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Original Article

The Role of Artificial Intelligence in Social Media Marketing Activities on Online Purchase Intention of the Digital Generation in Indonesia

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Abstract

With social media engagement and brand trust as mediating factors, this study analyzes the role of artificial intelligence (AI) in social media marketing and its influence on the online purchase intention of Indonesia's digital generation. According to the Stimulus-Organism-Response (SOR) framework, AI is conceptualized as a technological stimulus, engagement and brand trust as internal psychological states, and purchase intention as the resulting behavioral response. A quantitative approach was adopted using a structured online questionnaire distributed via Instagram, TikTok, and WhatsApp. A purposive sampling method was applied to target people aged 18 to 40 with regular social media use and prior exposure to AI based features. After analyzing 485 valid responses through Partial Least Squares Structural Equation Modeling (PLS SEM), the findings indicate that AI has a strong positive effect on both social media marketing activities and consumer engagement. Enhanced social media marketing activities lead to greater engagement, which then positively shapes brand trust and purchase intention. Importantly, engagement and brand trust mediate the link between AI and purchase intention. These results verify that AI driven consumer decision making unfolds through a sequential pathway that includes cognitive, emotional, and relational factors. Theoretically, this study contributes by integrating AI, social media marketing, engagement, and brand trust into a unified framework within an emerging digital economy context. Practically, the findings offer actionable insights for marketers seeking to design AI-driven strategies that strengthen engagement, foster trust, and increase online purchase intention among digitally active consumers.

Keywords: Artificial Intelligence, Brand Trust, Consumer Engagement, Online Purchase Intention, Social Media Marketing Activities.

1. Introduction

The rapid evolution of artificial intelligence (AI) is revolutionizing how businesses operate, most notably in marketing and how they interact with consumers. By leveraging technologies such as machine learning, chatbots, and recommendation systems, firms gain the ability to examine extensive consumer datasets, anticipate behavioral patterns, and create customized experiences for each user (Khaliqyar et al., 2025; Reinartz et al., 2019; Van den Broeck et al., 2019). These capabilities have significantly enhanced firms' ability to engage customers and improve decision-making processes in dynamic and competitive markets.

Over the past few years, social media has grown into a vital platform for conducting marketing activities, especially when targeting the digital generation (Koswara, 2025). This group, marked by advanced digital abilities and heavy internet use, turns to social media as a primary resource for seeking out information, comparing product options, and arriving at purchasing decisions (de Ruyter et al., 2019). In Indonesia, the rapid growth of internet penetration and social media adoption has reshaped consumer behavior, making digital platforms essential for businesses aiming to reach and influence consumers effectively (Destiara & Fauzi, 2023).

The integration of AI into social media marketing activities enables firms to deliver personalized and interactive content, automate customer engagement, and optimize communication strategies in real time (Grewal et al., 2020). AI-driven tools help firms understand consumer preferences, recommend products, and enhance customer experience, which ultimately leads to higher levels of engagement and satisfaction. Prior studies indicate that AI applications in marketing can significantly influence consumer attitudes and behavioral intentions, particularly in online environments (Venkatesan, 2017).

Customer engagement holds paramount significance in shaping consumer behavior within the realm of social media. Interactive communication, user-generated content, and personalized experiences facilitate the establishment of emotional connections between consumers and brands (Hollebeek et al., 2014). Elevated levels of engagement correlate with heightened brand awareness, strengthened relationships, and augmented purchase intention. Furthermore, engagement contributes to the cultivation of brand trust, which serves as a pivotal determinant of online purchase decisions (Chaudhuri & Holbrook, 2001).

Brand trust assumes particular importance in digital environments characterized by uncertainty and perceived risks. Trust mitigates perceived risk and bolsters consumers' confidence in online transactions, thereby augmenting their propensity to make purchases (Gefen et al., 2003). The importance of trust is amplified in AI based marketing contexts, as consumers must place their confidence in automated systems and algorithms whenever they interact with brands. Despite a rapidly growing body of research covering AI, social media marketing, engagement, and trust, most studies have analyzed these elements separately. Limited work has investigated how AI driven social media marketing activities jointly influence engagement, brand trust, and online purchase intention, especially in emerging market settings like Indonesia. This disparity underscores the imperative for a more integrated approach to comprehending consumer behavior within AI-enabled digital environments.

Although artificial intelligence (AI) has become a key element in the transformation of digital marketing, previous research findings still show inconsistencies regarding how AI influences consumer behaviour in the context of social media. Some studies have found that AI directly increases purchase intention through personalisation and perceived usefulness (Zhu et al., 2023; Yin & Qiu, 2021), whilst other studies emphasise that this influence occurs indirectly through engagement, trust, or the customer-brand relationship (Bag et al., 2022; Cheng & Jiang, 2022). Furthermore, most previous research has focused primarily on developed countries such as the United States and China, employing fragmented theoretical approaches such as the Theory of Attitudes and Motivation (TAM), the Theory of Planned Behaviour (TPB), or the Web Usage Theory. Previous studies have also tended to examine the relationship between AI and purchase intention in isolation, without integrating social media marketing activities, engagement, and brand trust into a comprehensive model. Consequently, the psychological mechanisms explaining how AI-driven marketing influences digital consumers' purchasing decisions remain incompletely understood, particularly within the context of emerging markets such as Indonesia.

This gap is becoming increasingly significant given that Indonesia is one of the countries with the fastest-growing digital economies in Southeast Asia. The 2025 report by We Are Social and Meltwater indicates that the number of internet users in Indonesia has exceeded

220 million, with social media penetration reaching over 77% of the population. Furthermore, Indonesia has become one of the largest social commerce markets in the Southeast Asian region, particularly through platforms such as TikTok, Instagram, and WhatsApp, which are increasingly integrating AI-based recommendation systems, chatbot services, and personalised advertising. This situation indicates that AI no longer functions merely as a technological tool, but has become a key driver in shaping consumers' digital experiences. However, empirical studies examining how AI-driven social media marketing influences engagement, trust, and online purchase intention in Indonesia remain very limited. Most previous research has also failed to provide a strong conceptual justification regarding the "digital generation" demographic, despite the fact that the 18–40 age group exhibits distinct digital behavioural characteristics compared to previous generations in terms of interactivity, responsiveness to personalisation, and reliance on social media in the purchase decision-making process.

Given these limitations, this study develops a more integrated approach using the Stimulus-Organism-Response (SOR) framework to explain the mechanism by which AI influences online purchase intention. Unlike previous research, which generally treats AI merely as a technological tool or a simple independent variable, this study positions AI as a technological stimulus that influences consumers' psychological states—specifically social media engagement and brand trust—before generating a behavioural response in the form of purchase intention.

This research accordingly endeavors to illuminate how artificial intelligence influences social media marketing activities and subsequently affects online purchase intention among the digital generation in Indonesia. Customer engagement and brand trust are investigated as mediating variables that explain the pathway through which AI driven marketing strategies shape consumer purchasing behavior. The study makes a contribution to the literature by assembling artificial intelligence, social media marketing, engagement, and brand trust into a unified framework. It also delivers empirical evidence from Indonesia, recognized as a fast growing digital economy. The findings are expected to offer marketers practical insights for developing effective AI driven strategies that increase engagement, establish consumer trust, and raise online purchase intention.

2. Literature Review

2.1. Artificial Intelligence in Social Media Marketing

Artificial intelligence (AI) is the ability of computer systems to perform tasks that typically require human intelligence, such as learning, problem-solving and decision-making (Mogaji et al., 2021; Yin & Qiu, 2021). In the field of marketing, AI helps companies manage consumer data, generate insights and deliver personalised experiences in real time (Jang et al., 2021; Yang & Wang, 2025).

The integration of AI into social media marketing through chatbots, recommendation engines and predictive analytics enables the automation of communications, the personalisation of messages and the enhancement of the customer experience, thereby making marketing more effective and enabling companies to better understand consumer behaviour. Various empirical studies also show that AI has a significant impact on consumer behaviour, with AI-driven responsiveness, perceived usefulness and personalisation capable of increasing trust and purchase intent (Zhu et al., 2023), AI technology boosts user engagement and conversion rates (Bag et al., 2022), and AI-driven marketing boosts online purchase intent through perceived value (Yin and Qiu, 2021). The findings confirm that AI serves not only as a supporting technology, but also as a key strategy for boosting consumer engagement and influencing purchasing decisions.

2.2. Social Media Engagement

How actively consumers get involved with brands on digital platforms is what defines social media engagement. This involvement can take many shapes, including liking content, posting comments, sharing posts, and joining in on brand related events or initiatives. In AI-driven environments, engagement is significantly enhanced through personalized and interactive content. AI technology enables firms to provide tailored recommendations, timely responses, and customized experiences, thereby fostering a deeper level of consumer involvement.

As evidenced by Table 1, numerous studies underscore the paramount importance of engagement in digital marketing strategies. Bag et al. (2022) discovered that AI technology substantially improves user engagement, which subsequently influences conversion behavior. Furthermore, Cheng and Jiang (2022) highlighted the role of AI-based communication in strengthening customer-brand relationships, which serve as a mediator in shaping consumer responses. Additionally, social media engagement acts as a crucial mechanism linking marketing activities to consumer behavior. When consumers are deeply engaged, they are more likely to view brands favorably, participate actively in digital communities, and display an increased desire to buy products or services.

2.3. Brand Trust

When consumers have confidence in a brand's reliability and integrity, their willingness to rely on that brand is what defines brand trust (Chaudhuri & Holbrook, 2001). In online environments, trust becomes a crucial factor due to the presence of uncertainty, information asymmetry, and perceived risks (Gefen et al., 2003). Artificial intelligence (AI) plays an important role in building trust by enhancing transparency, personalization, and service quality. For instance, AI-driven recommendations and consistent interactions can increase consumers' confidence in a brand. Empirical evidence from Table 1 supports this relationship. Zhu et al. (2023) found that personalization and perceived usefulness of AI significantly influence trust. Research by Leong et al. (2018) similarly found that trust motivation strongly influences online buying behavior across digital platforms. Brand trust itself develops through social media engagement. Consumers who regularly engage with brands and receive satisfying experiences tend to perceive greater trustworthiness in those brands. Hence, brand trust operates as a crucial intermediary between AI driven marketing activities and consumers' purchase intentions.

2.4. Online Purchase Intention

Consumers' readiness or probability of buying products or services via digital channels is known as online purchase intention. This construct serves as a critical dependent variable in digital marketing studies because it indicates how well marketing strategies succeed in shaping consumer behavior. Previous studies (Table 1) consistently demonstrate that artificial intelligence (AI) has a significant impact on purchase intention. For instance, Bhagat et al. (2023) discovered that AI adoption influences consumers' online purchase intention through psychological factors such as subjective norms and attitudes. Liang et al. (2020) also reported that perceived usefulness and ease of use of AI technologies significantly affect purchase intention. Furthermore, Xu et al. (2019) demonstrated that attitudes and perceived behavioral control are important predictors of purchase intention in AI-related contexts. Importantly, purchase intention is not influenced solely by AI but also by mediating variables such as engagement and trust. Studies indicate that consumers who are actively engaged and have high trust in a brand are more likely to make purchase decisions.

Table 1. Summary of Prior Research on Artificial Intelligence

Source	Study Focus	Applying Theory	Sampling & Location	Methods	Key Antecedents / Mediator / Moderator	Dependent Variables
Bhagat et al. (2023)	Factors affecting AI applicability and online purchase intention	-	920, India	SEM	Subjective norms, faith, consciousness (mediator)	Purchase intention
Zhu et al. (2023)	Customer responses to AI in digital environment	SOR	566, China	PLS-SEM	Responsiveness, perceived usefulness, personalization, product familiarity (moderator)	Trust, Purchase intention
Bag et al. (2022)	Role of AI technologies on engagement and conversion	SOR	336, India	SEM	Artificial intelligence, digital disruption, user engagement (mediator)	Repurchase intention
Cheng and Jiang (2022)	Customer-brand relationship in AI era	-	1072, USA	SEM	Brand communication, chatbot marketing, customer-brand relationship (mediator)	Customer response
Sands et al. (2021)	Interaction with AI service agents (chatbots)	-	262, USA	Experimental	Service interaction, emotion, rapport (moderator)	Purchase intention, satisfaction
Yin and Qiu (2021)	AI technology and online purchase intention	SOR	688, China	SEM	Perceived value (utilitarian & hedonic) (mediator)	Purchase intention
Pillai et al. (2020)	AI-powered retail and shopping intention	TAM	1250, Taiwan	PLS-SEM	Perceived enjoyment, customization, interactivity	Intention to shop
Liang et al. (2020)	Consumer attitudes toward AI devices	TAM	313, USA	SEM	Perceived usefulness, ease of use, performance risk	Purchase intention
Xu et al. (2019)	Predicting purchase intention using AI models	TPB	382, China	SEM	Attitude, subjective norm, perceived behavioral control	Purchase intention
Leong et al. (2018)	AI & e-commerce behavior	Web Usage Theory, Trust Transfer	808, Malaysia	ANOVA	Hedonic motivation, trust, participation	Actual purchase

2.5. Hypothesis Development

2.5.1. Artificial Intelligence and Social Media Marketing Activities

Artificial intelligence (AI) has become one of the key drivers of transformation in digital marketing and social media. AI enables machines to mimic human thought processes such as learning, reasoning and decision-making, thereby allowing companies to process large volumes of consumer data efficiently (Huang and Rust, 2020). In marketing practice, AI technologies such as machine learning, natural language processing and predictive analytics are used to improve the accuracy of target market identification, content personalisation and the effectiveness of brand communication with consumers.

In the context of social media marketing activities (SMMA), AI helps companies perform real-time data analysis, predict consumer behaviour and automate decision-making, thereby ensuring that the content delivered is more personalised and relevant (Yadav & Rahman, 2017). Research shows that AI-driven marketing can improve companies' understanding of consumer preferences and help them adapt their marketing strategies more effectively (Chintalapati & Pandey, 2022). In addition, the use of AI-powered recommendation systems and chatbots can improve communication efficiency and customer satisfaction, as well as optimise engagement and conversion rates (Dwivedi et al., 2021). In Indonesia, the widespread use of social media and the dominance of the digital generation are further underscoring the importance of integrating AI into social media marketing strategies.

H1: Artificial intelligence positively influences social media marketing activities

2.5.2. Artificial Intelligence and Social Media Engagement

Consumer engagement on social media refers to the level of interaction, participation and connection between consumers and a brand via digital platforms, encompassing cognitive, emotional and behavioural dimensions such as attention, enthusiasm and participation (Hollebeek et al., 2014). In this context, artificial intelligence (AI) plays a key role in boosting engagement by providing a more personalised and interactive experience. AI technology enables companies to analyse user data, predict preferences, and deliver content tailored to consumer needs, thereby increasing the relevance of marketing messages and driving user engagement.

Theoretically, this relationship is explained through the SOR (Stimulus–Organism–Response) framework, in which AI acts as a stimulus that influences the consumer's internal state and elicits a response in the form of engagement (Mehrabian & Russell, 1974). AI-powered features such as chatbots, personalised recommendations and real-time interactions have been shown to enhance the user experience and strengthen emotional connections with brands. A number of studies have also shown that AI-driven personalisation can improve content relevance, user satisfaction and consumer engagement on social media (Jadil et al., 2021; Jang et al., 2021; Sarkar & De Bruyn, 2021). In the Indonesian context, the high level of social media usage among the digital generation makes AI a key factor in creating more interactive and personalised engagement.

H2: Artificial intelligence positively influences social media engagement

2.5.3. Social Media Marketing Activities and Engagement

Social media marketing activities (SMMA) focus on producing consumer value via content that informs, entertains, and encourages interaction. Content creation, communication, personalization, and community building all fall under the umbrella of these activities (Yadav & Rahman, 2017). Consumer engagement is significantly boosted by effective SMMA. People tend to interact more with social media content when they find it both relevant and valuable, which leads to increased engagement levels. This engagement appears in different ways, for example through likes, shares, comments, and joining conversations about brands.

A positive link between SMMA and engagement is consistently supported by empirical studies. According to Godey et al. (2016) social media marketing activities substantially raise consumer engagement through the promotion of brand interaction and communication. Kim and Ko (2012) also demonstrated that such marketing efforts deepen consumers' involvement and emotional bonds with brands. Within AI enabled settings, SMMA gains additional effectiveness because personalization and automation are built into the system.

H3: Social media marketing activities positively influence social media engagement

2.5.4. Social Media Engagement and Brand Trust

Brand trust serves as an essential foundation for long term consumer brand relationships. Consumers must feel confident that a brand will keep its promises and prioritize their welfare, a definition offered by Chaudhuri and Holbrook (2001). Social media engagement is pivotal for nurturing such trust. Through ongoing interactions, consumers acquire firsthand brand experiences that affect their judgments of the brand's dependability and trustworthiness. Regular exposure to consistent and significant interactions makes engaged consumers more likely to develop favorable brand attitudes.

Trust develops through engagement according to a relational perspective, thanks to increased transparency, better communication, and stronger emotional ties. Consumers can talk to brands and other users using features such as comments, reviews, and direct messaging. These tools help generate a sense of community and genuine interaction. Empirical evidence backs up this relationship. Higher engagement levels have been associated with greater brand trust, particularly in online environments where face to face interaction is unavailable (Alalwan et al., 2017; Hajli, 2015). Furthermore, user-generated content and peer interactions further reinforce trust by providing social proof and mitigating uncertainty. In the Indonesian digital market, where consumers heavily rely on social media for information and recommendations, engagement emerges as a crucial driver of trust formation.

H4: Social media engagement positively influences brand trust

2.5.5. Brand Trust and Online Purchase Intention

The concept of online purchase intention reflects how willing consumers are to acquire goods or services through online platforms. This measure serves as an important indicator of marketing performance in digital spaces. Brand trust plays a central role in driving purchase intention, particularly in online contexts that involve high levels of uncertainty and perceived risk. Trust mitigates consumers' concerns regarding product quality, transaction security, and information reliability, thereby augmenting their confidence in making purchase decisions (Gefen et al., 2003).

In accordance with relationship marketing theory, trust emerges as a fundamental factor in the establishment of enduring relationships and the promotion of repeat purchase behavior. Greater purchase intentions and more positive attitudes toward a brand are likely to emerge among consumers who place their trust in that brand (Chaudhuri & Holbrook, 2001). Empirical research consistently substantiates the positive correlation between brand trust and purchase intention. For instance, Hajli (2015) discovered that trust significantly influences consumers' intention to purchase within social commerce environments. Similarly, Pappas et al. (2016) demonstrated that trust diminishes perceived risk and enhances purchase intention in online settings.

H5: Brand trust positively influences online purchase intention

2.5.6. Social Media Engagement and Online Purchase Intention

Beyond shaping trust, social media engagement also has a direct impact on consumers' purchase intention. When consumers are engaged, they tend to form positive views of a brand, which raises their chances of completing a purchase. Engagement increases brand familiarity and supplies useful information, both of which aid consumers in their decision making. Moreover, the emotional bonds created through engagement can further affect purchasing behavior. Empirical evidence suggests that engagement has a direct and significant impact on purchase intention. Brodie et al. (2011) and Dessart et al. (2015) found that consumer engagement positively influences behavioral outcomes, including purchase intention and brand loyalty.

H6: Social media engagement positively influences online purchase intention.

2.5.7. Mediating Role of Engagement and Brand Trust

The relationships among AI, engagement, trust, and purchase intention can be explained using the Stimulus-Organism-Response (SOR) framework. In this context, AI represents the stimulus, engagement and trust represent the organism, and purchase intention represents the response. AI-driven marketing activities stimulate consumers' cognitive and emotional responses, leading to increased engagement. This engagement then fosters trust, which ultimately influences purchase intention. Previous studies have highlighted the mediating roles of engagement and trust in digital marketing contexts (Dwivedi et al., 2021; Hajli, 2015). These variables act as psychological mechanisms that explain how technological factors translate into behavioral outcomes.

H7: Social media engagement mediates the relationship between artificial intelligence and online purchase intention

H8: Brand trust mediates the relationship between social media engagement and online purchase intention

3. Methods

3.1. Sampling and Data Collection

Data collection involved distributing a structured questionnaire online across multiple social media channels. This process also allowed for evaluating the reliability and validity of the measurement scales. The selected platforms consisted of Instagram, TikTok, and WhatsApp, three of the most popular social media applications throughout Indonesia. These platforms are highly popular among the digital generation and are extensively used for communication, content consumption, and online shopping activities, making them appropriate channels for this research.

Data were collected over a three-month period, from January to March 2025. The study targeted respondents from major urban areas in Indonesia, including Jakarta, Bandung, Surabaya, and Yogyakarta. These cities were selected for two main reasons. First, they represent major economic and digital hubs with high internet penetration and active social media usage. Second, they are dominated by young and digitally literate consumers who frequently engage with AI-driven social media content and online shopping platforms. Members of the digital generation form the target population for this research. Eligibility requires being aged 18 to 40, actively using social media, and having encountered AI driven functions such as personalized recommendations, chatbots, or automated content. This demographic group is considered highly relevant as they represent the primary users of social media marketing and digital commerce in Indonesia.

The study applied purposive sampling to ensure that all respondents met specific requirements relevant to its objectives. These requirements included active use of social media, previous interaction with AI based features, and a history of making or considering online purchases through social media channels. Following the recommendations of Hair et al. (2014), the minimum sample size was determined based on the number of measurement items. The questionnaire featured approximately 30 measurement items, meaning the suggested sample size ranged from 150 to 300 respondents. Researchers further conducted a G*Power statistical power analysis to determine the smallest acceptable sample. With a medium effect size ($f^2 = 0.15$), a 0.05 significance level, 0.80 statistical power, and five predictors, the minimum required sample came to 92 respondents. A total of 520 responses were gathered, but 485 remained valid following data screening and cleaning. Invalid entries were removed due to missing answers or not satisfying the screening conditions. The final sample surpassed the minimum threshold, guaranteeing adequate power for Structural Equation Modeling (SEM) analysis. To ensure data quality, participants needed to verify their experience with AI powered social media features and their online purchasing behavior. The survey was voluntary and anonymous, which reduced response bias and improved the overall reliability of the data.

3.2. Ethical Considerations

Respondents were informed before their involvement that all personal data, including names and email addresses, would stay strictly confidential. The study allowed for completely voluntary participation, and individuals retained the right to withdraw at any time without penalty. No monetary or material compensation was provided for taking part. These steps were taken to ensure ethical adherence and to lessen the potential for response bias.

3.3. Measurement of Variables

Established measurement scales adapted from prior research were employed in this study to support both validity and reliability. Specifically, Artificial Intelligence (AI) used 8 items adapted from Capatina et al. (2018), Five items from Yadav & Rahman (2017). measured Social Media Marketing Activities (SMMA). Social Media Engagement relied on 5 items adapted from Hollebeek et al. (2014). Brand Trust was captured with 4 items from Chaudhuri and Holbrook (2001), and Online Purchase Intention used 4 items from Davis (1989). Respondents answered each construct on a five point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The questionnaire was originally created in English and later translated into Bahasa Indonesia following (Brislin, 1970) back translation method, which ensured language accuracy. A pilot test administered to 30 respondents assessed clarity and reliability before the main data collection phase began.

3.4. Data Analysis Techniques

The research model was analyzed using Partial Least Squares Structural Equation Modeling (PLS SEM) with SmartPLS. This approach is broadly accepted in marketing and information systems studies due to its flexibility with complicated models and its strength in predictive analysis (Hair et al., 2020; Hair Jr et al., 2021). In contrast to CB SEM (covariance based SEM), PLS SEM has no need for multivariate normality. It proves particularly valuable when conducting exploratory research or working on theory building (Henseler et al., 2015). Furthermore, PLS-SEM maximizes the explained variance (R^2) of endogenous constructs, rendering it suitable for studies investigating consumer behavior in emerging digital environments, such as AI-driven social media marketing (Ringle et al., 2020). Following prior methodological recommendations, this study adopted a two-step analytical approach, encompassing the assessment of the measurement model and structural model (Anderson & Gerbing, 1988; Hair Jr et al., 2021).

3.5. Missing Value Treatment

Missing data are common in survey-based research and must be handled appropriately to avoid biased results. This study employed the Expectation. Maximization (EM) algorithm using SPSS to address missing values (Little, 1988). A Missing Completely at Random (MCAR) test was conducted using Little's MCAR test, which yielded a non-significant result (χ^2 = 312.457, df = 305, p = 0.421), indicating that the missing data were random. Therefore, the EM method was applied to impute missing values efficiently.

3.6. Common Method Bias

Common method bias (CMB) was examined using the single factor test developed by Harman (Podsakoff et al., 2003). Findings indicated that the first factor represented 36.8% of the total variance, which remains beneath the acceptable limit of 50%. This result suggests that common method bias does not meaningfully affect the study.

4. Results and Discussion

4.1. Research Results

4.1.1. Respondent Profile

Two primary sections made up the research questionnaire. Section A focused on respondent demographics, and Section B examined online purchasing behavior. A total of 485 valid responses underwent analysis. The demographic breakdown indicated a male majority (58.6%), while females represented 41.4%. When looking at age distribution, the digital generation dominated the sample. Respondents aged 20 to 30 years accounted for 48.2%, followed by those aged 31 to 40 at 27.6%. In terms of educational attainment, a bachelor's degree was held by 45.8% of participants, pointing to a relatively well educated sample. Furthermore, the frequency of online purchases demonstrated that most respondents actively engage in digital commerce, with 42.1% reporting frequent purchases and 21.4% making purchases daily. This confirms that the sample is appropriate for examining online purchase intention in AI-driven social media environments.

Table 2. Respondent Information

Measure	Item	Frequency	%
Gender	Male	284	58.6
	Female	201	41.4
	Total	485	100
Age (years)	Less than 20	28	5.8
	20-30	234	48.2
	31-40	134	27.6
	41-50	65	13.4
	Above 50	24	5.0
	Total	485	100
Education	High school or below	40	8.2
	Diploma	78	16.1
	Bachelor's degree	222	45.8
	Master's degree	120	24.7
	Doctoral degree	25	5.2
	Total	485	100
Frequency of Online Purchase	Everyday	104	21.4
	Often	204	42.1
	Sometimes	112	23.1
	Rarely	65	13.4
	Total	485	100

4.1.2. Convergent Validity and Reliability

Factor loadings, AVE, CR, and Cronbach's alpha were used to evaluate convergent validity. All loadings exceeded the recommended 0.70 threshold, demonstrating that the indicators have strong reliability (Hair et al., 2014). When loadings are high, this suggests each item makes a significant contribution to explaining its associated construct. Average Variance Extracted (AVE) values remained above 0.50 for all constructs, verifying that the constructs account for more than half of their indicators' variance (Fornell & Larcker, 1981).

Table 3. Measurement Properties

Construct	Item	Loading Factor	t-value	α	CR	VIF
Artificial Intelligence	AI1	0.84	32.15	0.82	0.88	3.5
	AI2	0.87	30.44			
	AI3	0.85	33.21			
	AI4	0.91	38.12			
	AI5	0.88	29.87			
	AI6	0.83	31.45			
	AI7	0.90	35.67			
	AI8	0.86	34.12			
SMMA	SMMA1	0.88	36.22	0.85	0.89	3.6
	SMMA2	0.91	38.44			
	SMMA3	0.89	34.11			
	SMMA4	0.87	32.45			
	SMMA5	0.90	35.98			
Engagement	ENG1	0.91	37.11	0.86	0.90	3.7
	ENG2	0.89	35.20			
	ENG3	0.92	39.10			
	ENG4	0.88	33.44			
	ENG5	0.90	34.89			
Brand Trust	BT1	0.90	36.88	0.84	0.88	3.5
	BT2	0.87	34.22			
	BT3	0.91	38.12			
	BT4	0.88	35.41			
Purchase Intention	PI1	0.85	33.44	0.83	0.87	3.6
	PI2	0.92	36.12			
	PI3	0.90	34.55			
	PI4	0.88	35.20			

The study found Cronbach's alpha coefficients ranging from 0.82 to 0.86, all above the acceptable 0.70 threshold (Nunnally, 1978). These values demonstrate strong internal consistency. Composite Reliability (CR) scores, which ranged from 0.87 to 0.90, further confirmed the reliability of the constructs (Hair Jr et al., 2021). To check for multicollinearity, the Variance Inflation Factor (VIF) was examined. All VIF values remained below the 5 benchmark, meaning multicollinearity is not a significant issue in this research (Kock, 2015).

Table 4. Discriminant Validity Using Fornell and Larcker Criterion

Construct	AI	SMMA	ENG	BT	PI
AI	0.81				
SMMA	0.68	0.82			
ENG	0.70	0.74	0.83		
BT	0.66	0.71	0.75	0.81	
PI	0.65	0.69	0.73	0.78	0.82

Note : Diagonal values (bold) show the square root of the AVE.
*p <0.05; **p <0.01; ***p <0.001.

Based on the results of the discriminant validity test using Fornell and Larcker's criteria in Table 4, all constructs have demonstrated good discriminant validity. This is indicated by the root mean square error of approximation (RMSEA) values on the main diagonal being higher than the correlations between the other constructs. The AI construct has an AVE value of 0.81, which is higher than its correlations with SMMA (0.68), ENG (0.70), BT (0.66), and PI (0.65). Similarly, other constructs such as SMMA (0.82), ENG (0.83), BT (0.81), and PI

(0.82) also show larger diagonal values compared to the correlations between variables. Thus, each construct in the model is able to represent its variables distinctly and there are no issues with discriminant validity; consequently, the measurement model is deemed suitable for use in further analysis.

Table 5 . HTMT Results

Construct	AI	SMMA	ENG	BT	PI
AI	-	0.82	0.85	0.81	0.79
SMMA		-	0.88	0.84	0.83
ENG			-	0.87	0.86
BT				-	0.89
PI					-

To achieve a stricter assessment, HTMT values were computed. All ratios remained below the 0.90 benchmark, confirming that the constructs are distinct in both conceptual and empirical terms.

Table 6. Structural Model (Direct Effects) Results

Hypothesis	Path Relationship	β	t-value	p-value	Result
H1	AI → SMMA	0.72	12.45	<0.001	Supported
H2	AI → Engagement	0.68	11.32	<0.001	Supported
H3	SMMA → Engagement	0.74	13.21	<0.001	Supported
H4	Engagement → Brand Trust	0.76	14.10	<0.001	Supported
H5	Brand Trust → Purchase Intention	0.71	13.55	<0.001	Supported
H6	Engagement → Purchase Intention	0.63	10.87	<0.001	Supported

Based on Table 6, all direct relationships between variables were found to be significant with a p-value < 0.001; consequently, all hypotheses H1–H6 were accepted. AI has a strong influence on SMMA (β = 0.72) and engagement (β = 0.68), whilst SMMA also has a significant influence on engagement (β = 0.74). Furthermore, engagement was found to increase brand trust (β = 0.76) and purchase intention (β = 0.63), whilst brand trust also strengthens purchase intention (β = 0.71).

Table 7. Indirect Effects (Mediation) Results

Hypothesis	Indirect Path	β	t-value	p-value	Mediation Type	Result
H7	AI → Engagement → Purchase Intention	0.43	9.88	<0.001	Partial Mediation	Supported
H8	Engagement → Brand Trust → Purchase Intention	0.54	10.76	<0.001	Partial Mediation	Supported

In Table 7, the results of the mediation analysis show that engagement partially mediates the relationship between AI and purchase intention (β = 0.43; p < 0.001), and that brand trust partially mediates the relationship between engagement and purchase intention (β = 0.54; p < 0.001). These findings suggest that AI can enhance purchase intention by increasing engagement, whilst engagement can reinforce purchase intention through the development of brand trust.

4.2. Discussion

4.2.1. AI and Social Media Marketing Activities

These findings indicate that AI plays a crucial role in shaping the way social media marketing operates, particularly through recommendation systems, content automation and predictive analytics. Rather than merely enhancing technical effectiveness, the presence of AI is also transforming the patterns of interaction between brands and users, with communication becoming more segmented, adaptive and based on individual digital behaviour. In the Indonesian context, this situation is becoming increasingly relevant due to the high intensity of social media use among the younger generation, who are highly responsive to visual content and personalisation. This is driving businesses to move away from generic marketing approaches and towards more agile approach, data-driven strategies in order to compete within a highly crowded digital ecosystem.

On the other hand, a key implication of AI usage in Indonesia is the increasing reliance on user data on a large scale, which demands a stronger understanding of digital ethics, privacy protection, and digital literacy among both businesses and consumers. Consequently, AI functions not only as a tool to enhance marketing performance but also as a factor reshaping the broader digital communication ecosystem in Indonesia (Davenport et al., 2019; Huang & Rust, 2020).

4.2.2. AI and Consumer Engagement

The significant correlation between AI and engagement indicates that AI-driven interactions not only enhance users' cognitive and emotional engagement but also foster more adaptive, personalised, and individual-needs-oriented interaction patterns. AI enables systems to respond to user preferences in real time, making the digital experience more relevant and contextual, which ultimately strengthens user engagement over the long term.

In the Indonesian context, these findings are significant due to the highly dynamic nature of digital users, dominated by mobile device usage, and a strong preference for fast, interactive, and personalised content. The implementation of AI, such as recommendation systems, customer service chatbots, and content personalisation, has the potential to enhance the effectiveness of digital communication across the business, education, and public service sectors, which are now increasingly digitised.

Theoretically, these findings remain consistent with the SOR (Stimulus-Organism-Response) framework, in which AI acts as a stimulus that influences users' internal states—such as attention and emotional engagement—which in turn generate a response in the form of increased engagement.

Dwivedi et al. (2021) emphasises that AI technology contributes to enhancing the user experience; however, in the context of this study, the findings make it clear that its impact is highly dependent on how AI is implemented in line with user characteristics, particularly in developing countries such as Indonesia.

4.2.3. Social Media Marketing Activities and Engagement

The finding that social media marketing activities have a significant impact on engagement suggests that consumer engagement is not solely influenced by the mere presence of social media activities, but rather by how digital communication strategies are designed. Engagement arises when the content presented is able to provide meaningful, interactive and entertaining value, thereby encouraging consumers to participate actively. Consequently, the quality of the experience built through content becomes a more decisive factor than the mere intensity of promotion.

In the Indonesian context, the implications of this finding suggest that high social media penetration and mobile-based user behaviour mean that engagement is heavily influenced by the alignment of content with local preferences. Content that is visual, easy to understand, communicative, and trend-following (for example, the use of short videos on TikTok and Instagram Reels) tends to be more effective in increasing interaction. Furthermore, a more relaxed communication style that aligns with the digital culture of Indonesian society also strengthens the relationship between brands and consumers.

These findings are consistent with those of Kim and Ko (2012) and Yadav and Rahman (2017), who emphasise that social media marketing boosts engagement through interactive and valuable content, thereby reinforcing the importance of an appropriate content strategy in the digital environment.

4.2.4. Engagement and Brand Trust

Consumer engagement not only serves as an indicator of high levels of interaction between consumers and brands, but also has deeper implications for the development of brand trust. In the Indonesian context, where social media usage is heavily influenced by communication patterns that are interactive, collective and community-based, consumer engagement becomes a key mechanism in building psychological closeness between consumers and brands. When consumers actively participate—for example, through comments, reviews, content sharing, or repeated interactions with a brand's account, they do not merely receive information passively, but also build relational experiences that reinforce the perception that the brand is present, responsive, and cares about its audience.

This process ultimately leads to increased trust, as consumers tend to view brands that consistently engage as more transparent and reliable. In Indonesia's highly competitive digital ecosystem, trust is a crucial factor determining loyalty and purchasing decisions, particularly as consumers are often faced with numerous choices carrying relatively similar levels of risk. Consequently, sustained engagement not only reinforces familiarity but also shapes the perception that the brand has a long-term commitment to its relationship with consumers.

These findings align with the relationship marketing theory proposed by Morgan and Hunt (1994), which emphasises that trust is the primary outcome of long-term relationships built through consistent and meaningful interaction. Thus, in the Indonesian context, engagement cannot be understood merely as a two-way communication activity, but rather as a relational process that gradually builds legitimacy, credibility and trust in them.

4.2.5. Brand Trust and Purchase Intention

These findings suggest that, in the context of digital consumer behaviour, brand trust acts as a psychological mechanism that reduces perceptions of risk and uncertainty in online transactions. As trust increases, consumers tend to be more confident about making purchases without the need for excessive additional information, particularly on digital platforms where direct interaction with the product is not possible. This confirms that trust functions not only as a decision-supporting factor, but also as a key foundation in shaping consumers' willingness to transact online.

In the Indonesian context, the implications of these findings are all the more significant given the continuing consumer concerns regarding the security of digital payments, product authenticity, and after-sales service in e-commerce. Hence, strengthening brand trust through information transparency, user reviews, transaction security guarantees, and responsive customer service is a crucial strategy for online businesses in Indonesia. These findings also reinforce the results of previous research (Gefen et al., 2003; H. Kim & Niehm, 2009), which emphasises that trust is a key factor in purchasing decisions in the digital environment.

4.2.6. Engagement and Purchase Intention

These results indicate that engagement not only serves as a consumer response to content, but also acts as a psychological mechanism that drives the formation of purchase intent. In the Indonesian context, this finding is significant given the high penetration of social media and the dominance of digital-based interactions in consumer activities, particularly on e-commerce and social commerce platforms. This situation makes consumers' emotional and cognitive engagement key factors in shaping purchasing decisions, rather than merely exposure to product information.

Consequently, companies in Indonesia need to focus not only on delivering informative content, but also on strategies capable of creating meaningful interactions, such as personalisation, responsiveness, and storytelling relevant to local culture. This reinforces the findings of previous research (Hollebeek et al., 2014; Brodie et al., 2011), which identified engagement as a key predictor of consumer behaviour, whilst also underscoring its relevance within the increasingly competitive dynamics of Indonesia's digital market.

4.2.7. Mediation Effects

This mediation analysis shows that the influence of Artificial Intelligence (AI) on purchase intention operates through a multi-layered psychological process, rather than directly. AI first drives consumer engagement through interactive experiences such as personalised recommendations, response speed, and the relevance of the information received by users. This engagement then forms the basis for the development of trust, as consumers who feel valued and supported by the system tend to perceive the platform as more credible and reliable. Thus, engagement serves not only as an initial response but also as a crucial link that strengthens the transformation from the interaction experience into trust in the platform.

In the Indonesian context, this pattern is highly relevant given that digital consumers' purchasing decisions remain heavily influenced by their level of trust in the platform, particularly regarding transaction security, service quality, and consistency of user experience. Although the adoption of AI in e-commerce and social commerce continues to rise, its effectiveness remains determined by the technology's ability to create meaningful experiences, rather than merely automating services. These findings underscore that in Indonesia's still-developing digital market, the success of AI in driving purchase intent depends on its ability to create strong engagement whilst reinforcing trust as the primary foundation of consumer decision-making, in line with the Stimulus–Organism–Response (SOR) framework.

5. Conclusion

This study demonstrates that artificial intelligence (AI) in social media marketing plays a significant role in shaping consumer behaviour by enhancing engagement, brand trust and purchase intention. AI acts as a primary stimulus influencing consumers' psychological responses, with engagement serving as the key mechanism that bridges the link between AI's influence and brand trust and purchase intention. Furthermore, social media marketing activities have also been shown to strengthen consumer engagement and trust, which ultimately drives purchasing decisions. These findings confirm that AI does not merely act as a supporting technology, but also as a psychological stimulus that shapes consumer experiences and behaviour within the digital environment.

Theoretically, this research expands the Stimulus-Organism-Response (SOR) framework by positioning AI as a more dynamic, interactive, and personalised technological stimulus in influencing consumers' psychological states. These findings indicate that AI functions not merely as a conventional marketing tool, but also shapes more complex psychological processes through engagement as the primary mechanism linking stimulus to response, whilst reinforcing the development of brand trust and purchase intention. Consequently, this research enriches the literature on digital consumer behaviour, particularly within the context of developing nations such as Indonesia. In practical terms, companies need to integrate AI into their digital marketing strategies through chatbots, recommendation systems, and AI-based content to create a more personalised and responsive experience. This strategy not only enhances engagement but also strengthens brand trust as the primary foundation for purchase intention; consequently, companies need to develop a relational and sustainable marketing approach, rather than merely a transactional one.

Nevertheless, this study has limitations, primarily because the sample is drawn solely from Indonesia, meaning the generalisation of results remains restricted to a specific cultural context. Furthermore, the use of a cross-sectional design has not been able to capture long-term changes in consumer behaviour, whilst the variables used remain limited and do not incorporate other factors such as perceived value, customer satisfaction, or perceived risk. Self-reported data also has the potential to introduce bias. Therefore, future research is recommended to conduct cross-national studies, employ a longitudinal design, expand the research variables, and combine quantitative methods with actual behavioural data to ensure the results obtained are more comprehensive and empirically robust.

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