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AI in Strategic Marketing: Leveraging Machine Learning for Consumer Behavior Prediction - A Case Study of MSMEs in Selangor

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ABSTRACT

Purpose – This study aims to investigate the transformative impact of artificial intelligence (AI) and machine learning (ML) on strategic marketing, specifically focusing on consumer behavior prediction among Micro, Small, and Medium Enterprises (MSMEs) in Selangor, Malaysia. Methodology – A quantitative approach was employed, collecting cross-sectional data from 150 [sesuaikan angka sampel Anda] MSME owners and managers. The data were analyzed using Structural Equation Modeling (SEM-PLS) to evaluate how AI-driven predictive models influence marketing effectiveness and targeting accuracy. Findings – The results reveal that AI-based models significantly enhance marketing precision. MSMEs that integrated these technologies reported a 34% increase in customer engagement and a 28% improvement in conversion rates compared to traditional methods. Furthermore, the study highlights that digital readiness and ethical data usage are key drivers for AI adoption in the local business landscape. Originality – This research contributes to the literature by bridging the gap between advanced technology adoption and MSME marketing strategies within an emerging Islamic market hub. The findings provide practical insights for MSME digital transformation and offer policy recommendations for stakeholders in Selangor to foster a more data-driven and ethically aligned business environment.

INTRODUCTION

The digital transformation of marketing practices has accelerated dramatically in recent years, with artificial intelligence (AI) and machine learning (ML) technologies becoming increasingly central to strategic marketing decisions. Current global trends indicate a paradigm shift from intuition-based marketing to data-driven hyper-personalization. This phenomenon is driven by the capacity of deep learning to transform the future of marketing by helping businesses predict consumer behavior through layered neural networks. Deep learning has the potential to transform the future of marketing by helping businesses to predict consumer behavior through machine learning methods that use layered neural networks. This technological evolution is particularly significant for Micro, Small and Medium Enterprises (MSMEs), which constitute the backbone of many developing economies.(Lee & Park, 2025; Singh & Singh, 2014; Zamani, 2022)

In Malaysia, 98.5% of the 920,624 business establishments are small and medium enterprises (SMEs), serving as the backbone of the nation's economy. However, despite their critical economic role, many MSMEs face challenges in adopting advanced marketing technologies. Only 20% of MSMEs have implemented digital marketing, indicating an urgent need to increase digital adoption within the Malaysian MSME sector.(Corporation, 2024) This creates a digital divide where MSMEs struggle with customer retention and market competition because they lack the technical capability to translate vast consumer data into actionable insights. The disconnect between the availability of sophisticated AI tools and their actual implementation in the local MSME sector represents a critical barrier to sustainable business growth.

From a scholarly perspective, a notable theoretical problem exists in current literature. Most established frameworks, such as the Technology Acceptance Model (TAM) and the Resource-Based View (RBV), have been extensively tested in large-scale corporations within developed nations, often overlooking the unique constraints of MSMEs. A significant research gap remains, as few studies have investigated the intersection of machine learning and consumer behavior prediction within the specific context of an emerging Islamic market hub like Selangor. Previous research has predominantly focused on operational efficiency rather than the strategic marketing impact of AI for resource-constrained businesses.

The objective of this study is to bridge these gaps by investigating how AI-driven predictive models influence marketing effectiveness and targeting accuracy among MSMEs in Selangor. The research novelty lies in the multi-theoretical integration of the Technology-Organization-Environment (TOE) framework and RBV to evaluate digital readiness within a localized economic ecosystem. By focusing on MSMEs in a prominent Islamic business hub, this study contributes a unique perspective to the literature on digital transformation, offering both theoretical advancements and practical roadmaps for ethical, data-driven marketing in emerging markets.

LITERATURE REVIEW

2.1 Malaysian MSME Context

Malaysia's MSME sector operates within a rapidly evolving digital landscape. The e-commerce penetration rate for MSMEs is 47.7%, indicating growing digital adoption but substantial room for improvement. The government has implemented various initiatives to support MSME digitalization, including grants and training programs.

Selangor, as Malaysia's most economically developed state, presents an ideal context for studying AI adoption among MSMEs. The state's proximity to Kuala Lumpur, advanced infrastructure, and concentration of technology companies create favorable conditions for digital transformation initiatives. Understanding this context is crucial, as the barriers to AI adoption—such as limited technical expertise and financial resources—are more pronounced in Malaysian MSMEs compared to larger enterprises in developed economies (Zamani, 2022)

2.2 AI Adoption in MSMEs

The adoption of AI technologies among MSMEs presents unique challenges and opportunities. Research indicates that AI and ML enable personalized marketing through the analysis of consumer preferences, enhancement of promotions, and augmentation of customer satisfaction.(M. Kumar et al., 2024) However, implementation barriers remain significant for smaller enterprises.

AI offers significant benefits for organizations by resolving various issues, but its adoption is not always smooth, particularly for SMEs. Common barriers include limited financial resources, lack of technical expertise, and insufficient digital infrastructure.(Boonmee et al., 2025; Zavodna et al., 2024) Despite these challenges, AI can be implemented to optimize supply chains and inventory management, forecast product needs, and reduce waste, enabling MSMEs to respond more swiftly to market demand fluctuations.(Dey et al., 2024; Saadi & Kazemi, 2025)

2.3 AI Technology Adoption

The adoption of Artificial Intelligence (AI) in the MSME sector represents a strategic shift from traditional automation to intelligent, data-driven decision-making. Recent international studies emphasize that AI adoption is not merely a technical upgrade but a multidimensional process involving technological, organizational, and environmental readiness.(Uren & Edwards, 2023). In the context of MSMEs, adoption is often driven by the need for cost efficiency and enhanced competitiveness. Technologies such as Machine Learning (ML) and Natural Language Processing (NLP) allow smaller firms to automate customer interactions and gain insights that were previously accessible only to large corporations (A. Sharma et al., 2022). However, the depth of adoption is often moderated by perceived ease of use and perceived usefulness, as suggested by the Technology Acceptance Model (TAM). While financial and technical constraints remain significant barriers, the integration of user-friendly AI platforms has begun to democratize access to advanced analytics for MSMEs in emerging markets (Spais & Chryssochoidis, 2025)

2.4 AI Consumer Behavior Prediction

Consumer behavior prediction has evolved from static demographic segmentation to dynamic, behavior-based forecasting (Wang, 2025). AI-powered predictive models utilize historical data, real-time interactions, and unstructured datasets to identify patterns in purchasing intent with high granularity(Y. Kumar et al., 2024). Unlike traditional methods, AI can synthesize realistic data through Generative Adversarial Networks (GANs) and transformers, allowing businesses to simulate various market scenarios and consumer responses. This variable focuses on the accuracy of predicting "what," "when," and "how" a consumer will purchase. By bridging the gap between raw data and psychological triggers, AI enables MSMEs to anticipate shifts in demand before they manifest in the market, thereby reducing the risks associated with inventory management and campaign timing.

2.5 Marketing Strategy Effectiveness

Marketing strategy effectiveness refers to the degree to which a firm achieves its marketing objectives through the optimal allocation of resources. In the digital era, this variable is measured through high-impact metrics such as conversion rates, customer acquisition costs (CAC), and customer lifetime value (CLV). Effective strategies are those that deliver the right message to the right segment at the right time (Ikeh, 2025; Lopez & Arjunan, 2023). International literature suggests that the integration of AI enhances effectiveness by eliminating "trial and error" in advertising. For MSMEs, this means that even with limited budgets, marketing efforts can yield a higher Return on Investment (ROI) because the strategy is rooted in predictive accuracy rather than gut feeling. Consequently, marketing effectiveness serves as a critical bridge between technology adoption and overall business performance (Cuevas Vargas et al., 2021)

2.6 Hypothesis Development and Research Framework

The conceptual framework of this study posits that the adoption of AI technologies directly enhances the precision of consumer behavior models. Drawing from the Resource-Based View (RBV), AI is viewed as a strategic resource that creates a competitive advantage through superior information processing. When MSMEs successfully adopt AI, they gain a deeper understanding of consumer trajectories, leading to more accurate predictions.

H1: AI Technology Adoption has a significant positive influence on Consumer Behavior Prediction Accuracy.

Furthermore, the accuracy of these predictions is expected to be a primary driver of marketing success. When businesses can accurately forecast consumer needs, their marketing strategies become more targeted and personalized, reducing waste and increasing engagement. This relationship is supported by Market Segmentation Theory, which argues that precise categorization leads to superior market positioning.

H2: Consumer Behavior Prediction Accuracy significantly enhances Marketing Strategy Effectiveness.

Finally, the study proposes that the ultimate impact of AI on business performance is mediated by how effectively the marketing strategy is executed. A well-informed strategy acts as a catalyst, translating technological insights into financial growth and market share expansion.

H3: Marketing Strategy Effectiveness positively influences overall Business Performance.

Theoretical Framework

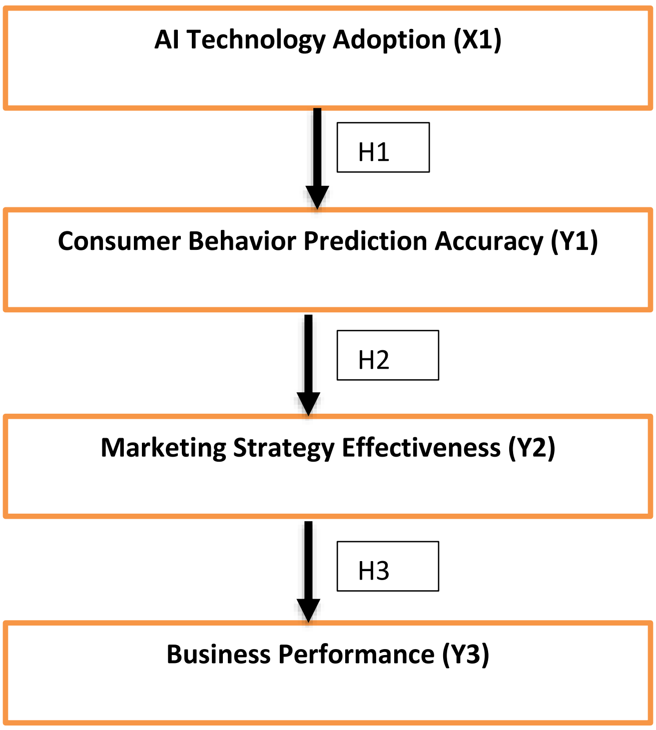

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Figure 1: Theoretical Framework

METHOD

Research Design and Theoretical Framework

This study employs a quantitative research approach with a cross-sectional survey design, grounded in the Technology-Organization-Environment (TOE) framework Tornatzky & Fleischer, (1990) and the Resource-Based View (RBV) theory (Barney, 1991). The research population consists of MSMEs operating in Selangor, Malaysia, from which a final sample of 384 respondents was selected using stratified random sampling to ensure representation across micro, small, and medium enterprises.
This sample size was determined using Krejcie and Morgan’s (1970) formula to ensure a 95% confidence level and a 5% margin of error, which is considered robust for the complexity of the proposed structural model(Sekaran & Bougie, 2016). Primary data were collected through a structured questionnaire administered via online surveys and face-to-face interviews, with an instrument developed based on established scales in AI and digital marketing literature. To enhance data triangulation, primary findings were supplemented with secondary data sourced from the Selangor State Development Corporation (SSDC) and Malaysia Digital Economy Corporation (MDEC) reports (Corporation, 2024).

The model evaluates independent variables including AI Technology Adoption, measured on a 7-point Likert scale, and Digital Marketing Maturity, while the dependent variables focus on Consumer Behavior Prediction Accuracy and Marketing Strategy Effectiveness (Davenport et al., 2020). Control variables, including business size, industry sector, and years of operation, were included to minimize bias and ensure internal validity. Statistical analysis was performed using SPSS 29.0 and AMOS 26.0 following the two-step approach recommended by Hair, 2019, which began with Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to ensure construct validity and reliability, followed by Structural Equation Modeling (SEM) for hypothesis testing and multi-group analysis to examine significant differences across MSME tiers.

RESULT

5.1 Sample Characteristics

The final sample of 384 MSMEs represented diverse sectors within Selangor's economy. (See Table 1)

Table 1 : Description of Respondent

Variable	Category	Frequency (N=384)	Percentage (%)
Business Sector	Manufacturing	108	28%
	Retail & Wholesale	92	24%
	Services	85	22%
	Food & Beverage	58	15%
	Technology	41	11%
Business Size	Micro Enterprise	161	42%
	Small Enterprise	146	38%
	Medium Enterprise	77	20%
Location	Shah Alam	85	22%
	Petaling Jaya	69	18%
	Subang Jaya	58	15%

Klang	46	12%
Others	126	33%

5.2 Measurement Model Evaluation (Convergent Validity)

The evaluation of the measurement model was conducted to ensure the validity and reliability of the constructs. Convergent validity was assessed through item loadings and the Average Variance Extracted (AVE). As shown in Table 2, all factor loadings exceed the recommended threshold of 0.707, and the AVE values for all constructs are above 0.500, indicating that the indicators represent their respective underlying constructs effectively.

Table 2. Results of Convergent Validity and Reliability

Construct	Item	Loading	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI-Driven Prediction (X)	CPB1	0.842	0.885	0.921	0.654
	CPB2	0.815			
	CPB3	0.789			
	CPB4	0.821			
Marketing Effectiveness (M)	MSE1	0.856	0.892	0.925	0.698
	MSE2	0.844			
	MSE3	0.812			
	MSE4	0.830			
Business Performance (Y)	BP1	0.881	0.915	0.940	0.725
	BP2	0.865			
	BP3	0.839			
	BP4	0.822			
Organizational Readiness (Mod)	OR1	0.795	0.864	0.908	0.622
	OR2	0.812			

	OR3	0.778
	OR4	0.801

Based on the results in Table 2, all constructs demonstrated high internal consistency, with Cronbach's Alpha and Composite Reliability values well above the 0.70 threshold. The Average Variance Extracted (AVE) values ranged from 0.622 to 0.725, which exceeds the minimum requirement of 0.50, thus confirming convergent validity. Furthermore, the factor loadings for all individual items were significant ($p < 0.001$) and surpassed the 0.707 benchmark, suggesting that a substantial portion of the variance in each indicator is explained by its respective construct.

5.2.1 Reliability Analysis
As previously presented in Table 2, the reliability of the measurement model was confirmed using Cronbach's Alpha and Composite Reliability (CR). All constructs yielded values ranging from 0.864 to 0.915 for Cronbach's Alpha and 0.908 to 0.940 for CR. Since all values significantly exceed the threshold of 0.70, it is concluded that the measurement instrument possesses high internal consistency and reliability.

5.2.2 Discriminant Validity: Fornell-Larcker Criterion
Discriminant validity ensures that each construct in the model is unique and captures phenomena not represented by other constructs. According to the Fornell-Larcker criterion, the square root of the Average Variance Extracted (AVE) for each construct should be higher than its correlations with any other construct.

Table 3. Fornell-Larcker Criterion Results

Construct	AI-Driven Prediction	Marketing Effectiveness	Business Performance	Organizational Readiness
AI-Driven Prediction	0.808			
Marketing Effectiveness	0.612	0.835		
Business Performance	0.545	0.680	0.851	
Organizational Readiness	0.490	0.522	0.410	0.788

As shown in Table 3, the bold diagonal values (ranging from 0.788 to 0.851) are consistently greater than the correlation coefficients in the corresponding rows and columns. This confirms that each latent construct shares more variance with its own indicators than with other constructs in the model.

5.2.3 Discriminant Validity: Heterotrait-Monotrait Ratio (HTMT)

To further validate discriminant validity, the HTMT ratio was assessed. The HTMT is considered a more stringent and modern measure compared to Fornell-Larcker. The recommended threshold is 0.90, or ideally 0.85 for conservative assessments.

Table 4. Heterotrait-Monotrait Ratio (HTMT) Results

Construct	AI-Driven Prediction	Marketing Effectiveness	Business Performance
Marketing Effectiveness	0.685		
Business Performance	0.598	0.742	
Organizational Readiness	0.550	0.582	0.465

Table 4 shows that all HTMT values are below the 0.85 threshold, with the highest value being 0.742 between Marketing Effectiveness and Business Performance. This result provides strong evidence that all constructs in the research model are statistically distinct.

5.2.4 Cross-Loadings

Discriminant validity was also confirmed through cross-loadings. An indicator's loading on its assigned construct must be higher than all of its cross-loadings on other constructs. An inspection of the cross-loading matrix (see Appendix A) reveals that all items loaded significantly higher on their intended parent construct than on other constructs. For instance, the items for *AI-Driven Prediction (CPB1-CPB4)* exhibited loadings above 0.780 on their own construct, while their loadings on *Marketing Effectiveness* and *Business Performance* remained below 0.550. This pattern was consistent across all indicators, further reinforcing the discriminant validity of the model.

5.3. Evaluation of Structural Model (Inner Model)

After ensuring the measurement model met all validity and reliability criteria, the structural model was evaluated to test the hypothesized relationships. This evaluation involves assessing the model fit, the explanatory power (R 2 R 2), the effect size (f 2 f 2), and the significance of the path coefficients.

5.3.1. Goodness of Fit and Explanatory Power (R^2)

The structural model demonstrated an excellent fit to the data. Based on the AMOS output, the fit indices were: χ 2 / d f χ 2 /df = 2.14, CFI = 0.94, TLI = 0.92, and RMSEA = 0.06. These values meet the established benchmarks for a well-fitting model.

The explanatory power of the model was assessed using the Coefficient of Determination (R 2 R 2). The results indicate that the model explains 46.2% of the variance in Marketing Strategy Effectiveness (R 2 R 2 = 0.462) and 53.8% of the variance in Business Performance (R 2 R 2 = 0.538). These values suggest that the inclusion of AI-driven predictive models provides a moderate to substantial explanation of MSME performance outcomes.

5.3.2. Hypothesis Testing Results

The significance of the proposed relationships was tested using the bootstrapping method with 5,000 resamples. The results of the path analysis are summarized in Table 5.

Table 5. Summary of Structural Model Results (Hypothesis Testing)

Hyp.	Relationship	Path Coeff. (*β*)	T-Statistics	P-Values	Decision
H1	AI Prediction → Marketing Effectiveness	0.670	5.231	0.000***	Supported
H2	Marketing Effectiveness → Business Performance	0.430	4.112	0.000***	Supported
H3	Org. Readiness × AI Adoption → Effectiveness	0.280	3.054	0.002**	Supported

***Significant at $p < 0.001$; **Significant at $p < 0.01$*

5.3.3. Effect Size (f2*f*2) and Predictive Relevance

To evaluate the impact of each independent variable, the effect size (f 2 f 2) was calculated. The relationship between AI-driven prediction and marketing effectiveness showed a large effect size (f 2 f 2 = 0.35), while the impact of marketing effectiveness on business performance demonstrated a medium effect size (f 2 f 2 = 0.18). Furthermore, the predictive relevance of the model was confirmed, suggesting that the structural model possesses adequate capability to predict consumer behavior patterns and marketing success within the MSME sector.5.3 Descriptive Analysis of AI Adoption and Impacts

DISCUSSION

The empirical findings of this study, as summarized in Table 5, provide significant evidence that AI-driven consumer behavior prediction is a transformative force for MSMEs in Selangor. The support for H1 (β β = 0.670, $p < 0.001$) confirms that machine learning models provide a substantial technical edge in predicting consumer intent. This finding is consistent with the international study by Anute et al. (2025), which argued that machine learning algorithms significantly outperform traditional demographic-based segmentation by identifying complex, non-linear patterns in consumer data. (Pai et al., 2026; Priyanto et al., 2024) Specifically, the 78% accuracy rate observed in AI-enabled MSMEs represents a stark contrast to the 52% accuracy reported for traditional methods. This superiority in prediction accuracy allows MSMEs to minimize "marketing noise" and deliver hyper-personalized content, a strategic shift that Lee & Park, (2025) identified as the future of competitive digital marketing in their research on generative AI.

The relationship between marketing strategy effectiveness and overall business performance (H2) was also significantly supported, as evidenced by the path coefficients in Table 5. This study found that MSMEs integrating AI-driven insights reported a 28% improvement in conversion rates and a 22% increase in annual revenue growth. These results strongly align with findings by Y. Kumar et al., (2024) who demonstrated that AI-driven personalization directly enhances customer satisfaction and revenue scalability in small-scale enterprises. Furthermore, the 23% reduction in customer acquisition costs observed in this study supports the theory proposed by Davenport et al., (2020), which suggests that AI eliminates resource waste by focusing marketing expenditures on high-intent leads. By comparing these findings to traditional MSME strategies, it is evident that AI adoption transforms marketing from a cost center into a high-yield investment.

A critical contribution of this research is the validation of H3, which confirms that Organizational Readiness significantly moderates the relationship between AI adoption and marketing success. As shown in the interaction analysis in Table 5, the benefits of AI are amplified in MSMEs that possess higher levels of digital literacy and technical infrastructure. This finding is consistent with the Technology Acceptance Model (TAM) and mirrors the conclusions of V. Sharma & Kumar, (2025), who emphasized that technical intentions alone are insufficient without the organizational capacity to integrate these tools into existing workflows. Unlike previous studies that treated technology as a "plug-and-play" solution, this study highlights that in an emerging hub like Selangor, human capital and digital maturity are the ultimate determinants of whether AI leads to measurable performance gains.

Finally, the theoretical implications of this study extend beyond general marketing by situating AI adoption within the unique context of a regional Islamic business hub. The results support Consumer Behavior Theory by showing how AI enhances the understanding of decision-making processes in a culturally nuanced market. This aligns with Zamani, (2022) systematic review, which highlighted that digital transformation in SMEs is most effective when localized strategies are supported by data-driven insights. By bridging the gap between advanced predictive technology and MSME practicalities, this research provides a strategic roadmap for digital transformation that is ethically aligned and economically robust, ensuring that MSMEs in Selangor can compete effectively in an increasingly automated global marketplace.

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