of recommendation algorithms and digital facilities further enhances user satisfaction and trust, solidifying consumer loyalty in the competitive e-commerce landscape.

### *2.5 Research Gaps and Hypotheses*

While the literature highlights the importance of recommendation algorithms and digital facilities, there is limited research that specifically examines their combined impact on purchasing patterns and consumer loyalty in the context of Jakarta's e-commerce market. This study aims to fill this gap by exploring the effects of these factors and providing insights into how they shape consumer behavior. Based on the literature reviewed, the following hypotheses are proposed:

H1: Recommendation algorithms positively influence consumer purchasing patterns.

H2: Digital facilities positively influence consumer purchasing patterns.

H3: Consumer purchasing patterns positively affect consumer loyalty.

H4: Recommendation algorithms positively influence consumer loyalty through their impact on purchasing patterns.

H5: Digital facilities positively influence consumer loyalty through their impact on purchasing patterns.

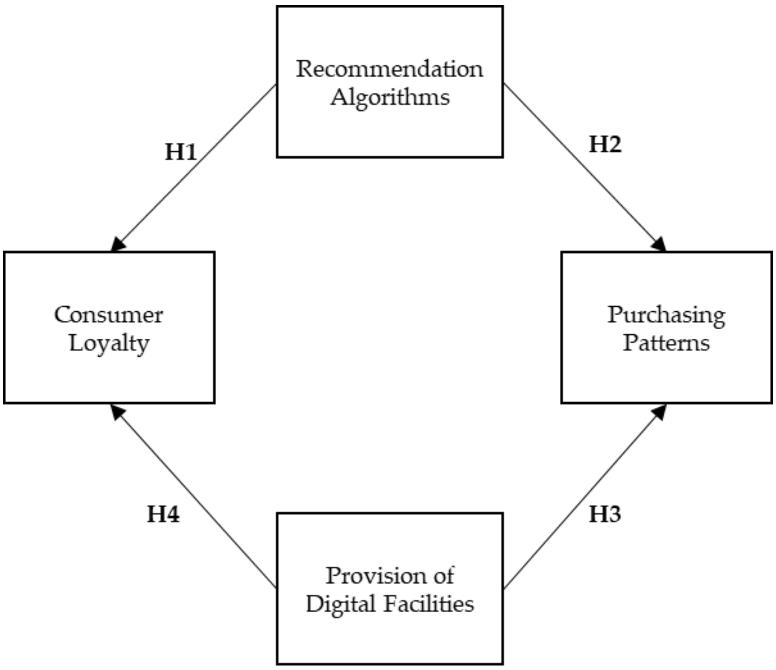


Figure 1. Conceptual Framework

## 3. METHODS

### 3.1 Research Design

This study employs a quantitative research design to measure the relationships between recommendation algorithms, digital facilities, purchasing patterns, and consumer loyalty. Quantitative research is suitable for this study because it allows for the collection and analysis of numerical data, which can provide objective insights into the factors influencing consumer behavior on e-commerce platforms. The research aims to test specific hypotheses using statistical methods, specifically Structural Equation Modeling - Partial Least Squares (SEM-PLS 3), to analyze the relationships between the variables.

### 3.2 Population and Sample

The population for this study consists of consumers using e-commerce platforms in Jakarta, Indonesia, one of Southeast Asia's largest e-commerce markets with a diverse demographic and varying levels of engagement in online shopping. The study focuses on individuals with prior purchasing experience on e-commerce platforms and familiarity with recommendation algorithms and digital facilities. A non-probability purposive sampling technique was employed to select participants based on their e-commerce usage in Jakarta and their experience with digital features. The sample size of 180 respondents is deemed sufficient for SEM-PLS analysis, as a minimum of 150 participants is generally required to ensure reliable and valid results [26]. The sample includes consumers aged 18 and above, representing diverse demographic characteristics such as gender, age, income level, and education background.

### 3.3 Data Collection

Data was collected through a structured online survey administered to participants who were selected based on the criteria outlined above. The survey included questions designed to measure the key variables in the study: recommendation algorithms, digital facilities, purchasing patterns, and consumer loyalty. The survey was distributed through social media platforms, e-commerce forums, and online communities to ensure that a diverse sample of e-commerce consumers in Jakarta was reached. The survey instrument was developed based on existing literature, with adaptations made to ensure relevance to the Jakarta context.

### 3.4 Data Analysis

The data collected from the survey responses were analyzed using Structural Equation Modeling - Partial Least Squares (SEM-PLS 3), a statistical technique commonly used in social sciences and business research. SEM-PLS is particularly suitable for studies with complex models and multiple constructs, as it enables testing relationships between latent variables and observed indicators while accommodating smaller sample sizes [27]. The analysis involved two stages: the measurement model and the structural model. In the measurement model stage, validity and reliability were assessed through convergent validity, which examines the correlation of items within a construct, and discriminant validity, which ensures constructs are distinct. Internal consistency was evaluated using Cronbach's alpha and Composite Reliability (CR), while Average Variance Extracted (AVE) was used for convergent validity assessment. The structural model stage tested the direct and indirect relationships between variables, analyzing path coefficients, t-values, and R-squared values to determine the strength and significance of these relationships. Hypotheses were tested using bootstrapping techniques to calculate t-statistics, with a significance level set at $p < 0.05$.

## 4. RESULTS AND DISCUSSION

### 4.1 Demographic Sample

This study's sample consisted of 180 respondents selected through a convenient sampling technique, with demographic characteristics analyzed across gender, age, education level, income level, shopping frequency, device usage, and trust in e-commerce platforms. The sample comprised 66.7% male and 33.3% female respondents, reflecting general consumer trends in online shopping. In terms of age distribution, the majority fell within the 25-34 age range (43.3%), highlighting the dominance of young, tech-savvy consumers, while participation from older generations was lower. Educationally, 53.3% of respondents held a Bachelor's degree, suggesting a relatively well-educated sample familiar with e-commerce platforms and digital technologies. Income-wise, 40% of respondents earned between IDR 3,000,000 and IDR 6,000,000 per month, representing the middle-class consumer base that actively engages in online shopping. Regarding shopping frequency, 53.3% shopped online at least once a week, indicating high engagement with e-commerce. Smartphones were the preferred shopping device for 83.3% of respondents, reinforcing Jakarta's mobile-first e-commerce landscape. Trust in e-commerce platforms was generally high, with 86.7% of respondents expressing high or very high trust, reflecting growing confidence in online shopping facilitated by secure transactions and reliable services. These demographic insights help contextualize consumer behaviors and preferences in Jakarta's e-commerce ecosystem.

### 4.2 Measurement Model

The measurement model in Structural Equation Modeling (SEM) serves as a tool for assessing the validity and reliability of the constructs (variables) in the study. In this study, four main constructs were evaluated: Recommendation Algorithms, Provision of Digital Facilities, Purchasing Patterns, and Consumer Loyalty. For each construct, the model evaluates the indicator loadings, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE). These parameters help in determining whether the constructs and their corresponding indicators are reliable and valid.

Table 1. Measurement Model

| Variable | Code | Loading Factor | Cronbach's Alpha | Composite Reliability | Average Variant Extracted |
|---|---|---|---|---|---|
| Recommendation Algorithms | REA.1 | 0.712 | 0.840 | 0.883 | 0.709 |
| | REA.2 | 0.822 | | | |
| | REA.3 | 0.753 | | | |
| | REA.4 | 0.818 | | | |
| | REA.5 | 0.769 | | | |
| Provision of Digital Facilities | PDF.1 | 0.915 | 0.899 | 0.937 | 0.832 |
| | PDF.2 | 0.922 | | | |
| | PDF.3 | 0.899 | | | |
| Purchasing Patterns | PPA.1 | 0.893 | 0.898 | 0.929 | 0.765 |
| | PPA.2 | 0.881 | | | |
| | PPA.3 | 0.867 | | | |
| | PPA.4 | 0.858 | | | |
| Consumer Loyalty | CLT.1 | 0.809 | 0.918 | 0.936 | 0.709 |
| | CLT.2 | 0.853 | | | |
| | CLT.3 | 0.826 | | | |
| | CLT.4 | 0.869 | | | |
| | CLT.5 | 0.853 | | | |
| | CLT.6 | 0.838 | | | |

*Source: Data Processing Results (2025)*

The measurement model assessment confirmed the reliability and validity of the study's constructs: Recommendation Algorithms (REA), Provision of Digital Facilities (PDF), Purchasing Patterns (PPA), and Consumer Loyalty (CLT). REA, measured by five indicators, showed strong reliability with loadings above 0.70, Cronbach's Alpha of 0.840, and Composite Reliability of 0.883. PDF, with three indicators, demonstrated excellent reliability, with loadings above 0.8, Cronbach's Alpha of 0.899, and Composite Reliability of 0.937. PPA, measured by four indicators, exhibited strong internal consistency, with Cronbach's Alpha of 0.898 and Composite Reliability of 0.929. CLT, assessed through six indicators, showed excellent reliability, with Cronbach's Alpha of 0.918 and Composite Reliability of 0.936. These results confirm the constructs' reliability and validity, ensuring a robust measurement model.

Discriminant validity measures the extent to which a construct is distinct from others in the model, ensuring each construct represents a unique concept and is not highly correlated with others.

A common method for assessing discriminant validity is the Fornell-Larcker criterion, which compares the square root of the Average Variance Extracted (AVE) for each construct with its correlations with other constructs. To establish discriminant validity, the square root of the AVE must be greater than the construct's correlations with others. This study evaluates discriminant validity using the Fornell-Larcker criterion for the constructs Consumer Loyalty (CLT), Provision of Digital Facilities (PDF), Purchasing Patterns (PPA), and Recommendation Algorithms (REA).

Table 2. Discriminant Validity

| | CLT | PDF | PPA | REA |
|---|---|---|---|---|
| Consumer Loyalty | 0.842 | | | |
| Provision of Digital Facilities | 0.681 | 0.712 | | |
| Purchasing Patterns | 0.825 | 0.702 | 0.815 | |
| Recommendation Algorithms | 0.709 | 0.708 | 0.706 | 0.776 |

*Source: Data Processing Results (2025)*

For discriminant validity to be confirmed, the square root of the AVE for each construct must be greater than the correlations between that construct and the other constructs. For Consumer Loyalty (CLT), the square root of AVE is 0.842, which is greater than the correlations with PDF (0.681), PPA (0.825), and REA (0.709), confirming discriminant validity for CLT. For Provision of Digital Facilities (PDF), the square root of AVE is 0.712, which exceeds the correlations with CLT (0.681), PPA (0.702), and REA (0.708), confirming discriminant validity for PDF. For Purchasing Patterns (PPA), the square root of AVE is 0.815, but the correlation with CLT (0.825) slightly exceeds the square root of AVE, indicating a borderline case, suggesting further checks may be necessary to confirm discriminant validity for PPA in relation to CLT. For Recommendation Algorithms (REA), the square root of AVE is 0.776, which is greater than the correlations with CLT (0.709), PDF (0.708), and PPA (0.706), confirming discriminant validity for REA.

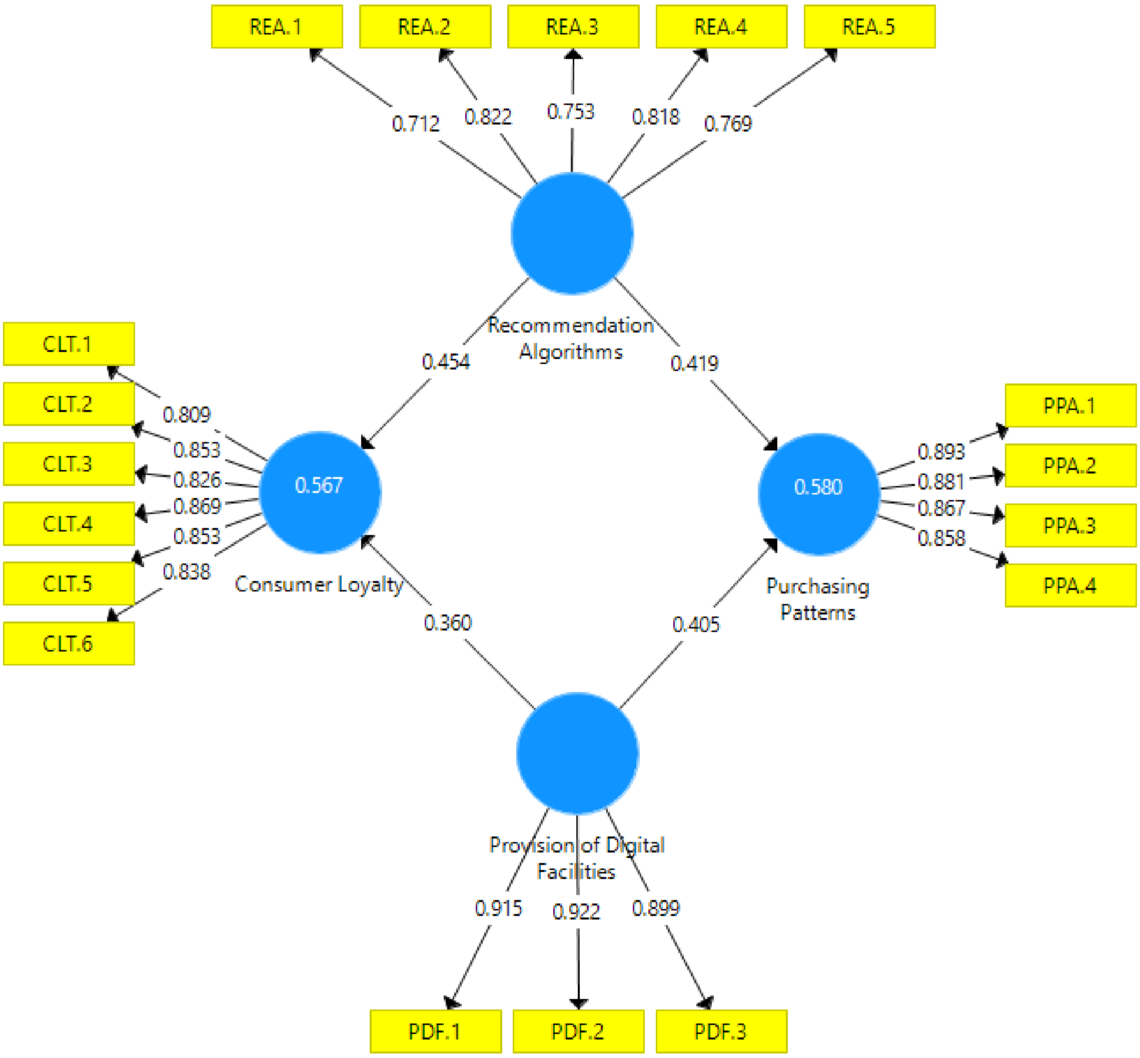


Figure 2. Model Results

*Source: Data Processed by Researchers, 2025*

### 4.3 Model Fit

In structural equation modeling (SEM), assessing model fit is crucial to determine how well the model represents the relationships among the constructs. There are several indices used to assess the overall fit of the model, such as Standardized Root Mean Square Residual (SRMR), d_ULS, d_G, Chi-Square, and Normed Fit Index (NFI). These indices help us to evaluate the discrepancy between the observed and estimated data.

Table 3. Model Fit Results Test

| | Saturated Model | Estimated Model |
|---|---|---|
| SRMR | 0.099 | 0.127 |
| d_ULS | 1.006750 | 2.755 |
| d_G | 0.760 | 0.931 |
| Chi-Square | 476.616 | 535.452 |
| NFI | 0.751 | 0.721 |

*Source: Process Data Analysis (2025)*

The model fit was assessed using several indices, including SRMR, d_ULS, d_G, Chi-Square ($\chi^2$), and NFI. The SRMR values for both the Saturated Model (0.099) and Estimated Model (0.127) exceed the recommended threshold of 0.08, indicating some misfit, with the Saturated Model being closer to the acceptable threshold. The d_ULS values for the Saturated Model (1.006750) and Estimated Model (2.755) show that the Saturated Model fits the data better, with a lower discrepancy between observed and predicted data. Similarly, the d_G values (Saturated Model: 0.760, Estimated Model: 0.931) also suggest a better fit for the Saturated Model, as its value is lower. The Chi-Square values for both models (Saturated Model: 476.616, Estimated Model: 535.452) indicate a poorer fit for the Estimated Model, which has a higher Chi-Square value. Lastly, the NFI values (Saturated Model: 0.751, Estimated Model: 0.721) are below the 0.90 threshold, indicating that both models could be improved, with the Saturated Model fitting slightly better.

Table 4. Coefficient Model

| | R Square | Q2 |
|---|---|---|
| Consumer Loyalty | 0.567 | 0.559 |
| Purchasing Patterns | 0.580 | 0.573 |

*Source: Data Processing Results (2025)*

In Structural Equation Modeling (SEM), R-Square ($R^2$) and Q-Square ($Q^2$) are key indicators for assessing the model's predictive power and relevance. $R^2$ measures the variance in the dependent variable explained by the independent variables, with values closer to 1 indicating stronger explanatory power, while $Q^2$ assesses the model's predictive relevance, showing how well it can predict data points. For $R^2$, the values for Consumer Loyalty (0.567) and Purchasing Patterns (0.580) suggest moderate explanatory power, with 56.7% of the variance in consumer loyalty and 58% in purchasing patterns explained by the independent variables in the model. These values indicate that while the model has a good explanatory power, other factors not included in the model still influence these variables. For $Q^2$, the values for Consumer Loyalty (0.559) and Purchasing Patterns (0.573) suggest strong predictive relevance, with 55.9% of the data for consumer loyalty and 57.3% for purchasing patterns well-predicted by the model. These results indicate that the model has a solid ability to predict both consumer loyalty and purchasing patterns based on the included variables.

### 4.4 Structural Model Discussion

The structural model in Partial Least Squares Structural Equation Modeling (PLS-SEM) assesses the relationships between latent variables and helps to evaluate how well the independent variables predict the dependent variables. The results of the structural model analysis, based on the paths and significance levels (T-statistics and P-values), reveal insights into the strength and direction of these relationships.

Table 5. Hypothesis Testing

| | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics | P Values |
|---|---|---|---|---|---|
| Provision of Digital Facilities -> Consumer Loyalty | 0.360 | 0.363 | 0.099 | 3.633 | 0.000 |
| Provision of Digital Facilities -> Purchasing Patterns | 0.405 | 0.407 | 0.091 | 4.428 | 0.000 |
| Recommendation Algorithms -> Consumer Loyalty | 0.454 | 0.453 | 0.092 | 4.918 | 0.000 |
| Recommendation Algorithms -> Purchasing Patterns | 0.419 | 0.420 | 0.095 | 4.396 | 0.000 |

*Source: Process Data Analysis (2025)*

The study reveals several significant relationships between key constructs. The path coefficient for Provision of Digital Facilities to Consumer Loyalty is 0.360, indicating a moderate positive impact, with a T-statistic of 3.633 and a P-value of 0.000, confirming statistical significance. Similarly, the path coefficient for Provision of Digital Facilities to Purchasing Patterns is 0.405, with a T-statistic of 4.428 and a P-value of 0.000, suggesting that the availability of digital facilities positively influences consumer purchasing behavior. For Recommendation Algorithms to Consumer Loyalty, the path coefficient is 0.454, with a T-statistic of 4.918 and a P-value of 0.000, indicating a moderate to strong positive effect, suggesting that recommendation algorithms significantly enhance consumer loyalty. Lastly, the path coefficient for Recommendation Algorithms to Purchasing Patterns is 0.419, with a T-statistic of 4.396 and a P-value of 0.000, indicating a moderate positive impact on purchasing patterns, showing that personalized recommendations not only enhance loyalty but also influence purchasing decisions.

**Discussion**

The results of this study provide valuable insights into the impact of Recommendation Algorithms and Provision of Digital Facilities on Purchasing Patterns and Consumer Loyalty on e-commerce platforms. By examining the path coefficients, $R^2$ values, and model fit indices, we can assess the extent to which these variables contribute to consumer behavior and loyalty in Jakarta's e-commerce market.

**1. Impact of Recommendation Algorithms**

The findings suggest that Recommendation Algorithms play a critical role in influencing both Consumer Loyalty (path coefficient = 0.454) and Purchasing Patterns (path coefficient = 0.419). The positive and significant relationships between recommendation algorithms and these two constructs indicate that personalized recommendations significantly enhance consumer loyalty by offering tailored product suggestions. These algorithms leverage data from previous consumer behavior to predict preferences, which can increase the likelihood of repeat purchases and improve customer retention. This aligns with previous research, which suggests that personalized recommendations are highly effective in e-commerce settings by enhancing user experience and engagement [6], [7], [10].

In terms of purchasing patterns, recommendation algorithms encourage more frequent and higher-value purchases by promoting products that align with consumers' tastes and interests. This is particularly important in a competitive e-commerce environment where consumers are overwhelmed by choices. By providing personalized experiences, recommendation algorithms reduce decision fatigue and guide consumers toward products they are more likely to purchase.

**2. Provision of Digital Facilities**

The Provision of Digital Facilities (path coefficient = 0.405 for purchasing patterns and 0.360 for consumer loyalty) also demonstrates significant positive effects on both Purchasing Patterns and Consumer Loyalty. E-commerce platforms that offer easy navigation, efficient search functions, and secure payment options are more likely to enhance consumer satisfaction and loyalty. The convenience of digital platforms allows consumers to shop more easily and with less friction, which directly influences their decision to return to the platform for future purchases.

Additionally, the availability of digital facilities such as mobile apps, multiple payment options, and user-friendly interfaces contributes to an improved shopping experience, leading to higher customer retention rates. When consumers find e-commerce platforms that are easy to use, they are more likely to remain loyal and make repeat purchases. This supports existing research that highlights the importance of digital infrastructure in building customer trust and satisfaction [22], [28].

**3. Consumer Loyalty and Purchasing Patterns**

The positive relationships observed between both recommendation algorithms and digital facilities on consumer loyalty and purchasing patterns reinforce the idea that consumer behavior is heavily influenced by the quality of the shopping experience. In an era where convenience and personalization are key, e-commerce platforms that leverage technology to enhance both aspects are likely to see improved customer satisfaction and increased sales. The findings indicate that improving consumer loyalty not only enhances repeat business but also impacts purchasing patterns, as loyal customers are more likely to make purchases based on their past experiences with the platform.

**4. Implications for E-Commerce Platforms**

The results of this study have practical implications for e-commerce platforms aiming to enhance customer retention and sales in Jakarta. By focusing on improving recommendation algorithms and ensuring robust digital facilities, platforms can significantly improve both customer loyalty and purchasing behavior. E-commerce companies should invest in data analytics to refine recommendation systems and enhance personalization. Additionally, ensuring that digital infrastructure is seamless and convenient for users will help in retaining customers and driving higher sales.

**5. Limitations and Future Research**

While the study provides important insights into the role of recommendation algorithms and digital facilities, there are some limitations. For instance, the study focused on e-commerce platforms in Jakarta, which may limit the generalizability of the findings to other regions or countries. Future research could explore how these factors affect consumer behavior across different geographical regions or demographic groups. Furthermore, additional factors such as social influence, brand trust, and pricing strategies could be incorporated to provide a more comprehensive understanding of consumer loyalty and purchasing patterns.

## CONCLUSION

This study highlights the critical role of recommendation algorithms and digital facilities in shaping purchasing patterns and consumer loyalty in Jakarta's e-commerce platforms. The findings demonstrate that both personalized recommendations and user-friendly digital infrastructures significantly enhance customer retention and encourage repeat purchases. The statistical analyses, including path coefficients, $R^2$ values, and model fit indices, support the hypothesis that these two factors are essential drivers of consumer behavior. E-commerce platforms in Jakarta can leverage these insights to improve user experience, foster consumer loyalty, and ultimately increase sales. However, future research could expand on these findings by including other variables such as social influence or pricing strategies to provide a more holistic understanding of consumer behavior. This study serves as a valuable guide for e-commerce businesses looking to refine their strategies and strengthen their position in the competitive digital marketplace.

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