

## The Influence of AI-Based Hyper-Personalization and Live Streaming Interaction on Consumer Purchase Intention on E-Commerce Platforms in Cirebon

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**Abstract:** *In the current era of digital transformation, a major challenge in e-commerce is mitigating the risk of fraud in online transactions, which can erode consumer trust. This study aims to evaluate the impact of AI-driven hyper-personalization and live streaming interactions on consumer purchase intention. A quantitative approach was employed using the Partial Least Squares-Structural Equation Modeling (PLS-SEM) method. Data were collected from online shopping platform users and analyzed using SmartPLS. The results indicate that AI-driven hyper-personalization has a positive and significant influence on purchase intention; this confirms that the effectiveness of algorithms in providing relevant recommendations enhances the technology's value as perceived by consumers. Furthermore, live streaming interactions exert a more dominant positive and significant influence on purchase intention, demonstrating that social presence and visual transparency facilitated by direct interaction are crucial elements in alleviating concerns regarding fraud risks. Overall, both variables demonstrate strong predictive power regarding purchase intention. The study concludes that while AI technology forms the foundation for intelligent personalization, the human touch provided through direct interaction remains a key factor in building trust and driving sales conversions within an increasingly competitive digital marketplace.*

## INTRODUCTION

The rapid advancement of digital technology has drastically changed the e-commerce landscape worldwide, including in Indonesia, where the distinction between entertainment and business is increasingly blurred (Edhie Rachmad et al., 2024). Reported by e-Conomy SEA 2025, nationally, the Indonesian e-commerce market is estimated to reach US\$5.25 billion by 2025. However, the impact of this digital transformation is not only felt in metropolitan cities like Jakarta, but is also starting to spread to developing areas like Cirebon. The increase in internet

penetration in Cirebon City, accompanied by the increasingly intensive use of social media and e-commerce platforms, has brought changes to people's shopping patterns, especially millennials and Gen Z. The availability of widespread internet access has made digital platforms the main channel for young consumers to search for information, evaluate, and make online product purchases, where the role of influencers and social media content also influences the purchasing decision-making process (Elok Faiko et al., 2025).

Data from Databoks shows that the estimated number of e-commerce users in Indonesia has increased significantly over time (Ahdiyat, 2025). Along with this growth in user numbers, competition between e-commerce platforms in Indonesia is increasingly fierce. Various platforms, including Tokopedia, Blibli, Lazada, JD ID, Bukalapak, and Shopee, are striving to attract and retain customers (Witro et al., 2021). Amidst this intense competition, consumers today expect a more personalized, participatory, and real-time shopping experience (Zhang et al., 2024). In this competitive ecosystem, Artificial Intelligence (AI) plays a crucial role in creating Hyper-Personalization. This technology works predictively to provide highly accurate and relevant product recommendations, thereby accelerating the decision-making process and increasing consumer engagement (Jihan et al., 2025; Raian et al., 2025). Beyond technical aspects such as AI, social factors through Live Streaming also play a key role. Live Streaming enables direct interaction between sellers, influencers, and consumers in Cirebon, building trust through spontaneous social presence (Sumarsid, 2024). In Indonesia, this form of interaction has proven more effective than traditional promotions in driving purchase intent, even to the point of encouraging impulse purchases (Juliana, 2023).

Despite the significant market potential in regions like Cirebon, the existing literature remains fragmented. Many studies focus solely on the effectiveness of AI alone or on live streaming interactions independently. A common theme is the synergy between these two variables: how AIHP recommendations direct the right audience to relevant live streaming sessions, which then translates into purchase intent through human interaction.

Recent research highlights the growing importance of Artificial Intelligence (AI) and interactive technologies in shaping consumer behavior within the e-commerce landscape. (Witro et al., 2021) found that AI-driven recommendation systems enhance customer satisfaction and purchasing decisions by presenting product suggestions tailored to user preferences, although their study focused primarily on recommendation accuracy rather than interactive communication features. Similarly, (Juliana, 2023) reported that live streaming commerce significantly boosts purchase intention by strengthening perceptions of authenticity, social presence, and seller credibility through real-time interaction; however, that study did not examine the complementary role of AI-based personalization. Furthermore, (Zhang et al., 2024) highlighted that AI-driven hyper-personalization enhances consumer engagement and shopping convenience through predictive analytics and personalized recommendations, while suggesting that future research investigate the integration of AI with social interaction mechanisms to provide a more comprehensive explanation of consumer purchasing behavior. Despite these findings, existing literature remains fragmented, as most studies examine AI-driven hyper-personalization and live streaming interactions in isolation rather than as complementary factors influencing purchase intention. Moreover, empirical evidence remains limited in developing cities like Cirebon, where rising internet penetration, digital adoption, and concerns regarding online fraud may shape consumer behavior differently than in major metropolitan areas. Therefore, this study aims to bridge this gap by examining the combined influence of AI-driven hyper-personalization and live streaming interactions on the purchase intentions of e-commerce consumers in Cirebon, with the

hope of contributing to the development of an integrated theoretical model and providing practical insights for businesses and MSMEs to optimize sustainable digital commerce strategies.

These prior studies indicate that AI-driven personalization and live streaming interactions each have a significant impact on consumer behavior. However, these variables have generally been investigated in isolation. There is limited research exploring the integrated impact of AI-driven hyper-personalization and live streaming interactions within a single conceptual framework, particularly in developing cities like Cirebon, where digital adoption is rising and consumer trust remains a critical issue. Therefore, this study addresses this gap by examining the combined effect of AI-based hyper-personalization and live streaming interaction on consumer purchase intention among e-commerce users in Cirebon.

This research needs to be conducted in Cirebon to understand whether consumer behavior patterns in developing cities share characteristics with national trends, or whether there are specific local dynamics related to data privacy and trust in content. By examining the impact of AI-based Hyper-Personalization and Live Streaming interactions, this research is expected to provide theoretical contributions through an integrative model, as well as practical contributions for businesses and MSMEs in Cirebon in optimizing their e-commerce strategies to be more efficient, attractive, and sustainable in the future (Ding et al., 2025).

## **LITERATURE REVIEW**

### **Consumer Purchase Intention**

Consumer Purchase Intention refers to a consumer's subjective tendency or likelihood to purchase a product or service within a specific time period (Sandris et al., 2025). In a social commerce environment, purchase intention is influenced by factors that reduce uncertainty and increase perceived consumer value, such as convenience, enjoyment, and social value (Patty & Djakasaputra, 2025). Technology Acceptance Model (TAM): This theory states that purchase intention is strongly influenced by perceived ease of use and perceived usefulness generated by hyper-personalization technology (Wahyuni Nazwa et al., 2025).

### **AI-Based Hyper-Personalization**

The implementation of Artificial Intelligence (AI)-based Hyper-Personalization marks the evolution of marketing strategies from mass customization to a more targeted approach, leveraging AI as the primary driver (Parmini & Yuliasuti, 2025). Thanks to AI's superior ability to analyze consumer behavior in real-time, companies can activate proactive driver mechanisms that provide targeted content to minimize search friction and increase purchase intent (Ding et al., 2025; Guendouz, 2024). From a Technology Acceptance Model (TAM) perspective, the effectiveness of these systems depends on user perceptions of usefulness and ease of use; accurate AI recommendation systems are considered to provide significant added value to consumers in decision-making, thus positively strengthening technology acceptance and user engagement in the digital ecosystem (Mei et al., 2025).

### **Live Streaming Interaction**

Livestreaming commerce is an innovative shopping channel that combines social commerce with streaming media technology, with its competitive advantage centered on the dynamics of live interaction (Tan, 2024). Theoretically, the effectiveness of this interaction can be explained through Social Presence Theory, which states that media technology can create the sensation of consumers being in the same physical space as the seller, thus forming a deep psychological intimacy (Yeboah et al., 2023). This interaction is realized through three main dimensions: first,

personalization, which allows the broadcaster to provide professional advice tailored to specific individual needs; second, responsiveness, which relates to the speed and effectiveness of responses to alleviate buyer doubts; and third, entertainment, which provides enjoyment value in content delivery (Bariyyatul Qibtiyah, 2024; Tan, 2024). The combination of these three elements through high social presence has been shown to significantly strengthen emotional bonds and drive consumer purchase intention in live streaming environments (Bariyyatul Qibtiyah, 2024).

### **Research Hypothesis**

- H1: AI-based hyper-personalization has a positive and significant effect on consumer purchase intention.
- H2: Live streaming interaction has a positive and significant effect on consumer purchase intention.
- H3: AI-based hyper-personalization and live streaming interaction simultaneously have a significant effect on consumer purchase intention.

### **METHOD**

This study uses a quantitative approach with an associative approach, aiming to analyze the causal relationships or influences between variables. The variables studied include Artificial Intelligence (AI)-based Hyper-Personalization ( $X_1$ ) and Live Streaming Interaction ( $X_2$ ) as independent variables, and Consumer Purchase Intention ( $Y$ ) as the dependent variable on e-commerce platforms. This research design was designed to test a dual-stimulus model that combines the role of AI-based predictive technology with real-time human interaction in influencing consumer purchase intentions.

The population in this study was all active e-commerce users in the Cirebon area who had watched live streaming content and made a purchase. Because the number of users meeting these characteristics cannot be precisely determined and is dynamic, the study population is categorized as an infinite population. The sampling technique used was purposive sampling, a method of selecting respondents based on certain criteria to ensure the data obtained is relevant to the research objectives. The respondent criteria included: (1) residing in the Cirebon area; (2) have an active account and have made transactions on an e-commerce platform; and (3) have watched live streaming interactions and been exposed to artificial intelligence-based product recommendations on the platform.

The sample size in this study was determined based on the guidelines proposed by (Hair et al., 2019), considering that population size cannot be determined with certainty. According to Hair et al., research using Structural Equation Modeling (SEM) analysis can determine sample size based on the number of research indicators multiplied by a constant between 5 and 10. This research instrument consisted of 18 statements, so using a constant of 10 resulted in a minimum sample size of 180 respondents. This number was deemed sufficient and representative for analysis using the Partial Least Squares-Structural Equation Modeling (PLS-SEM) method.

### **RESULT AND DISCUSSION**

#### **Convergent Validity**

Outer loading is used to evaluate an indicator's ability to describe the latent construct being

measured. The higher the outer loading value, the stronger the relationship between the indicator and the latent construct, indicating convergent validity. Indicators with an outer loading value of at least 0.70 are considered to meet adequate measurement standards and are suitable for application in a reflective measurement model (Hair et al., 2019).

**Table 1. Outer Loading Result**

| Indicator | Variable                       | Outer Loading | Description |
|-----------|--------------------------------|---------------|-------------|
| X1.1      | AI-Based Hyper-Personalization | 0,909         | VALID       |
| X1.2      |                                | 0,876         | VALID       |
| X1.3      |                                | 0,871         | VALID       |
| X1.4      |                                | 0,845         | VALID       |
| X1.5      |                                | 0,872         | VALID       |
| X1.6      |                                | 0,865         | VALID       |
| X2.1      | Live Streaming Interaction     | 0,888         | VALID       |
| X2.2      |                                | 0,885         | VALID       |
| X2.3      |                                | 0,895         | VALID       |
| X2.4      |                                | 0,896         | VALID       |
| X2.5      |                                | 0,854         | VALID       |
| X2.6      |                                | 0,889         | VALID       |
| Y1        | Consumer Purchase Intention    | 0,878         | VALID       |
| Y2        |                                | 0,882         | VALID       |
| Y3        |                                | 0,884         | VALID       |
| Y4        |                                | 0,833         | VALID       |
| Y5        |                                | 0,885         | VALID       |
| Y6        |                                | 0,882         | VALID       |

*Source: Processed Data (2025)*

The test results show that each indicator used in this study has a factor loading value exceeding the minimum threshold, which is  $\geq 0.70$ . This indicates that all indicators in the measurement model meet the convergent validity criteria. This finding indicates that the research instrument has an adequate level of validity and is ready for use in the next stage of analysis.

### Reliability Testing

Reliability testing was conducted to measure the extent to which the indicators in the study consistently reflect the latent construct. In this study, reliability assessment used several measurement approaches, namely Cronbach's Alpha and Composite Reliability, which include rho\_a and rho\_c values. Referring to the guidelines of Hair et al. (2021), a variable is considered

to have good reliability if the Cronbach's Alpha and Composite Reliability values are at 0.70 or higher. Achieving these values indicates strong stability and internal consistency among the indicators that make up the construct. Furthermore, convergent validity was evaluated using Average Variance Extracted (AVE), with a minimum required value of 0.50.

**Table 2. Cronbach's Alpha, Composite Reliability & Average Variance Extracted**

|             | <b>Cronbach's Alpha</b> | <b>Composite Reliability (rho_a)</b> | <b>Composite Reliability (rho_c)</b> | <b>Average Variance Extracted (AVE)</b> | <b>Keterangan</b> |
|-------------|-------------------------|--------------------------------------|--------------------------------------|-----------------------------------------|-------------------|
| <b>AIHP</b> | 0.938                   | 0.940                                | 0.951                                | 0.763                                   | Reliabel          |
| <b>LSI</b>  | 0.944                   | 0.946                                | 0.956                                | 0.784                                   | Reliabel          |
| <b>CPI</b>  | 0.939                   | 0.941                                | 0.952                                | 0.766                                   | Reliabel          |

*Source: Processed Data (2025)*

The data presented in Table 2 shows that all variables in this research model have met the required reliability and validity standards. The Cronbach's Alpha value for each construct is above 0.70, indicating that these indicators have very strong internal consistency. Similarly, all Composite Reliability values, including rho\_a and rho\_c, exceed the minimum threshold of 0.70, thus it can be concluded that this research instrument is highly reliable. Furthermore, the Average Variance Extracted (AVE) value obtained above 0.50 confirms that each construct is able to explain more than half of the variance of its indicators. Therefore, all variables are considered valid and reliable, and ready to be applied in further structural analysis.

### **Coefficient of Determination (R-Square)**

The coefficient of determination, also known as R-Square, is used to determine the extent to which independent variables can explain changes or variations in the dependent variable. The R-Square value indicates the overall contribution of the independent variables in the model to the dependent variable. In this study, model strength was categorized into three levels: low ( $\leq 0.5$ ), medium (0.5–0.7), and high ( $\geq 0.7$ ). This grouping serves as a guideline for evaluating the effectiveness of the structural model in describing the relationships between variables. A summary of the R-Square test results is presented in the following table:

**Table 3. R-Square and Adjusted R-Square Results**

|            | <b>R-Square</b> | <b>R-square Adjusted</b> |
|------------|-----------------|--------------------------|
| <b>CPI</b> | <b>0.939</b>    | <b>0.938</b>             |

*Source: Processed Data (2025)*

Based on the coefficient of determination analysis presented in Table 3, the Consumer Purchase

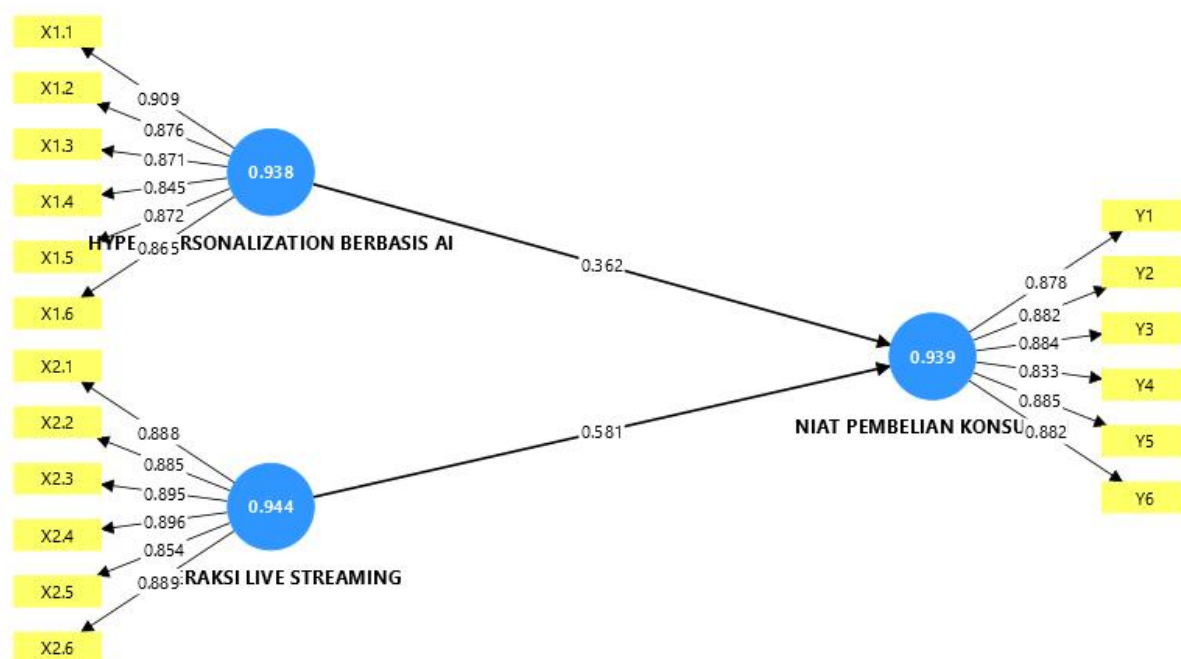
Intention variable achieved an R-squared value of 0.939. This finding indicates that 93.9% of the variation in Consumer Purchase Intention can be accurately explained by the AI-based Hyper-Personalization and Live Streaming Interaction variables. Conversely, the remaining 6.1% is influenced by other factors outside the scope of this research model.

Furthermore, the adjusted R-squared value of 0.938 confirms that, despite considering the number of independent variables in the model, the predictive ability of Consumer Purchase Intention remains at a very high level. This confirms that the constructed structural model has strong consistency and explanatory power, making it highly suitable for explaining the relationships between the variables at the heart of this research.

### Inner Model

Inner model analysis shows that AI-Based Hyper-Personalization and Live Streaming Interaction have a positive effect on Consumer Purchase Intention. The path coefficient from AI-Based Hyper-Personalization to Consumer Purchase Intention is 0.362, indicating that enhanced AI-based personalization experiences tend to increase consumers' intention to purchase products on e-commerce platforms. Meanwhile, the path coefficient from Live Streaming Interaction to Consumer Purchase Intention is 0.581, indicating a stronger positive influence compared to AI-Based Hyper-Personalization. These findings imply that communication and interactive engagement during live streaming sessions play a more substantial role in driving consumer purchase intention. Furthermore, the endogenous construct of Consumer Purchase Intention has an  $R^2$  value of 0.939, meaning that 93.9% of the variance in Consumer Purchase Intention can be explained by AI-Based Hyper-Personalization and Live Streaming Interaction, while the remaining 6.1% is influenced by other factors outside the research model.

**Figure 2. Structural Model**



Source: Processed Data (2025)

### Hypothesis Testing

In this study, the relationships between variables were explored using the bootstrapping method to assess path coefficients (based on the original sample), T-statistics, and P-values. A

hypothesis is considered empirically supported if the T-statistic exceeds the threshold of 1.96 and the P-value is below the 0.05 (or 5%) significance level. A summary of the structural path testing results is presented in the table below:

**Table 4. Hypothesis Test Results (Path Coefficient)**

|                   | Original Sample (O) | Sample Mean (M) | Standard Deviation | T Statistics | P Values |
|-------------------|---------------------|-----------------|--------------------|--------------|----------|
| <b>AIHP → CPI</b> | 0.362               | 0.360           | 0.045              | 8.044        | 0.000    |
| <b>LSI → CPI</b>  | 0.581               | 0.583           | 0.038              | 15.289       | 0.000    |

*Source: Processed Data (2025)*

The results of the hypothesis testing show that Live Streaming Interaction (LSI) has the strongest positive and significant influence on Consumer Purchase Intention (CPI) with a path coefficient value (Original Sample) of 0.581 and a P value of 0.000. Furthermore, AI-based Hyper-Personalization (AIHP) also has a positive and significant influence on Consumer Purchase Intention, with a path coefficient value of 0.362 and a P value of 0.000. These findings indicate that the better the implementation of AI-based hyper-personalization and the higher the live streaming interaction on the e-commerce platform, the higher the consumer purchase intention. In addition, based on the magnitude of the path coefficient value, Live Streaming Interaction is a variable that has a more dominant influence than AI-based Hyper-Personalization in increasing consumer purchase intention.

## Discussion

### The Effect of AI-Based Hyper-Personalization on Consumer Purchase Intention

Statistical test results indicate that the Hyper-Personalization approach using Artificial Intelligence (AI) has a positive and significant impact on consumer purchase intention. This finding is supported by a path coefficient of 0.362, a T-statistic of 8.044, and a P-value of 0.000, which overall meet the acceptance criteria for the first hypothesis (H1). This confirms that the more sophisticated and precise the AI system is in tailoring the customer experience, the stronger the consumer's motivation to make a purchase.

In this study, the concept of Hyper-Personalization reflects the algorithm's ability to provide precise product suggestions, curate content based on direct behavior, and deliver highly personalized promotions to each individual. The high outer loading value for the AI variable indicates that respondents highly value the technology's effectiveness in simplifying the product search process. With the help of AI, consumers can avoid useless information, thereby increasing the convenience of navigating digital applications. This study's findings align with those of (Kumar Singhal et al., 2025)), who stated that artificial intelligence plays a key role in changing consumer behavior patterns and accelerating the decision-making process through efficient recommendation systems.

### The Effect of Live Streaming Interaction on Consumer Purchase Intention

The results of the structural path analysis indicate that live streaming interaction has a positive and meaningful impact on shaping purchase intention. Empirical evidence indicates a

path coefficient of 0.581 (the highest value in the model), with a t-statistic of 15.289 and a p-value of 0.000, strongly supporting the second hypothesis (H2). This suggests that active engagement between sellers and buyers on live streaming platforms plays a significant role in driving direct purchase intention.

In this study, the interaction dimension includes personalization by the broadcaster, responses to questions, and the entertainment elements displayed. High values for this variable indicate that consumers feel more confident when they can interact with others and obtain direct visual evidence of the product. This strong social presence can reduce the doubt and uncertainty common in online shopping. These findings align with research by (Sulistyaningsih & Ashidiqy, 2025), who stated that live interaction is a key determinant in strengthening customer bonds and increasing their purchase intention through a more transparent and participatory shopping experience.

## CONCLUSION

Based on the findings of this study, it can be concluded that AI-Based Hyper-Personalization and Live Streaming Interaction simultaneously contribute significantly to Consumer Purchase Intention, with a model power of 93.9%. Separately, although AI algorithms play a significant role in delivering efficiency and customized content ( $\beta = 0.362$ ), the Live Streaming Interaction variable proves to be a stronger driving factor ( $\beta = 0.581$ ) because it can provide a human element, direct product transparency, and deep emotional bonds. These results indicate that in an era of rampant fraud in online shopping, consumers prioritize direct visual evidence and seller responsiveness as social verification mechanisms to reduce uncertainty before making a transaction. Therefore, it is recommended that e-commerce businesses not only rely on advances in AI automation technology but also combine it with improving the quality of interactions during live streaming sessions through training for streamers to be more responsive, honest, and informative, thereby building stronger consumer trust. In addition, companies must continue to develop transparent AI-based security systems to maintain the confidentiality of user data, so that the risk of fraud can be proactively prevented while driving increased sales conversions in the future.

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