



Exploring the Role of AI in Marketing and Technology Readiness in Enhancing Customer Satisfaction and Business Performance in E-commerce

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Citation:

Hariguna, T.; Waluyo, R.; Dianingrum, M.; Wahid, A. M. Exploring the role of AI in marketing and technology readiness in enhancing customer satisfaction and business performance in e-commerce. *ASEAN J. Sci. Tech. Report.* **2026**, 29(1), e258998. <https://doi.org/10.55164/ajstr.v29i1.258998>.

Article history:

Received: April 26, 2025

Revised: October 4, 2025

Accepted: October 18, 2025

Available online: December 14, 2025

Publisher's Note:

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Abstract: This study examines the relationships between technology readiness (TR), AI in marketing (AIM), customer satisfaction (CS), customer performance (CP), customer experience (CE), and financial performance (FP) in the context of Indonesian e-commerce businesses. Using structural equation modeling (PLS-SEM) on survey data from 314 business owners, the study finds strong positive relationships, with CS and CP acting as key mediators. The findings indicate that higher levels of TR significantly enhance CS, which in turn drives improved financial outcomes. Furthermore, the integration of AIM, particularly through personalized marketing tools, was found to have a substantial impact on both customer engagement and financial performance. The Sobel test results confirm that CS serves as a crucial mediator in the relationships between AIM, TR, and FP. This paper contributes to the existing literature by offering a comprehensive model that integrates several key constructs, providing new insights into the intersection of technology adoption and business performance in e-commerce. However, results are limited by convenience sampling and demographic concentration, which constrain generalizability. Practical recommendations emphasize prioritizing staff readiness, adopting AI-powered personalization tools, and actively tracking CS metrics to improve profitability.

Keywords: Technology readiness; AI in marketing; customer satisfaction; customer performance; financial performance

1. Introduction

The evolution of AI in marketing (AIM) has transformed how businesses operate and interact with consumers. In the past decade, technologies such as machine learning, natural language processing, and predictive analytics have become central to digital marketing, enabling more precise targeting and personalization. By analyzing vast datasets quickly and accurately, businesses can tailor campaigns to individual needs, improving efficiency and reducing resource waste [1, 2]. Beyond automation, AI also complements human judgment through collaborative intelligence, where machines handle data-driven tasks and marketers focus on strategic decisions and customer relationships [3, 4]. As e-commerce expands, AIM plays a critical role in enhancing operations, customer service, and competitiveness. AI algorithms can

predict consumer behavior with high accuracy, allowing firms to personalize recommendations and marketing strategies [5, 6]. This ability creates precision marketing, where customer segmentation and personalized campaigns strengthen engagement and loyalty [7, 8]. With real-time tracking, businesses can adapt campaigns instantly, ensuring responsiveness to shifting market trends. Such agility provides firms with a vital edge in today's highly competitive digital environment.

The adoption of AIM, however, depends heavily on technology readiness (TR). TR reflects the optimism, innovativeness, discomfort, and insecurity that shape an organization's willingness to adopt new technologies [8, 9]. Optimism and innovativeness drive positive adoption, while discomfort and insecurity can slow implementation. Understanding these readiness dimensions is crucial for firms seeking to integrate AI successfully into marketing strategies. Despite extensive research on AI adoption, customer experience (CE), and performance metrics, prior studies often examine these constructs in isolation [10, 11]. Few have investigated how TR and AIM jointly influence customer satisfaction (CS), customer performance (CP), and financial performance (FP) in e-commerce. This gap limits understanding of the systemic impact of AI adoption on business outcomes. Furthermore, measurement overlaps between constructs such as AIM and CE remain unresolved, creating ambiguity in how these factors interact [12, 13]. To address this gap, this study develops and tests an integrated model that links TR, AIM, CE, CS, CP, and FP in the context of Indonesian e-commerce. The objective is to clarify the pathways through which technology readiness and AI-driven marketing enhance satisfaction, customer outcomes, and ultimately financial performance. By highlighting these relationships, the study contributes both theoretically—by extending technology adoption frameworks—and practically—by offering actionable strategies for e-commerce businesses.

2. Literature Review

2.1. Exploring Technology Readiness (TR) in the Context of AI Adoption

Technology readiness (TR) refers to the extent to which individuals or organizations are prepared to adopt new technologies [14, 15], influencing how AI is integrated into marketing strategies. It is shaped by personal [16], organizational [17], and cultural factors such as age [18], education [19], innovativeness [20], and national culture [21] that determine openness to AI-driven tools [22, 23]. The Technology Acceptance Model (TAM) emphasizes that perceived ease of use [24, 25] and usefulness drive adoption [26], while the Technology Organization Environment (TOE) framework highlights the importance of organizational resources and leadership support [27, 28]. Together, these frameworks suggest that TR is a multidimensional construct that reflects both individual attitudes [29, 30] and organizational capacity for adoption [31, 32]. The Technology Readiness Index (TRI) further refines this concept [33, 34] through four dimensions: optimism, innovativeness, discomfort, and insecurity [35, 36]. Optimism and innovativeness encourage early adoption and experimentation, while discomfort and insecurity reflect barriers such as fear of errors, data privacy concerns, or lack of trust in AI systems [29, 30]. Prior studies show that higher optimism and innovativeness correlate with stronger adoption of AI tools, leading to improved customer engagement and satisfaction [37, 38]. By contrast, discomfort and insecurity can delay or weaken adoption, limiting the benefits of AI-enabled marketing [39].

TR is critical not only for organizations but also for consumers interacting with AI-powered services [40]. Consumers with high TR are more likely to engage with chatbots, recommendation systems, or AI driven personalization [41], which enhances their satisfaction and loyalty [37, 42]. Conversely, those with low TR may resist or disengage, reducing the effectiveness of AIM initiatives. This dual role of TR shaping both organizational adoption and consumer response underscores its importance in e-commerce [43]. Overall, TR provides the foundation for understanding how AI in marketing creates value [45]. Organizations with higher TR are better positioned to integrate AI tools, improve customer experience (CE), and foster satisfaction (CS), which in turn drives loyalty and financial performance (FP). Thus, TR represents a starting point in the proposed model, influencing not only the adoption of AIM but also its downstream effects on CE, CS, and business outcomes.

2.2 Understanding Customer Experience (CE) in E-Commerce Marketing

Customer experience (CE) encompasses all interactions a customer has with a brand across product usage, service encounters, and online engagement that collectively shape perceptions of the brand [46, 47]. In digital commerce, CE is not limited to transactions but reflects the overall journey from awareness to post-purchase, making it a critical driver of satisfaction and loyalty [48, 49]. Technology readiness (TR) plays an important role in shaping CE, as customers with higher optimism and innovativeness are more likely to engage with AI enabled services such as chatbots, recommendation systems, or personalized interfaces [44, 50]. These customers perceive AI tools as enhancing value and convenience, while those experiencing discomfort or insecurity may hesitate to adopt them, requiring additional support or intuitive design [29, 51]. Balancing the needs of both technologically ready and reluctant customers is therefore essential to ensure a positive and inclusive CE [48].

CE is inherently multidimensional, integrating cognitive, emotional, and relational components that influence customer reactions and long-term loyalty [52, 53]. Positive experiences such as responsive service, seamless digital platforms, or personalized interactions strengthen satisfaction, while negative experiences quickly lead to churn. Emotional connections are particularly powerful; when customers feel valued through personalization or exceptional service, they are more likely to advocate for the brand, extending their engagement beyond transactions [6, 54, 55]. In summary, CE directly shapes customer satisfaction (CS) and mediates the influence of technology adoption on loyalty and business performance. As AI-driven personalization becomes more widespread, understanding CE provides the link between TR and downstream outcomes such as CS, CP, and FP. This connection positions CE as a central construct in the integrated model developed in this study.

2.3 The Role of AI in Marketing (AIM) and Its Impact on E-Commerce

AI in marketing (AIM) refers to the integration of intelligent technologies such as machine learning, natural language processing, and predictive analytics into marketing activities to enhance customer interactions, streamline decision-making, and improve performance [56]. Unlike traditional data analysis, AIM enables real-time personalization by analyzing customer behavior and preferences at scale, making it a cornerstone of digital competitiveness. Personalization is AIM's key contribution: tailored recommendations, dynamic content, and individualized messages strengthen customer relationships and increase satisfaction [56, 57]. By delivering relevant offers and anticipating needs, AIM fosters deeper engagement and long term loyalty. In parallel, technologies such as chatbots and virtual assistants provide 24/7 personalized support, improving responsiveness and building emotional connections with customers [58, 59]. Predictive analytics further enhances this process by identifying patterns in customer data, allowing businesses to act proactively and prevent dissatisfaction [60].

The rise of AIM has also redefined the omnichannel experience. By integrating websites, mobile apps, and service touchpoints into seamless journeys, businesses can ensure consistency and brand trust, which directly strengthens CE and CS [58]. At the same time, challenges remain: technological anxiety, resistance to change, and lack of organizational readiness can limit adoption [61, 62]. Addressing these barriers is essential for firms to realize the full potential of AIM. Ultimately, AIM contributes not only to customer satisfaction and loyalty but also to measurable business outcomes [63, 64]. Studies confirm that AI-driven personalization, campaign optimization, and real-time customer engagement lead to sales growth [65], profitability [66], and stronger financial performance [67, 68]. Thus, AIM serves as both a driver of improved CE and CS [69], as a direct enabler of customer performance (CP) and financial performance (FP), making it a central construct in the integrated model developed in this study.

2.4 The Relationship Between Customer Satisfaction (CS) and Business Performance

Customer satisfaction (CS) is commonly defined as the degree to which a product or service meets or exceeds customer expectations [70], representing both an emotional and cognitive evaluation [71, 72]. As a key driver of loyalty, retention, and advocacy, CS is widely recognized as a foundation of long-term business success [6, 55]. Several mechanisms explain how CS develops. The disconfirmation of expectations theory suggests satisfaction arises when actual performance matches or exceeds expectations, while perceived value

theory highlights the balance between benefits received and costs incurred [73, 74]. Positive customer experiences, responsive service quality, and emotional connections with a brand have all been shown to strengthen CS and increase loyalty [75, 76]. Conversely, poor experiences or unfulfilled expectations lead to dissatisfaction and churn [77, 78].

CS not only affects immediate behaviors, such as repurchase intention [79] and word-of-mouth [80], but also contributes to broader financial outcomes [81]. Studies consistently show that higher CS improves profitability [82], Return on Assets (ROA) [83], Return on Equity (ROE) [84], and market capitalization [85, 86]. Satisfied customers spend more, return more often [87], and are less sensitive to price fluctuations [88], creating a stable revenue base and strengthening competitive advantage [89, 90]. CS also functions as a mediator between customer experience (CE) [91], organizational practices [92], and financial performance (FP). Engaged employees and seamless digital touchpoints amplify CS, which in turn drives repeat purchases [93], loyalty, and profitability [91, 94]. Integrating CS metrics with financial indicators ensures that firms align customer value with strategic growth, making CS a central metric for evaluating marketing effectiveness [95, 96]. In summary, CS links customer experience to financial outcomes and acts as a pathway through which AIM and TR can influence profitability. Its mediating role makes it a crucial construct in the integrated model developed in this study.

2.5. Assessing Customer Performance (CP) in the Digital Marketing Landscape

Customer performance (CP) refers to how effectively customers engage with and utilize AI driven tools such as recommendation systems, personalized content, and self-service technologies [97] to enhance their experience [98, 99]. Unlike customer satisfaction, which reflects perceptions, CP captures actual behavioral engagement and value co-creation between customers and firms. Three main drivers shape CP. First, personalization is critical: AI powered tools that deliver tailored recommendations and content increase relevance, engagement, and repeat usage [100, 101]. Second, system usability matters: user friendly, intuitive AI interfaces encourage active participation, while complex systems discourage adoption [102, 103]. Third, customer traits such as openness and extraversion influence willingness to experiment with AI enabled features [104], leading to stronger engagement outcomes [105, 106].

Emotional engagement further strengthens CP. Chatbots and virtual assistants can simulate empathy [107], creating meaningful interactions that increase trust and repeat usage [108]. Predictive analytics also improves CP by anticipating customer needs [109] and providing proactive solutions [110]. When customers perceive AI interactions as valuable, they are more likely to deepen their engagement [111], which in turn enhances both CP and CS [112]. Ultimately, CP is not an isolated outcome; it reinforces customer satisfaction and loyalty, thereby contributing to financial performance (FP) [113, 114]. In the integrated model, CP represents the behavioral mechanism through which AIM translates into measurable business success.

2.6. How Customer Satisfaction Drives Financial Performance (FP) in E-Commerce

Financial performance (FP) in e-commerce is typically measured through indicators such as profitability, Return on Assets (ROA), and Return on Equity (ROE), which reflect how effectively a firm generates and sustains growth [70, 115]. Customer satisfaction (CS) has been consistently identified as a key driver of these outcomes, as satisfied customers are more likely to return, repurchase, and advocate for the brand, thereby reducing acquisition costs and increasing customer lifetime value [86, 87]. AIM enhances this process by strengthening CS through personalization, predictive analytics [115], and real-time engagement [116]. Recommendation systems, tailored marketing campaigns [117], and responsive chatbots improve satisfaction and loyalty [118], which in turn translate into higher sales, repeat purchases, and stronger profitability [119, 120]. By aligning AI driven personalization with customer needs, firms can generate sustainable revenue streams and improve efficiency in marketing resource allocation [121].

Research across industries confirms that CS positively influences financial metrics, especially in sectors where customer retention and loyalty are vital, such as retail and services [90, 122]. Moreover, CS functions as a mediator: it translates positive experiences (CE) and behavioral engagement (CP) into long term financial outcomes, making it a crucial link between marketing practices and profitability [91]. In summary, FP is not only a direct outcome of effective AI enabled marketing but also the result of CS and CP working

together to foster loyalty, retention, and advocacy. This mediating role underscores why FP is positioned as the ultimate dependent variable in the integrated model proposed in this study.

2.7 Summary of Literature Review

The literature review has demonstrated that technology readiness (TR) and AI in marketing (AIM) are essential drivers of digital transformation in e-commerce, influencing customer experience (CE), customer satisfaction (CS), and customer performance (CP), which ultimately determine financial performance (FP). Prior studies confirm the significance of each construct individually, yet most have examined them in isolation, failing to capture the cumulative and interdependent effects of readiness, adoption, and outcomes. This review highlights three key insights. First, TR shapes both organizational capacity and consumer willingness to adopt AI enabled tools, establishing the conditions for effective AIM. Second, AIM enhances CE and CS through personalization, predictive analytics, and automation, thereby strengthening engagement and loyalty. Third, CS and CP serve as crucial pathways that translate these technological and experiential factors into long term FP. Despite these advances, existing research lacks an integrated model that combines TR, AIM, CE, CS, CP, and FP within a unified framework. Addressing this gap is vital for understanding how AI adoption creates measurable value for e-commerce businesses. This study responds to that need by developing and empirically testing a model that connects these six constructs, offering both theoretical contributions and practical guidance for firms seeking to leverage AI for sustainable performance.

3. Research Methods

3.1 Research Design and Data Collection

This study employed a quantitative survey design to examine the impact of technology readiness (TR), AI in marketing (AIM), customer experience (CE), customer satisfaction (CS), customer performance (CP), and financial performance (FP) in e-commerce. Respondents were business owners actively implementing AI tools such as chatbots, recommendation systems, and AI-generated content. Data were collected in August 2024 using an online questionnaire distributed via Google Forms, resulting in 314 valid responses. The survey instrument captured demographic information and items related to the study constructs. The final sample was dominated by younger respondents (aged 25–34), predominantly male, with bachelor's degrees, and from small-sized enterprises. While this profile reflects early AI adopters in Indonesian e-commerce, it introduces demographic concentration and sampling bias, which limit the generalizability of findings to broader populations. A target of 334 responses was set to ensure statistical reliability. Although the final sample size fell slightly short, 314 respondents exceeded the '10 times rule' and other guidelines for PLS-SEM, making it sufficient to test the proposed structural model [123]. As the study relied on a single self-reported survey, there is a risk of common method bias (CMB). To reduce this risk, several procedural remedies were implemented, including assuring respondent anonymity and randomizing item order. Nonetheless, the possibility of CMB cannot be fully eliminated and should be considered when interpreting the results. Overall, the survey design is appropriate for the study's exploratory objective of identifying predictive relationships between TR, AIM, CE, CS, CP, and FP, rather than establishing strict causal inference. The structured data collection process ensures alignment with the research objectives and provides a valid basis for empirical testing of the proposed model.

3.2 Research Model and Hypothesis Development

The conceptual framework for this study integrates technology readiness (TR), AI in marketing (AIM), customer experience (CE), customer satisfaction (CS), customer performance (CP), and financial performance (FP) to explain how technology adoption influences business outcomes. In this model, TR and AIM are proposed as key antecedents, while CE, CS, and CP act as mediators linking adoption to financial performance. According to the Technology Readiness Index (TRI), optimism and innovativeness increase openness to adopting new technologies, while discomfort and insecurity act as barriers [39, 40]. Higher TR enables smoother integration of AI tools into marketing strategies, improving personalization, responsiveness, and

ultimately satisfaction. This brings us to H1, which proposes that TR significantly influences CS by facilitating the adoption and effective use of AI technologies in marketing strategies [123].

H1: TR significantly influences CS

Customer experience (CE) encompasses all interactions across touchpoints product use, service encounters, and digital engagement and strongly shapes customer satisfaction (CS). According to service quality and disconfirmation theory, positive experiences that meet or exceed expectations foster trust, value, and loyalty [46, 52, 53]. This brings us to H2, which posits that CE significantly influences CS by shaping perceptions of value through positive interactions.

H2: CE significantly influences CS

AI in marketing (AIM) further enhances satisfaction by improving the quality of customer experiences. Through personalization, predictive analytics, and automated interactions, AIM allows businesses to anticipate needs and deliver timely, relevant engagement, leading to higher CS [5, 56]. This brings us to H3, which proposes that AIM influences CS by leveraging AI tools to personalize and optimize customer interactions, directly enhancing satisfaction.

H3: AIM significantly influences CS

Customer performance (CP) refers to how effectively customers engage with AI driven tools such as personalized content, recommendation systems, and automated support to improve their overall experience [100, 102]. AIM facilitates this engagement by empowering customers with relevant information, intuitive interfaces, and predictive insights, thereby enhancing their ability to interact meaningfully with brands. This brings us to H4, which proposes that AIM influences CP by equipping customers with tools that support informed decisions and efficient interactions, ultimately strengthening engagement.

H4: AIM significantly influences CP

Financial performance (FP) reflects a firm's ability to sustain profitability and growth, and is strongly shaped by customer engagement and loyalty. AIM supports FP by optimizing marketing campaigns, delivering personalized services, and fostering satisfaction that drives repeat purchases and advocacy [115, 121]. This brings us to H5, which proposes that AIM influences FP by enhancing customer engagement and satisfaction, leading to improved profitability and market competitiveness.

H5: AIM significantly influences FP

Customer satisfaction (CS) is one of the most consistent predictors of financial performance (FP). Higher CS strengthens loyalty, encourages repeat purchases, and generates positive word-of-mouth, all of which reduce acquisition costs and create stable revenue streams [92, 122]. CS also enhances brand advocacy, attracting new customers and sustaining long-term profitability. This brings us to H6, which proposes that CS influences FP by fostering loyalty, driving repeat business, and promoting advocacy that directly contribute to improved financial outcomes.

H6: CS significantly influences FP

Figure 1 illustrates the hypothesized model, showing the direct and mediated paths from TR and AIM through CE, CS, and CP toward FP. The framework highlights the cascading effects of technology readiness and AI adoption on customer outcomes and ultimately on financial performance, serving as a basis for the empirical analysis in this study.

3.3 Measurement Instruments

The accuracy of this study depends on the proper measurement of the six key constructs: technology readiness (TR), AI in marketing (AIM), customer experience (CE), customer satisfaction (CS), customer performance (CP), and financial performance (FP). To ensure validity and reliability, measurement scales were adapted from prior studies and established frameworks, with modifications made to fit the context of e-commerce and AI adoption. Content validity was strengthened through a review of relevant literature and consultation with academic experts. Particular care was taken to avoid conceptual overlap between constructs, especially AIM and CE. AIM items emphasized technology-enabled marketing functions such as personalization, predictive analytics, and automation, while CE items focused on customers' perceptions of service interactions and touchpoints. This distinction ensured that constructs captured different but complementary dimensions of the research model. Each construct was assessed using multiple Likert scale

items to capture its multidimensional nature. All items were drawn from validated instruments in prior research and were tested for clarity and contextual relevance through a pilot study. The use of multi item scales supports comprehensive measurement and allows for later testing of convergent validity, discriminant validity, and internal consistency reliability in the PLS-SEM analysis. Table 1 presents the measurement items and their sources, providing a clear overview of how TR, AIM, CE, CS, CP, and FP were operationalized in this study.

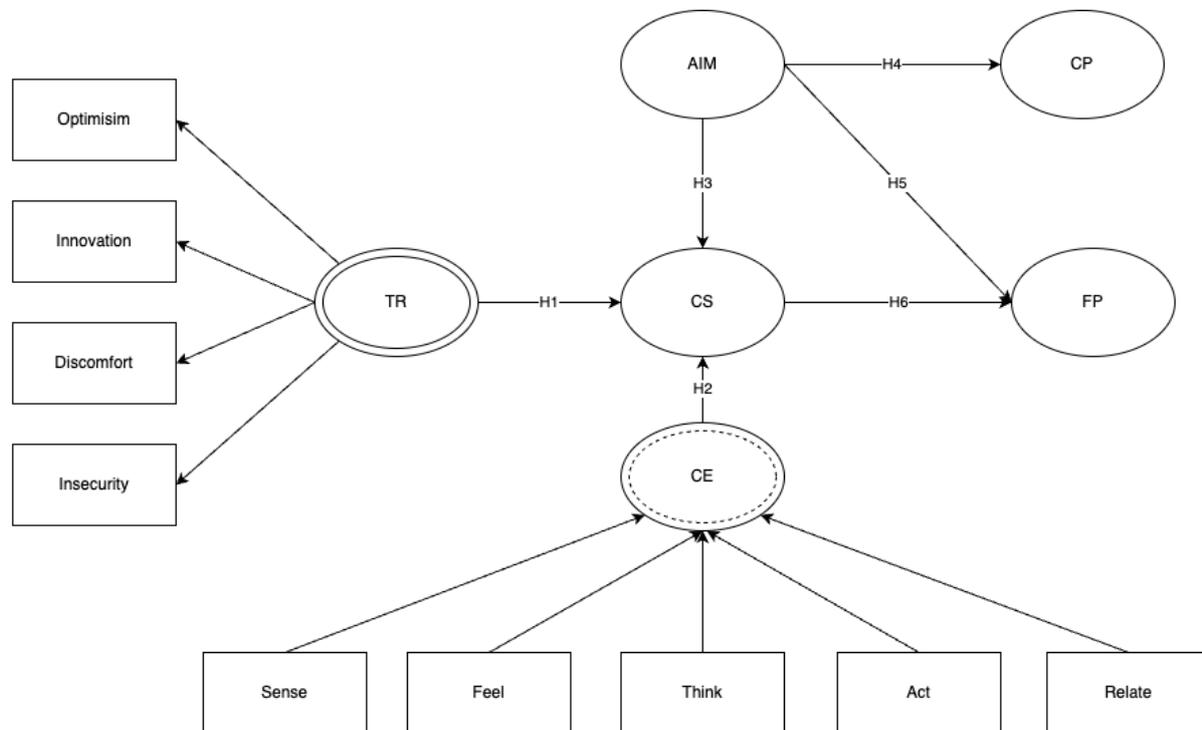


Figure 1. Research model framework

3.4 Data Analysis

The data collected through the survey were analyzed using SmartPLS 4.0, which is appropriate for complex models with multiple constructs and indicators, and for data that may not meet the strict assumptions of covariance-based SEM [129]. This approach allowed for simultaneous assessment of the measurement and structural models. Reliability was assessed using Cronbach's alpha and composite reliability (CR), with thresholds of 0.70 indicating acceptable internal consistency. Convergent validity was evaluated through average variance extracted ($AVE > 0.50$), while discriminant validity was tested using both the Fornell Larcker criterion and the heterotrait–monotrait (HTMT) ratio ($HTMT < 0.90$). Variance inflation factor (VIF) values were also examined to check for multicollinearity, with all values below 5, indicating no critical collinearity issues. Once measurement validity was established, the structural model was assessed. Path coefficients (β) and their significance were estimated through bootstrapping with 5,000 resamples. Relationships were considered significant when $t > 1.96$ at the 5% level. Coefficient of determination (R^2) values were reported for CS, CP, and FP, with values of 0.20 or higher considered acceptable. Effect sizes (f^2) were calculated to evaluate the contribution of each predictor (0.02 = small, 0.15 = medium, 0.35 = large). Model fit was evaluated using the standardized root mean square residual ($SRMR < 0.08$) and normed fit index ($NFI > 0.90$). Predictive relevance (Q^2) values were obtained using blindfolding procedures, with values greater than zero confirming meaningful predictive capacity. Together, these analyses ensured that the constructs were measured reliably, discriminated clearly from one another, and that the structural model provided both explanatory power and predictive relevance. This approach allowed robust testing of the hypothesized relationships between TR, AIM, CE, CS, CP, and FP in the e-commerce context.

Table 1. Questionnaire items in measurement instruments

Variable	Item	Source	
CE	SENSE1	My AI tools speed up marketing tasks in my enterprise.	Adapted from [124]
	SENSE2	AI systems simplify marketing tasks for my enterprise.	
	SENSE3	AI in marketing saves money on tasks.	
	FEEL1	AI tools improve marketing performance in my enterprise.	
	FEEL2	AI enhances marketing strategy effectiveness.	
	FEEL3	AI systems help correct marketing errors.	
	THINK1	AI helps my enterprise meet future marketing goals.	
	THINK2	AI tools help acquire new marketing knowledge.	
	ACT1	AI helps acquire new marketing skills.	
	ACT2	AI tools generate innovative marketing ideas.	
	RELATE1	AI systems improve customer relationships.	
	RELATE2	AI tools make customer interactions more personalized.	
	RELATE3	AI in marketing strengthens our connection with customers.	
TR	OPT1	AI technologies improve the consumer quality of life.	Adapted from [125]
	OPT2	AI gives consumers more flexibility in brand interactions.	
	INNO1	I appreciate AI tools that fit my enterprise's needs.	
	INNO2	AI allows my enterprise to interact with customers beyond business hours.	
	DISC1	I feel uneasy using AI tools I don't fully understand.	
	DISC2	AI in marketing feels intrusive, especially when collecting personal data.	
	DISC3	Implementing AI-powered chatbots in customer service is challenging.	
	INSEC1	I'm concerned about customer data security with AI systems.	
	INSEC2	I'm unsure if AI systems will always fulfill promises.	
AIM	AIM1	AI predicts customer needs for my enterprise.	Adapted from [2]
	AIM2	AI eliminates human errors in marketing promotion.	
	AIM3	AI helps interact with internet users via analyzed data.	
CP	CP1	AI tools improve products and services based on feedback.	Adapted from [126]
	CP2	Customers think we excel in AI-driven innovations.	
	CP3	Our company outperforms competitors in AI for product development.	
CS	CS1	I am happy with our AI-powered services.	Adapted from [127]
	CS2	I am satisfied with our AI-driven marketing procedures.	
	CS3	I enjoy using AI-based marketing tools and recommendations.	
FP	FP1	AI in marketing boosts our profitability.	Adapted from [128]
	FP2	AI-driven strategies contribute to profit growth.	
	FP3	AI tools help achieve higher sales growth.	

4. Results and Discussion

4.1 Descriptive Statistics

The sample consisted of 314 Indonesian e-commerce business owners actively using AI in marketing. Table 2 presents the demographic breakdown. The majority of respondents were male (60.19%), aged 25–34 (46.18%), held a bachelor's degree (65.61%), and operated small enterprises with fewer than 50 employees

(71.34%). Nearly half had been in business for 2–5 years (46.82%), and most had used AI tools for over one year (71.02%). More than half (52.55%) reported business growth in the past year, while 40.76% remained stable and 6.69% reported a decline. This profile reflects the characteristics of early AI adopters in Indonesian e-commerce young, well-educated entrepreneurs managing small to medium sized firms consistent with global technology adoption patterns. However, the demographic concentration introduces limitations: the findings may not generalize to older, less-educated business owners or to large scale enterprises. As the data were collected using convenience sampling, caution should be exercised when extending these results to the broader e-commerce population. Nevertheless, the demographic profile provides valuable context for interpreting the role of technology readiness and AI in driving business outcomes.

Table 2. Demography data

Demography	Category	Frequency	Percentage
Age	Under 25	60	19.11%
	25-34	145	46.18%
	35-44	75	23.89%
	45 and above	34	10.83%
Gender	Male	189	60.19%
	Female	125	39.81%
Education Level	High school or less	53	16.88%
	Bachelor's degree	206	65.61%
	Master's degree or higher	55	17.52%
Business Size	1-10 employees	119	37.90%
	11-50 employees	105	33.44%
	51-200 employees	49	15.61%
	201+ employees	41	13.06%
Years in Business	Less than 2 years	68	21.66%
	2-5 years	147	46.82%
	6-10 years	72	22.93%
	10+ years	27	8.60%
AI Adoption Experience	Less than 1 year	91	28.98%
	1 year and more	223	71.02%
Business Growth Rate (Last 12 months)	Decreased	21	6.69%
	Stayed the same	128	40.76%
	Increased	165	52.55%

4.2 Measurement Model Evaluation

The reliability and validity of the constructs were assessed using Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and factor loadings. Cronbach's alpha and CR values for all constructs exceeded the recommended threshold of 0.70, indicating strong internal consistency. AVE values were above 0.50, confirming convergent validity, and factor loadings were generally above 0.70. Items with slightly lower loadings were retained only when they contributed meaningfully to content validity. Table 3 shows the results of the reliability and convergent validity analysis.

Table 3. Reliability analysis and convergent validity

Measurement	Factor Loading/Weight	Composite Reliability	AVE
SENSE	0.244	N/A (Formative Construct)	N/A (Formative Construct)
FEEL	0.239		
THINK	0.221		
ACT	0.208	0.735	0.833
RELATE	0.253		
SENSE1	0.726		
SENSE2	0.889	0.895	0.843
SENSE3	0.795		
FEEL1	0.702		
FEEL2	0.754	0.724	0.975
FEEL3	0.907		
THINK1	0.776		
THINK2	0.726	0.734	0.822
ACT1	0.847		
ACT2	0.775		
RELATE1	0.73	0.87	0.734
RELATE2	0.802		
RELATE3	0.971		
OPT1	0.959	0.787	0.737
OPT2	0.752		
INNO1	0.733		
INNO2	0.709	0.769	0.764
DISC1	0.899		
DISC2	0.728		
DISC3	0.836	0.846	0.722
INSEC1	0.87		
INSEC2	0.789		
AIM1	0.715	0.708	0.776
AIM2	0.872		
CP1	0.877		
CP2	0.733	0.82	0.827
CP3	0.935		
CS1	0.755		
CS2	0.778	0.71	0.963
CS3	0.897		
FP1	0.714		
FP2	0.872	0.726	0.747
FP3	0.729		

Discriminant validity was evaluated using both the Fornell Larcker criterion and the heterotrait-monotrait (HTMT) ratio. Fornell Larcker results showed that each construct's square root of AVE exceeded its correlations with other constructs, while HTMT values were all below 0.90, confirming that constructs were empirically distinct. Particular attention was given to AIM and CE, where items were reviewed to minimize conceptual overlap. Table 4 shows the Fornell Larcker discriminant validity results, with diagonal values exceeding off diagonal correlations.

Table 4. Discriminant validity

	ACT	AIM	CP	CS	DISC	FEEL	FP	INNO	INSEC	OPT	RELATE	SENSE	THINK
ACT	0.907												
AIM	0.315	0.871											
CP	0.356	0.162	0.909										
CS	0.346	0.584	0.101	0.981									
DISC	0.422	0.353	0.576	0.405	0.850								
FEEL	0.532	0.305	0.459	0.581	0.332	0.918							
FP	0.321	0.548	0.392	0.142	0.414	0.306	0.864						
INNO	0.501	0.497	0.405	0.322	0.311	0.483	0.521	0.874					
INSEC	0.409	0.327	0.506	0.466	0.456	0.445	0.489	0.111	0.881				
OPT	0.442	0.482	0.567	0.513	0.107	0.538	0.317	0.539	0.439	0.858			
RELATE	0.522	0.567	0.454	0.325	0.305	0.421	0.359	0.357	0.302	0.405	0.857		
SENSE	0.112	0.415	0.346	0.154	0.409	0.143	0.537	0.309	0.346	0.305	0.117	0.913	
THINK	0.405	0.323	0.406	0.326	0.508	0.484	0.462	0.472	0.542	0.422	0.509	0.152	0.987

Variance inflation factor (VIF) values for all indicators were below 5, indicating that multicollinearity was not a concern. Together, these results provide strong evidence of construct reliability, convergent validity, and discriminant validity.

4.3 Structural Model Evaluation

The structural model was tested after confirming the adequacy of the measurement model. Path coefficients (β) and their significance were estimated via bootstrapping with 5,000 resamples. R^2 values for CS, CP, and FP exceeded 0.20, confirming substantial explanatory power. Table 5 shows the results of the structural model, including path coefficients, t-values, and effect sizes. Model fit indices indicated acceptable overall fit (SRMR = 0.072; NFI = 0.91). Predictive relevance (Q^2) values were greater than zero for CS, CP, and FP, supporting predictive validity. Effect sizes (f^2) showed that TR and AIM contributed medium effects on CS, while AIM had a strong effect on CP.

Table 5. Inner model results (summary)

Hypotheses	Path	Path Coefficient	t-value	result
H1	TR → CS	0.723	3.673	Supported
H2	CE → CS	0.552	2.725	Supported
H3	AIM → CS	0.566	4.572	Supported
H4	AIM → CP	0.964	9.336	Supported
H5	AIM → FP	0.681	12.631	Supported
H6	CS → FP	0.864	5.388	Supported

All six hypotheses were supported, indicating strong positive relationships between constructs. TR and AIM significantly influenced CS, while AIM also showed strong effects on CP and FP. CS strongly predicted FP, confirming its mediating role between experiences and financial outcomes. However, the coefficients for AIM → CP ($\beta = 0.964$) and CS → FP ($\beta = 0.864$) were unusually high, suggesting possible conceptual overlap or model over-specification. These results should therefore be interpreted cautiously, and future research should test simplified frameworks to validate these relationships. Figure 2 illustrates the inner model results.

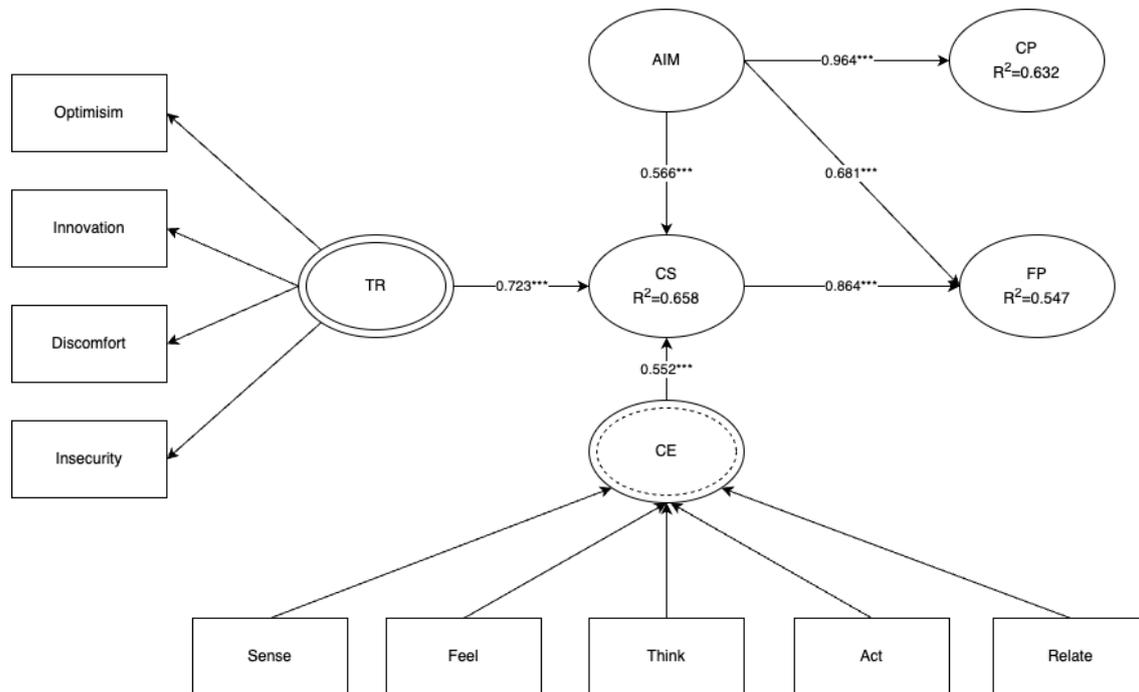


Figure 2. Inner model results framework

4.4 Testing of Mediating Effect

The mediating role of customer satisfaction (CS) was tested for the relationships between TR, AIM, CE, and financial performance (FP). Mediation was first examined using the Sobel test, and then confirmed through bootstrapping with 5,000 resamples, which is recommended in PLS-SEM because it does not assume normality of indirect effects. Table 6 shows the results of the mediation analysis. All three indirect paths were significant, confirming CS as a key mediator in transforming technology readiness, AI adoption, and customer experience into improved financial performance.

Table 6. Sobel test results

Construct	Construct Relationship	t-value	Sobel Test z-Value
TR → CS → FP	TR → CS	3.673	25.68
	CS → FP	5.388	
AIM → CS → FP	AIM → CS	4.572	28.245
	CS → FP	5.388	
CE → CS → FP	CE → CS	2.725	21.709
	CS → FP	5.388	

These findings underscore CS’s pivotal role in converting technological and experiential investments into financial outcomes. Higher levels of readiness (TR) and greater use of AI in marketing (AIM) improve

satisfaction, which in turn drives loyalty, repeat purchases, and profitability. Similarly, positive customer experiences (CE) translate into stronger satisfaction and better financial results. However, the high z-values and strong indirect effects suggest potential model inflation due to overlapping constructs or over-specification. These results should therefore be interpreted cautiously. Future research should refine construct measures and test alternative mediation pathways to validate these findings.

5. Conclusions

This research examined the relationships between technology readiness (TR), AI in marketing (AIM), customer experience (CE), customer satisfaction (CS), customer performance (CP), and financial performance (FP) in Indonesian e-commerce. The findings suggest that TR and AIM play critical roles in shaping CE and CS, which in turn influence CP and FP. CS and CP emerged as important pathways that help explain how technological investments are translated into business outcomes. However, the unusually strong coefficients in some paths indicate potential model inflation, suggesting that future studies should test simplified frameworks to validate these mediation effects. From a practical perspective, the study underscores the strategic importance of investing not only in AI technologies such as chatbots, recommendation systems, and predictive analytics but also in building organizational and individual readiness for adoption. Managers should invest in digital skills training to strengthen TR, personalize customer experiences responsibly while safeguarding data privacy, and treat CS metrics as strategic performance indicators rather than secondary measures. By aligning technological readiness with AI-driven personalization, firms can enhance customer loyalty, engagement, and ultimately profitability. The study also acknowledges important limitations. The sample was skewed toward younger, male, bachelor-educated entrepreneurs managing small firms, limiting generalizability to larger or more diverse business contexts. The cross-sectional design prevents strong causal inferences, and reliance on self-reported survey data raises the possibility of common method bias. Furthermore, some overlap between constructs (e.g., AIM and CE) may have contributed to inflated path coefficients. These limitations highlight the need for future studies to replicate and refine the model in different contexts, incorporate objective performance data, and adopt longitudinal designs to capture the long-term impact of AI adoption. Overall, this study contributes to the literature by integrating TR, AIM, CE, CS, CP, and FP into a unified framework, offering insights into how technology readiness and AI-driven marketing strategies influence both customer outcomes and financial performance. While the results demonstrate the potential of AI in e-commerce growth, they also emphasize the need for cautious interpretation and continued refinement of measurement and theoretical models.

Author Contributions: Conceptualization, T.H. and M.D.; methodology, T.H. and R.W.; software, A.M.W.; validation, T.H. and M.D.; formal analysis, R.W.; investigation, T.H.; resources, T.H.; data curation, R.W. and A.M.W.; writing—original draft preparation, M.D.; writing—review and editing, T.H.; visualization, A.M.W.; supervision, T.H.; project administration, R.W.; funding acquisition, T.H. All authors have read and agreed to the published version of the manuscript

Funding: This research was funded by the Ministry of Higher Education, Science and Technology of Indonesia.

Conflicts of Interest: The authors declare no conflict of interest

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