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An Integrating AI-Driven Hyper-Personalization, Customer Experience, and E-Trust to Explain E-Loyalty in Indonesian E-Commerce: A PLS-SEM Study

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ABSTRACT: This study extends TAM and Relationship Marketing Theory by positioning hyper-personalization as a central explanatory mechanism linking AI capability to e-loyalty. The sample in this study consisted of 400 respondents, aged 18 years and over, who had shopped online for at least the past month. The data analysis technique used SEM analysis with the Smart PLS application. The results showed that of the twelve proposed hypotheses, ten were accepted and two were rejected. Artificial intelligence plays a crucial role in creating hyper-personalization, significantly enhancing the customer experience. Customer experience and hyper-personalization also directly strengthen customer loyalty by providing relevant and personalized experiences. E-trust serves as a crucial foundation for creating a sense of security and trust in customers, thus increasing loyalty. However, its role as a moderator of the relationship between hyper-personalization and e-loyalty is insignificant.

Keywords: Artificial intelligence, Customer experience, Hyper-personalization, E-trust, E-loyalty.

I. INTRODUCTION

Technological shifts have enabled e-commerce businesses to shift from traditional advertising and marketing methods to more sophisticated, data-driven approaches. AI-powered hyper personalization strategies are among the most profound advancements in digital marketing strategy, offering brands the power to tailor experiences at an individual level [1]. AI-driven personalization is based on analyzing vast amounts of consumer data, such as browsing history, previous purchases, and social media interactions, to predict and respond to individual needs in real-time [2]. As a result, the consumer experience becomes more engaging and intuitive, fostering a stronger relationship between customers and brands [3]. However, this personalization has also increased reliance on sensitive consumer data, which has raised new challenges in data privacy and ethical data use.

Several studies have shown that consumers are increasingly skeptical and selective about sharing personal information with companies, especially when privacy practices are unclear [1, 4]. Therefore, trust has emerged as a critical component of AI-driven personalization strategies, as consumers may abandon brands that fail to demonstrate transparency and ethical data practices [5]. Such innovations illustrate the evolving role of AI in not only driving engagement but also redefining brand loyalty. E-commerce loyalty relies heavily on consistent, high-quality user experiences that are relevant to consumers [6] Studies show that personalization fosters emotional connections, which can be a key determinant in building loyalty. When consumers feel understood and valued, they are more likely to return to the same platform, even in the face of competitive options [7, 8]. Recent studies emphasize that personalization is not just a trend, but a key driver of consumer satisfaction and brand loyalty [9, 10]. The purpose of this study is to examine the impact of AI-driven personalization on consumer loyalty in Indonesian e-commerce with the following problem-solving approach:

- This study uses the Technology Acceptance Model (TAM) and Relationship Marketing Theory to understand the dynamics between personalization and consumer loyalty [11].
- On the other hand, Relationship Marketing Theory emphasizes the importance of building and maintaining long-term consumer relationships [12].
- This research is important to conduct in order to provide an understanding for Indonesian e-commerce regarding customer loyalty.

II. RELATED WORK

In recent years, Artificial Intelligence (AI) has moved beyond being a mere technological trend to become a vital partner in how Indonesian e-commerce businesses connect meaningfully with their customers. Indonesia, with its vast and diverse population, presents unique challenges and opportunities for AI-powered marketing. Platforms like Tokopedia, Bukalapak, and Go-Jek have embraced AI not just to automate tasks but to understand and anticipate the needs of millions of consumers, creating experiences that feel personal, timely, and relevant [10, 13]. AI models in Indonesian e-commerce extend well beyond cold algorithms. They embody a deep effort to humanize the digital shopping journey. For example, Go-Jek's AI-driven marketing strategies have led to a 40% increase in customer retention by promoting services and products tailored to each user's daily patterns and preferences [14]. This kind of strategy highlights that AI is not about replacing human touch but about augmenting it helping brands listen better and respond faster in a culturally sensitive way [15]. The ability of AI to analyze behavioral and demographic data allows businesses to craft marketing messages that resonate on a personal level, breaking through the noise of Indonesia's competitive online marketplace. However, this relies on a delicate balance companies must use data ethically and transparently to preserve trust, a recurring theme in studies exploring consumer sentiment in Indonesia [16].

Hyper-personalization powered by AI allows businesses to engage customers at a level previously only imaginable in face-to-face commerce. By integrating real-time data analytics, machine learning, and natural language processing, e-commerce platforms tailor what customers see from promotions to product recommendations, so precisely that it creates a feeling of personal care. Indonesian consumers value this approach highly, associating it with respect for individual preferences and convenience [17]. Yet, the human element remains crucial. Hyper-personalization must not feel intrusive or manipulative but should be experienced as an empowering tool allowing customers greater control and satisfaction. Indonesian consumers' growing awareness of privacy rights puts the onus on companies to maintain openness and respect in their AI-driven engagements [18]. E-loyalty in Indonesia's e-commerce is cultivated by consistent, thoughtful interactions enabled by AI. Chat bots, predictive tools, and automated CRM not only provide rapid responses but create a sense of ongoing relationship and understanding. For many Indonesian users, such experiences help them feel valued and heard despite the scale of these platforms. Indonesian case studies reveal that when companies successfully leverage AI to nurture these connections, they see tangible benefits higher retention rates, increased average purchases, and positive word-of-mouth. This reinforces the idea that technology, when applied with empathy and cultural awareness, can foster genuine loyalty and community among digital consumers [19, 20].

In Indonesia's vibrant e-commerce landscape, AI is a powerful enabler of human-centric marketing strategies. It helps businesses listen to and anticipate customer needs, creating hyper-personalized experiences that respect privacy while building trust [21]. More than tools and algorithms, these AI systems are catalysts for genuine connection and lasting loyalty [22]. As this digital revolution unfolds, the brands that combine technological innovation with heartfelt human understanding will define the future of retail in Indonesia. Technological shifts have enabled e-commerce businesses to shift from traditional advertising and marketing methods to more sophisticated, data-driven approaches. AI-powered hyper personalization strategies are among the most profound advancements in digital marketing strategy, offering brands the power to tailor experiences at an individual level [1]. AI-driven personalization is based on analyzing vast amounts of consumer data, such as browsing history, previous purchases, and social media interactions, to predict and respond to individual needs in real-time [2]. As a result, the consumer experience becomes more engaging and intuitive, fostering a stronger relationship between customers and brands [3]. However, this personalization has also increased reliance on sensitive consumer data, which has raised new challenges in data privacy and ethical data use.

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III. MATERIAL AND METHOD

1. DATA COLLECTION

The study is essentially a cross-sectional survey using PLS-SEM. The population in this study was e-commerce customers in Indonesia. The sample size was measured using Hair's theory. There are various minimum sample size criteria that can be used for PLS-SEM, one of which is the ten-times rule for endogenous variables [26]. Study [27] explained that the number of samples used to carry out the PLS SEM analysis technique was between 30 – 100. However, in order for the research to be optimal, the researcher doubled it to 400 (four hundred) e-commerce customer respondents with the criteria of being over 21 years old, and having made online purchases for at least the last 1 (one) month. Respondents were recruited using purposive sampling via online survey distribution Data collection was conducted over eight months.

The operational variables in this study contain indicators of a variable, allowing researchers to collect relevant data, allowing for more focused analysis of each variable and aligning with the planned measurement method. The operational variables in this study are illustrated in the following table:

Table 1. Operational definition of variables.

No.	Variables	Indicator	Variable Types
1.	Artificial Intelligence (AI)(X1)	1. Chatbots, 2. Data Analysis, And 3. Recommendation System	Exogenous
2.	Customer Experience (X2)	1.Sense 2. Feel 3. Think 4. Relate 5. Act	Exogenous
3.	Hyper Personalization (Y1)	1. Brand interaction history 2. Purchase history 3. Demographic data 4. Location	Intervening

		5. Average spends 6. Satisfaction ratings	
4.	E-Trust (Y2)	1. Can trust online vendors 2. Credible website 3. Can trust the information presented on the website 4. Trust the claims and promises on the website 5. Trust what online websites say about products	Moderating
5.	E-Loyalty (Z)	1. visit the website regularly 2. access product information 3. make purchases or use services through the website 4. strong trust and loyalty towards online shopping applications 5. actively contribute to the reputation and attractiveness of the website	Endogen

2. RESEARCH DESIGN

This study adopted a quantitative research design to examine the relationship between AI-based personalization strategies and consumer loyalty in e-commerce. A survey method was chosen to collect data from a large and diverse sample of e-commerce consumers, enabling statistical analysis of the impact of AI-based personalization on loyalty outcomes. This study aimed to explore how various AI-based personalization techniques, such as personalized recommendations, targeted advertising, and dynamic website customization, impact consumer loyalty metrics, including repurchase intention, brand advocacy, and emotional connection with the brand.

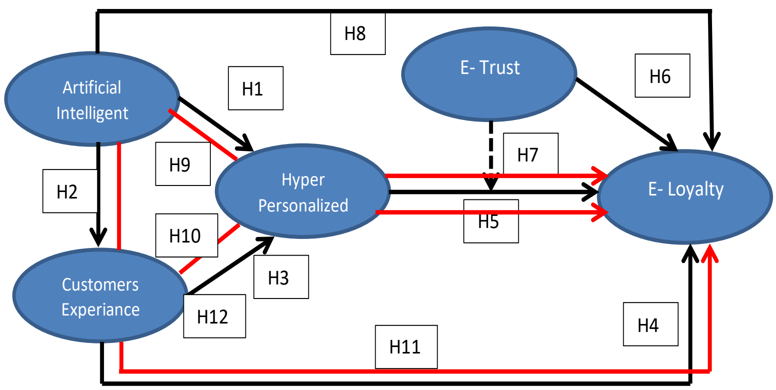

FIGURE 2. Conceptual framework.

This study develops and tests a comprehensive structural model examining the direct, indirect, and moderating effects of Artificial Intelligence, Hyper-Personalization, Customer Experience, and E-Trust on E-Loyalty. The proposed hypotheses also capture mediation and interaction effects to explain how AI-driven mechanisms enhance customer loyalty in e-commerce contexts.

HH1 Artificial Intelligence has a direct impact on Hyper Personalized.
HH2 Artificial Intelligence has a direct impact on Customer Experience.
HH3 Customer Experience has a direct impact on Hyper Personalized.
HH4 Customer Experience has a direct impact on E-Loyalty.

HH5	Hyper Personalized has a direct impact on E-Loyalty.
HH6	E-Trust has a direct impact on E-Loyalty.
HH7	E-Trust moderates the influence of Hyper Personalized on E-Loyalty.
HH8	Artificial Intelligence has a direct impact on E-Loyalty.
HH9	Artificial Intelligence has an indirect influence on E-Loyalty through Hyper Personalized.
HH10	Customer Experience has an indirect effect on E-Loyalty through Hyper Personalized.
HH11	Artificial Intelligence has an indirect effect on E-Loyalty through Customer Experience.
HH12	Artificial Intelligence has a direct impact on Hyper Personalized through Customer Experience.

The data analysis technique in this study will use SEM PLS because the SEM PLS data analysis technique does not require the use of a large sample size [27]. PLS measurement consists of:

- Outer Model (Measurement Model): This model specifies the relationship between latent variables and indicators, or defines how each indicator relates to its latent variable. The tests performed on the outer model are: Convergent Validity, Discriminant Validity, Composite Reliability, and AVE Value.
- Inner Model (Structural Model): Tests on the structural model to test the relationship between latent constructs, there are several tests for the structural model, including: R Square on Endogenous Constructs. The R Square value is the coefficient of determination on the endogenous construct where the R Square value of 0.67 is strong, 0.33 is moderate, 0.19 is weak. Estimate for Path Coefficient is the value of the path coefficient or the magnitude of the relationship / influence of the latent construct, carried out by the bootstrapping procedure.

Hypothesis Testing: In this hypothesis testing, the t-statistic and probability values can be seen. For hypothesis testing using statistical values, the t-statistic value used for alpha 5% is 1.96. Therefore, the criteria for accepting/rejecting the hypothesis are Ha is accepted and H0 is rejected when the t-statistic is > 1.96. To reject/accept the hypothesis using probability, Ha is accepted if the p-value is < 0.05 [29].

IV. DATA ANALYSIS

1. RESPONDENT CHARACTERISTICS

Respondent characteristics in this study were classified into three categories: gender, age, and highest level of education. These characteristics can be seen in the following graphic illustration:

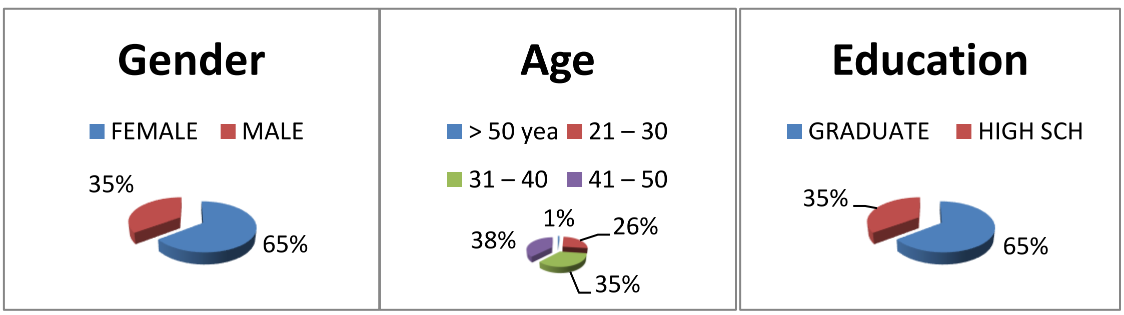

FIGURE 3. Respondent characteristics.

2. RESULTS AND DISCUSSION

2.1 Evaluation of the Measurement Model (Outer Model)

Evaluation of the measurement model (outer model) was conducted for each PLS scheme used, namely the path scheme, the centroid scheme, and the factor scheme. Evaluation of the measurement model for the reflexive indicator included assessing the validity and reliability of each indicator against its latent variable. Validity is a measure that describes the correlation between the reflexive indicator score and its latent variable. The evaluation began by examining the validity indicator indicated by the loading factor (λ) value. If the loading value (λ) is $\geq$0.6, the indicator is considered valid, and vice versa. From the loading factor test, a structural image was obtained as shown in the following figure.

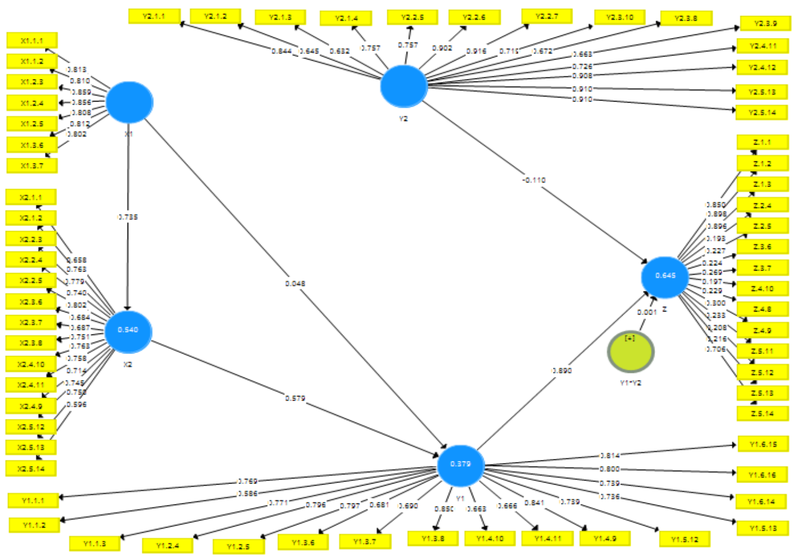

FIGURE 4. Outer model.

From the results of processing the loading factor, the values obtained were greater than several indicators with values smaller than 0.6 so that the indicators were discarded, then the data was reprocessed with results as shown in the following image.

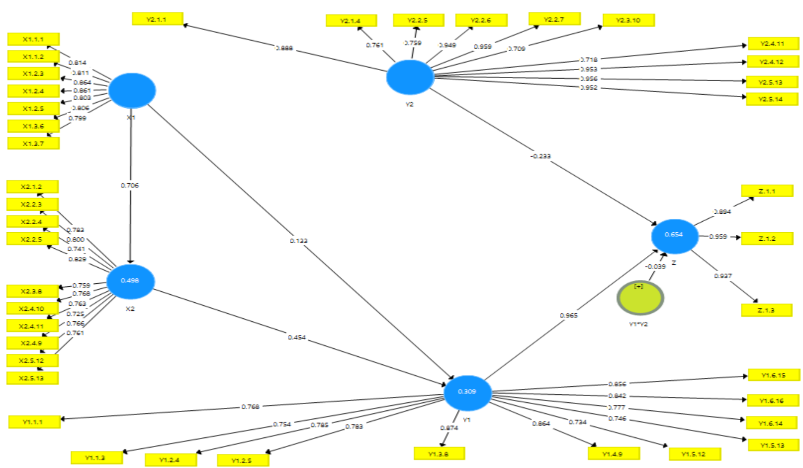

FIGURE 5. Fix outer model.

Next is the reliability testing of the research instrument. Reliability testing is conducted to prove the accuracy, consistency, and precision of the instrument in measuring the construct. Construct reliability testing using reflective indicators in PLS-SEM can be conducted in two ways: Cronbach's alpha and composite reliability, often referred to as Dillon-Golstein's. Using Cronbach's alpha to test construct reliability will result in a lower value (underestimation), so it is more advisable to use composite reliability to test the reliability of a construct.

Table 2. Reliability of variables.

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Artificial Intelligence (X1)	0.921	0.928	0.936	0.677
Customer Experience (X2)	0.924	0.927	0.936	0.593
Hyper Personalization (Y1)	0.944	0.951	0.951	0.640
Moderating (Y1*Y2)	1,000	1,000	1,000	1,000
E-Trust (Y2)	0.961	0.967	0.967	0.751
E Loyalty (Z)	0.922	0.923	0.951	0.866

Source: Researcher, data processed (2025).

Rule of thumb the composite reliability value, which is usually used to assess construct reliability, must be greater than 0.7 for confirmatory research and 0.6–0.7 for exploratory research. The table above shows that the Cronbach's alpha and composite reliability values of all variables are above 0.7, and the average variance extracted value is also above 0.5, thus meeting reliability requirements.

2.2 Structural Model Evaluation (Inner Model)

Structural model evaluation is conducted to examine the relationships between previously hypothesized latent constructs. The metrics used to evaluate the structural model (inner model) are R-square, Q-square Predictive Relevance, and GoF Index. The R-square (R2) value is the coefficient of determination for the endogenous construct and the path parameter coefficient. The Q-square Predictive Relevance (Q2) value can be used to validate the model's predictive ability. The stipulation is that if the Q2 value is closer to 1, the structural model can be said to fit the data or have relevant predictions. The GoF Index value is used for model evaluation and simply measures the overall model predictions. The results of the R2 and Q2 measurements are as follows:

Table 3. R square value of structural model.

Latent Variables	R Square (R2)
Customer Experience (X2)	0.498
Hyper Personalized (Y1)	0.309
E-Loyalty (Z)	0.654

$$Q^2 = 1 - [(1 - R1^2)(1 - R2^2)(1 – R3^2)]$$
$$Q^2 = 1 - [(1 - 0.496)(1 - 0.309)(1 – 654)] = 0.880$$

Source: Researcher, processed data (2025).

2.3 Effect Size F Square (F2)

Model quality testing is conducted to determine the effects between variables. The effect size (f2) is defined as: If the f2 value is <0.02, there is no effect; an F2 value between 0.02 and 0.15 indicates a small effect;

an F2 value of 0.15 and 0.35 indicates a moderate effect; and an F2 value >0.35 indicates a large effect. The results of the F2 assessment are presented in Table 5 below:

Table 4. F Square (F^2) Value.

	X1	X2	Y1	Y1*Y2	Y2	Z
Artificial Intelligence (X1)		0.993	0.013			
Customer Experience (X2)			0.149			
Hyper Personalization (Y1)						1,012
Moderating (Y1*Y2)						0.007
E-Trust (Y2)						0.056
E Loyalty (Z)						

Source: Researcher, processed data (2026)

The study's findings indicate that AI's largest effect size is on customer experience. This is due to its ability to analyze big data in real time to create more personalized and efficient interactions. AI can analyze customer preferences and behavior through machine learning, providing relevant product recommendations and tailored special offers. This can create a sense of emotional connection with customers.

3. BOOTSTRAP HYPOTHESIS TESTING

The significance of the model parameters, both the measurement model and the structural model, was evaluated through a bootstrapping procedure. The decision to reject H0 if the calculated t-value is greater than the t-table of 1.96 using an α of 0.05. The iteration used is according to the default, namely 500 iterations. The parameter testing for the measurement model is as follows:

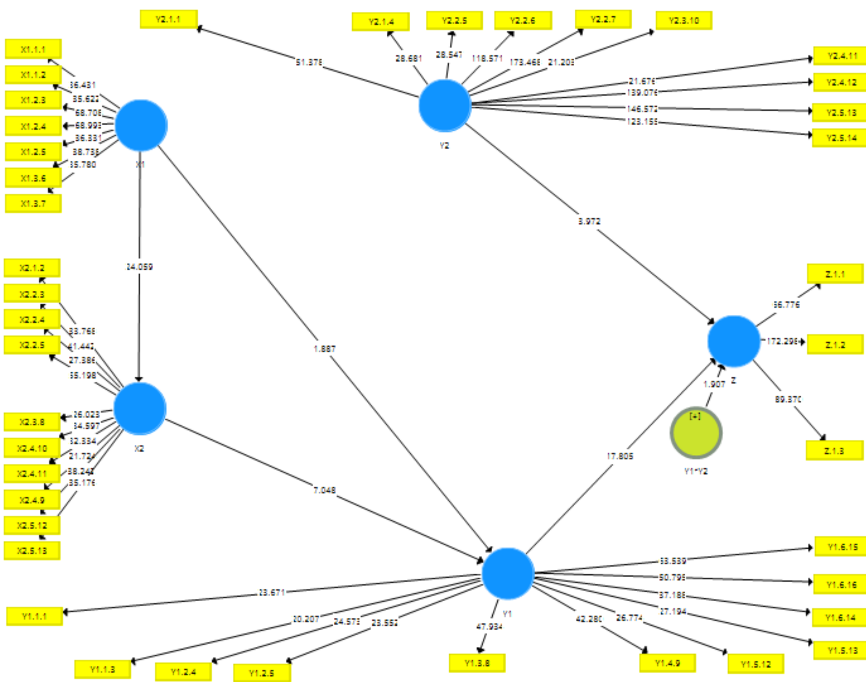

FIGURE 6. Inner model.

The next step is testing the parameters for the structural model with the hypothesis used being: H0: βij = 0 and H1: βij ≠ 0. The bootstrapping results for the structural model are as follows:

Table 4. Structural model hypothesis test.

No.	Hypothesis	P Values	Conclusion
H1	Artificial Intelligence (X1) has a direct influence on Hyper Personalized (Y1)	0,000	Accepted
H2	Artificial Intelligence (X1) has a direct impact on Customer Experience (X2)	0,000	Accepted
H3	Customer Experience (X2) has a direct influence on Hyper Personalized (Y1)	0,000	Accepted
H4	Customer Experience (X2) has a direct influence on E-Loyalty (Z)	0,000	Accepted
H5	Hyper Personalized (Y1) has a direct influence on E-Loyalty (Z)	0,000	Accepted
H6	E-Trust (Y2) has a direct effect on E-Loyalty (Z)	0,000	Accepted
H7	E-Trust (Y2) moderates the influence of Hyper Personalized (Y1) on E-Loyalty (Z)	0.057	Rejected
H8	Artificial Intelligence (X1) has a direct influence on E-Loyalty (Z)	0,000	Accepted
H9	Artificial Intelligence (X1) has an indirect effect on E-Loyalty (Z) through Hyper Personalized (Y1)	0.061	Rejected
H10	Customer Experience (X2) has an indirect effect on E-Loyalty (Z) through Hyper Personalized (Y1)	0,000	Accepted
H11	Artificial Intelligence (X1) has an indirect effect on E-Loyalty (Z) through Customer Experience (Y2)	0,000	Accepted
H12	Artificial Intelligence (X1) has a direct influence on Hyper Personalized (Y1) through Customer Experience (X2)	0,000	Accepted

Source: Researcher, processed data (2025).

The results of Bootstrapping in the hypothesis test concluded that H7 and H9 were rejected because the calculated t-value was smaller than the t-table, which was 1.96. This means that E-Trust was not able to moderate the relationship between Hyper Personalized and E-Loyalty and AI did not have a direct effect on E-Loyalty through Hyper Personalized. This is because consumers feel overly monitored if recommendations are too accurate, triggering psychological reactivity and rejection, rather than loyalty. Furthermore, AI is often perceived as impersonal or failing to capture authentic emotional responses, so its effects are cut off before achieving loyalty. Meanwhile, H2, H3, H4 H5, H6, H8, H10, H11 and H12 obtained t-count results greater than t-table so the hypothesis is accepted.

4. DISCUSSION

Artificial Intelligence (AI) has a direct impact on hyper-personalization because it can collect and analyze user behavior data in real time with a high degree of accuracy. AI uses machine learning to deeply understand individual preferences, not just based on general segmentation.[9]. In this way, AI can create highly relevant and personalized content, recommendations, and ads that perfectly match each customer's specific needs and desires.[30]These factors include AI's ability to collect data from various sources such as purchase history, browsing activity, and social media interactions, analyze user behavior patterns with intelligent algorithms, create experiences that feel like a "digital friend" that knows exactly what customers want and need, and increase customer engagement and marketing effectiveness through targeted recommendations. In short, AI is a major factor due to its sophistication in processing big data and providing hyper-personalized experiences that go far beyond traditional personalization.

Customer experience directly impacts hyper personalization because a good customer experience creates relevant and personalized interactions with customers. When customers perceive that interactions with a brand or business meet their specific needs and preferences, this increases customer satisfaction and loyalty.

Hyper personalization enables businesses to deliver highly tailored experiences at the right moment and on the right channel, making customer experiences more meaningful and personalized [31]. E-trust influences e-loyalty because e-trust is the primary foundation that makes customers feel safe and confident in online transactions. When customers trust a digital platform or service, they are more likely to continue using that service repeatedly and loyally [17].

When e-trust is unable to moderate the relationship between hyper personalized and e-loyalty, this may be due to its role as a more direct factor influencing loyalty, or due to the specific conditions of trust levels and consumer characteristics in that context. When Artificial Intelligence (AI) has an indirect effect on e-loyalty through hyper personalization but is not significant, this could be caused by weak mediation relationships, contextual variables that have not been integrated, less than optimal data, and variations in customer responses to personalization [32].

V. CONCLUSION

AI plays a crucial role in creating hyper-personalization, significantly enhancing the customer experience. While AI indirectly impacts e-loyalty through hyper-personalization, this impact is sometimes insignificant due to the complexity of mediation relationships, suboptimal data utilization, and varying customer responses to personalization. Customer experience and hyper-personalization also directly strengthen customer loyalty by providing relevant and personalized experiences. E-trust serves as a crucial foundation that creates a sense of security and trust in customers, thus increasing loyalty. However, its role as a moderator of the relationship between hyper-personalization and e-loyalty is not always significant. This study has several weaknesses, such as the small sample size, which requires further development. Furthermore, future research could include additional variables to improve the model.

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Author Contributions

Conceptualization, N.I., A.M., and Z.; methodology, N.I., A.M., and T.Z.; software, N.I.; validation, Z. and R.; formal analysis, N.I.; investigation, N.I. and A.M.; resources, Z., T.Z., and R.; data curation, N.I.; writing—original draft preparation, N.I.; writing—review and editing, A.M., Z., T.Z., and R.; visualization, N.I.; supervision, R.; project administration, Z. and R.; funding acquisition, R.

Conflicts of Interest

The authors declare that they have no conflicts of interest

Data Availability Statement

Data is available from the authors upon request.

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Not applicable.

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