

# Modeling Marketing Strategies in Small and Medium-Sized Food Industry Enterprises Using Reinforcement Learning and Natural Language Processing Approaches

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## ABSTRACT

In the age of digital transformations, artificial intelligence serves as a crucial tool for revising marketing patterns, especially for small and medium-sized food industry enterprises that face fierce competition, resource scarcity, diverse customer preferences, and infrastructure limitations. This study aims to design a local model to enhance marketing strategies for these businesses using DQN and DistilBERT algorithms, examining the effective factors, optimizing dynamic decision-making, and analyzing customer behavior. The research methodology employed a mixed qualitative-quantitative approach with an interpretivist philosophy and inductive strategy. In the qualitative phase, semi-structured interviews with 12 experts (theoretical saturation after 10 interviews) and thematic analysis using Attride-Stirling's method were conducted. In the quantitative phase, a five-point Likert scale questionnaire based on 25 organizing themes was distributed to 384 managers and experts (Cronbach's alpha: 0.78 to 0.88; Kolmogorov-Smirnov test:  $p < 0.08$ ). Findings showed that the average factors ranged from 3.45 to 4.25, with the highest averages for "technology adoption by senior managers" (4.25) and "personalization capability" (4.25). The DQN model achieved an accuracy of 0.94, MSE of 0.15, F1-Score of 0.92, and an average reward of 98.5, while DistilBERT achieved an accuracy of 0.91, Cross-Entropy of 0.12, Precision of 0.89, and Recall of 0.90. The DQN model outperformed with 130 samples, showing errors under 0.3. The conclusion suggests that DQN is suitable for dynamic optimization, and DistilBERT is effective for textual customer analysis. This native model, combining local factors (such as privacy laws and innovative culture), is predicted to increase the competitiveness of food SMEs by 25% in conversion rates and reduce forecasting costs by 15%, offering a practical solution for the Iranian market.

**Keywords:** Marketing Strategies, Small and Medium Enterprises, Food Industry, DQN Algorithm, DistilBERT Algorithm

## 1. Introduction

In today's rapidly changing digital world, artificial intelligence (AI) has emerged as a strategic tool that can significantly enhance business operations, particularly in marketing. This technology holds immense potential for small and medium-sized enterprises (SMEs), enabling them to analyze large volumes of data, predict market trends, and improve customer interactions. For SMEs in the food industry, AI presents an opportunity to overcome competitive pressures, limited financial and human resources, and the ever-evolving consumer preferences (Magableh et al., 2024). These businesses, often constrained by high costs associated with traditional marketing methods, can leverage AI to remain competitive by exploiting new opportunities in the digital marketplace (Esmaeily et al., 2024). However, despite its potential, the adoption of AI by SMEs, especially in food industries, faces significant barriers such as limited infrastructure and high implementation costs (Shaik, 2023). In particular, food industry SMEs in developing countries like Iran lack the necessary financial resources and technological infrastructure to fully integrate AI into their marketing strategies (Magableh et al., 2024). This research aims to design a localized framework for the application of AI in marketing for food industry SMEs, addressing their specific needs and constraints while improving their marketing effectiveness.

Previous studies have largely focused on large organizations with abundant resources and have rarely explored the challenges and limitations faced by SMEs, especially those in the food industry (Rosário & Raimundo, 2025). This research highlights the need for a localized approach that considers the specific cultural, economic, and operational realities of food businesses, especially in emerging markets. The lack of such frameworks has created a significant gap in both research and practical applications. By developing a customized model, this study aims to bridge this gap and provide SMEs with actionable strategies to effectively implement AI in their marketing processes. Furthermore, AI's ability to analyze consumer data and predict behaviors is increasingly seen as an essential tool for enhancing personalized marketing strategies. As consumers demand more tailored experiences, AI-driven solutions that provide insights into consumer preferences can significantly improve customer engagement and satisfaction (Aghababaei et al., 2025). AI tools can help SMEs understand their customers' behavior,

predict trends, and personalize their marketing efforts, enabling them to compete with larger companies that already leverage advanced AI technologies (Akbar & Widowati, 2024).

Despite the growing recognition of AI's benefits, research on AI adoption in small food businesses in emerging economies remains scarce. In Iran, fewer than 10% of food industry SMEs use AI for marketing purposes, while 74% of consumers expect personalized experiences (Esmaeily et al., 2024). This gap between consumer expectations and the ability of SMEs to meet those expectations emphasizes the importance of this research. The findings suggest that AI adoption can significantly enhance SMEs' ability to meet customer demands for personalization, thus improving customer loyalty and increasing revenue (Geetha et al., 2024). AI adoption in marketing is also influenced by management support and market competition. Previous studies highlight the importance of top management's commitment to technological change in driving AI adoption (Kshetri et al., 2024). In SMEs, where decision-making is concentrated at the top, strong leadership support is critical to overcoming the barriers to AI integration. Moreover, in highly competitive environments, SMEs are more likely to adopt AI technologies to stay ahead of their competitors (Stancu & Panait, 2025). Therefore, understanding the role of management and market pressures in AI adoption can help SMEs align their strategies to maximize the benefits of AI. In conclusion, AI presents significant opportunities for SMEs in the food industry to enhance their marketing strategies, increase competitiveness, and improve customer engagement. However, these businesses must overcome several challenges, including infrastructure limitations, financial constraints, and lack of skilled labor, to effectively integrate AI into their operations. This research contributes to the literature by offering a localized framework for AI adoption in the food sector, which considers the unique constraints and opportunities of SMEs in emerging markets. The findings provide practical insights that can help SMEs overcome these barriers and adopt AI-driven marketing strategies to improve their market performance.

## 2. Methods

This study adopts a mixed-methods approach to explore the application of artificial intelligence (AI) in marketing for small and medium-sized food businesses (SMEs). The

research is designed to identify the factors that influence AI adoption and to develop a localized framework for optimizing marketing strategies using AI. The methods section is divided into both qualitative and quantitative components, ensuring comprehensive data collection and analysis. The qualitative component of the study employs a phenomenological design to explore the perspectives of managers and experts in SMEs in the food industry regarding the use of AI in marketing. The primary method for data collection is semi-structured interviews. These interviews aim to gather in-depth insights into the experiences, challenges, and perceptions of key stakeholders involved in marketing and AI adoption. The target participants include managers, marketing professionals, and technology experts from various sub-sectors within the food industry, such as dairy, confectionery, packaging, and protein products. A purposive sampling technique is used to select a sample of 12 experts based on their experience with AI or their roles in marketing decision-making. These participants were chosen to ensure diversity across different food sub-sectors and levels of experience with AI. The interviews are conducted in a face-to-face or virtual format, lasting between 45 and 75 minutes each. The data is recorded with the participants' consent and transcribed for analysis. Data analysis is carried out using thematic analysis, following the steps. The transcripts are coded to identify common themes related to the barriers and enablers of AI adoption in food industry SMEs. The analysis will also address the role of organizational culture, technological infrastructure, and management support in the integration of AI-driven marketing strategies. The quantitative component involves the use of a structured survey to validate and quantify the findings from the qualitative analysis. The survey, designed using the themes extracted from the interviews, employs a Likert-type scale with five response options ranging from "Strongly Disagree" to "Strongly Agree." This allows participants to express their level of agreement with statements regarding the influence of various factors, such as infrastructure availability, data quality, and managerial support, on AI adoption. The target population for the survey consists of managers and experts from SMEs in the food sector, with a sample size of 384 respondents. The sampling frame is determined using the unlimited population method, ensuring a broad and representative sample. The survey is distributed both online and in-person, with the goal of achieving a high response rate to ensure the reliability and generalizability of the findings.

### 2.1. Deep Q-Network (DQN) Algorithm

The Deep Q-Network (DQN) algorithm is a deep reinforcement learning method that utilizes deep neural networks to address complex decision-making problems. In this study, DQN is employed to optimize marketing strategies for small and medium-sized food businesses based on themes derived from qualitative analysis. Reinforcement learning is grounded in the principle that an agent learns by performing actions in a given environment to maximize future rewards. DQN improves this process by using neural networks to estimate the Q-function (action value). In this research, the marketing environment is defined as a simulation consisting of states (market conditions), actions (advertising strategies such as online ads or discounts), and rewards (increased sales or customer satisfaction). DQN combines deep learning with the Q-learning algorithm, wherein a neural network predicts the value of each action in various states. The algorithm uses two key techniques: Experience replay, which stores and replays past experiences, and Target network, which ensures learning stability by preventing fluctuations during the learning process. In modeling, the quantitative data from surveys is used to define the environment and actions, with DQN optimizing marketing strategies to achieve the best market performance. This algorithm is particularly well-suited for optimizing marketing strategies that require decision-making in dynamic and complex conditions (AbdelAziz et al., 2025).

### 2.2. DistilBERT Algorithm

In the modeling process with DistilBERT, text data from surveys or interviews is first collected and transformed into a suitable format for the model, such as converting it into standard tokens using a specialized Tokenizer. The model is then fine-tuned using training data, which involves adjusting parameters like learning rate and number of epochs to maximize accuracy. In this study, DistilBERT is used to analyze customer behavior, where inputs such as customer reviews or manager explanations are fed into the model to generate outputs like purchase likelihood or customer preferences. The algorithm uses an attention mechanism to identify keywords such as "quality" or "price" and models relationships between them, helping improve prediction accuracy. Furthermore, DistilBERT can handle multilingual data. The model outputs probabilities or classifications, assisting managers in better understanding customer behavior. This process is evaluated

using metrics like accuracy and F1-score to assess model performance (Adel et al., 2022). A key advantage of DistilBERT is its ability to process complex texts with limited computational resources, making it suitable for budget-constrained research in comparison to BERT, which requires more powerful hardware. In this research, DistilBERT is used to analyze textual data derived from qualitative themes, which may include managers' explanations of customer behavior or customer feedback. The mechanism involves using Transformer layers to learn textual representations, enabling the model to extract hidden meanings, such as determining whether customers are more sensitive to price or quality. In modeling, the model is fine-tuned with training data to focus on specific tasks such as predicting purchase patterns, and this process is implemented using Python software. Additionally, DistilBERT can work with incomplete or noisy textual data, which is common in real-world marketing data. The model outputs analytical reports that can help managers adjust marketing strategies accordingly (Oh et al., 2023).

### 2.3. Data Analysis

Data collected from the survey will be analyzed using statistical software to perform descriptive and inferential analysis. The normality of the data is assessed using the Kolmogorov-Smirnov test, and internal consistency is evaluated using Cronbach's alpha. For hypothesis testing and model validation, parametric tests will be applied to determine the relationships between AI adoption factors and marketing performance. By combining qualitative and quantitative methods, this study aims to provide a comprehensive understanding of how AI can be leveraged to optimize marketing strategies in SMEs, offering both theoretical insights and practical recommendations.

## 3. Results

The findings are presented in three parts: (i) qualitative outputs and the finalized factor structure, (ii) descriptive–inferential results of the survey instrument, and (iii) performance of the proposed AI models (DQN for dynamic strategy optimization and DistilBERT for customer-text analytics), followed by a direct model comparison. Across all phases, results converged on a consistent conclusion: organizational readiness (especially senior management adoption) and market-facing capabilities (especially personalization) are the strongest levers for implementing AI-driven marketing in Iranian food SMEs.

### 3.1. Qualitative findings: extraction and organization of themes

To address Research Question 1 (factors influencing AI adoption in marketing of food SMEs), semi-structured interviews were conducted with 12 experts; theoretical saturation was reached after the 10th interview, and two additional interviews were used to confirm stability of codes and meanings. Using Attride–Stirling's thematic analysis, the interview transcripts were coded and aggregated into basic themes, organizing themes, and overarching/global themes (see table 1). A recurring pattern in expert narratives emphasized that “legal-ethical assurance” is not a peripheral issue but a primary enabling condition for AI adoption in marketing. For example, multiple basic themes centered on privacy compliance, transparency, and security (e.g., “observing local data protection rules,” “global privacy alignment,” “transparency of data usage,” “data security protocols,” “monitoring compliance,” “customer trust in data security,” and “clarity of AI processes”). In these narratives, compliance reduced perceived risk, increased institutional trust, and decreased resistance to AI-mediated customer engagement—thereby acting as an adoption catalyst. The thematic network culminated in six overarching/global themes, each composed of multiple organizing themes (25 in total): (1) technology infrastructure, (2) human resources and knowledge, (3) financial and economic resources, (4) organizational factors, (5) data and analytics, (6) market factors, (7) legal and ethical factors, and (8) strategic factors. The resulting structure provided the basis for the questionnaire items used in the quantitative phase and the feature set fed into modeling.

### 3.2. Trustworthiness and rigor of the qualitative phase

Quality assurance steps indicated acceptable credibility and dependability of the qualitative findings. Interview audio was reviewed carefully; codes and extracted meanings were checked with interviewees (member checking) to confirm accuracy. After the coding scheme stabilized, a second review of the codebook was conducted to assess potential bias; no systematic bias was observed in code allocation. Additionally, themes were discussed with informed staff and managers outside the interview set to verify that the extracted statements reflect real adoption conditions in food SMEs. Collectively, these steps support the internal validity of the theme structure and justify its translation into measurable questionnaire constructs.

**Table 1**

*Global theme structure and key organizing themes (derived from thematic analysis)*

Global (overarching) theme	Examples of organizing themes (non-exhaustive)
Technology infrastructure	Access to IT infrastructure; access to advanced analytics platforms; technical support and after-sales services
Human resources & knowledge	Staff AI skills; access to AI specialists; innovative organizational culture
Financial & economic resources	Implementation cost; R&D investment; access to financial resources for AI investment
Organizational factors	Senior management adoption; firm size/scale; AI compatibility with current marketing processes; CRM integration capability
Data & analytics	Data quality; analyzable data patterns
Market factors	Market competition level; customer behavior and preferences; market digitalization acceptance; supply chain complexity
Legal & ethical factors	Privacy/data regulations; customer trust in AI technologies
Strategic factors	Awareness of AI competitive advantage; personalization capability; AI-driven advertising cost reduction; partnerships with AI firms/startups

**3.3. Quantitative findings: descriptive statistics, distributional assumptions, and reliability**

To address the quantitative component, a five-point Likert questionnaire (built from 25 organizing themes) was administered to 384 managers and experts. Descriptive statistics showed that mean scores across the 25 factors ranged from 3.45 to 4.25, indicating respondents generally perceived most factors as moderately to highly important for adopting AI in marketing. The highest mean values were observed for “senior management technology adoption” (Mean = 4.25, SD = 0.70) and “personalization capability” (Mean = 4.25, SD = 0.70), signaling that adoption is primarily driven by leadership commitment and the ability to tailor marketing to customer segments. Relatively lower means were observed for “AI implementation costs” (Mean = 3.45, SD = 0.95) and “R&D investment” (Mean = 3.55, SD = 0.95), which is consistent with the financial constraints typical of SMEs and suggests that cost sensitivity may slow adoption even when perceived benefits are high.

Normality testing (Kolmogorov–Smirnov) indicated Sig values for all 25 variables exceeded 0.05 (range ≈ 0.08 to 0.19), supporting the assumption of approximate normal distribution for the measured constructs and permitting the use of parametric analyses for subsequent modeling stages. Reliability assessment via Cronbach’s alpha showed acceptable-to-excellent internal consistency across all constructs, with alpha values ranging from 0.78 to 0.88. The highest alpha values were associated with “personalization capability” ( $\alpha = 0.88$ ), “senior management adoption” ( $\alpha = 0.87$ ), and “awareness of AI competitive advantage” ( $\alpha = 0.87$ ), indicating strong

coherence among questionnaire items within these constructs.

**3.4. Modeling results: DQN optimization performance**

Research Question 3 examined how marketing strategies for food SMEs can be optimized using DQN based on the extracted themes. In the implemented reinforcement learning environment, states represented marketing conditions (e.g., market competition intensity, availability of analyzable data, managerial support), actions represented marketing interventions (e.g., discounting, targeted digital ads, personalization intensity, channel selection), and rewards reflected a weighted outcome function combining sales, customer engagement, and cost. The trained DQN achieved strong predictive and optimization performance with an Accuracy of 0.94, MSE of 0.15, F1-Score of 0.92, and an Average Reward of 98.5. Error distribution analyses indicated that 130 samples fell within the lowest error band (0 to 0.3), and only 1 sample exceeded 1.2 error, implying both high accuracy and stability. These outcomes suggest that the DQN effectively learned long-term, reward-maximizing marketing policies in a dynamic setting. The model’s internal prioritization (via Q-values) also indicated that managerial adoption and personalization remain central determinants of optimal strategy selection, consistent with the descriptive findings.

**3.5. Modeling results: DistilBERT customer-text analytics performance**

To address Research Question 3 (text-driven customer behavior and purchase pattern analysis), DistilBERT was used to process and learn from customer-related texts (e.g., feedback, reviews, and language markers linked to

preferences and purchase intent). The model achieved an Accuracy of 0.91, Cross-Entropy Loss of 0.12, a Precision of 0.89, and a recall of 0.90. Error distribution showed 145 samples in the lowest error band (0 to 0.3), though the number of large errors (>1.2) was slightly higher than DQN (3 samples), indicating strong but somewhat less stable performance relative to DQN when assessed via tail errors. The DistilBERT results support the capability of

transformer-based distilled models to generate robust classification and prediction for customer text with relatively high efficiency. In practical marketing terms, this performance indicates suitability for continuous monitoring of customer sentiment, topic clustering, and intent cues that can feed into campaign design and personalization logic (see table 2).

**Table 2**

*Model evaluation metrics for DQN and DistilBERT*

Metric	DQN	DistilBERT
Accuracy	0.94	0.91
Error/Loss	MSE = 0.15	Cross-Entropy = 0.12
Precision	—	0.89
Recall	—	0.90
F1-Score	0.92	0.87
MAE	0.35	—
Average Reward	98.5	—

**3.6. Comparative results: key factor importance and error stability**

To answer Research Question 4 (comparative performance of DQN and DistilBERT), the models were compared along (i) standard metrics, (ii) factor importance, and (iii) error distribution. Both models converged on a similar hierarchy of top drivers but expressed them through different mechanisms: DQN via Q-values (reflecting long-horizon reward contribution) and DistilBERT via attention weights (reflecting salience in language-driven prediction). In both models, “senior management adoption” ranked first and “personalization capability” ranked second, indicating consistent agreement that adoption and effective

deployment are anchored in managerial commitment and customer-level customization.

Error distribution analyses further illustrated that DistilBERT placed more samples in the smallest error band (145 vs. 130), reflecting very high accuracy for text-based tasks, whereas DQN showed fewer extreme errors (1 vs. 3), reflecting superior stability for decision optimization under dynamic conditions. Overall, the DQN’s higher accuracy, higher F1, and higher stability supports its prioritization for real-time decision policies in marketing environments, while DistilBERT remains the stronger component for extracting actionable customer intelligence from unstructured text (see table 3).

**Table 3**

*Key factor importance and error distribution summary*

Comparison dimension	DQN	DistilBERT
Top factor 1	Senior management adoption (Q = 20.4)	Senior management adoption (attention = 0.65)
Top factor 2	Personalization capability (Q = 19.1)	Personalization capability (attention = 0.58)
Samples with error 0–0.3	130	145
Samples with error > 1.2	1	3

**3.7. Integrated interpretation of results**

Taken together, the results show a coherent logic across methods. The qualitative phase identified a broad set of adoption determinants, emphasizing legal-ethical trust, infrastructure readiness, skills, and strategic awareness. The quantitative phase confirmed that respondents rate these

determinants highly overall, but the strongest emphasis falls on managerial adoption and personalization, while financial constraints appear as a comparative limiter. Finally, the modeling phase demonstrated that combining these factors into an operational AI system is feasible: DQN delivers strong performance for dynamic optimization, and DistilBERT provides reliable customer-

text analytics. The combined evidence supports a native/localized model for Iranian food SMEs in which (1) leadership commitment triggers adoption readiness, (2) privacy/ethical assurance reduces resistance, (3) data quality and integration capacity enable effective deployment, and (4) AI methods can measurably improve strategy selection and customer understanding.

#### 4. Discussion

The findings from this study provide valuable insights into the factors influencing the adoption of artificial intelligence (AI) in marketing strategies for small and medium-sized food businesses (SMEs). This discussion will interpret these findings in the context of the existing literature, highlighting the challenges and opportunities that SMEs face in integrating AI into their marketing operations. The study's results align with prior research while also addressing gaps in the current understanding of AI adoption in SMEs, particularly within the food industry.

##### AI Adoption Challenges in SMEs

A key finding of this study is the critical role of technology infrastructure and financial resources in the successful adoption of AI in marketing strategies. SMEs often face significant barriers to AI implementation due to limited financial resources and insufficient technological infrastructure (Magableh et al., 2024). This aligns with the findings of Esmaeili et al. (2024), who also noted that SMEs in developing markets, including Iran, struggle with the costs associated with acquiring and maintaining AI technologies (Esmaeily et al., 2024). Despite the availability of AI tools, the financial burden of these technologies remains a major barrier, especially in food industry SMEs, where margins are often tight, and budgets are constrained. Therefore, it is essential for these businesses to find cost-effective solutions or collaborate with external technology providers who can offer affordable AI tools suited to their specific needs.

Furthermore, the qualitative analysis revealed that human resources and knowledge significantly influence AI adoption. Several respondents emphasized the importance of staff expertise in AI, which is consistent with previous research suggesting that a lack of skilled professionals and training opportunities in SMEs impedes the successful integration of AI (Tian et al., 2025). This highlights the need for SMEs to invest in training and development programs to ensure their workforce is equipped with the necessary skills to harness the potential of AI effectively.

By addressing this gap, SMEs can better manage AI tools and develop more efficient marketing strategies.

##### The Role of Management Support

Management support emerged as one of the most significant factors influencing AI adoption. This finding is consistent with previous studies that emphasize the role of top-level leadership in driving technological change within organizations (Kshetri et al., 2024). In SMEs, where decision-making is often concentrated at the top, management's commitment to AI integration can determine whether the business adopts AI technologies at all. The study found that businesses with strong management support were more likely to invest in AI, explore its potential, and implement it in their marketing strategies. This highlights the importance of fostering a culture of innovation and ensuring that senior leaders prioritize AI as a strategic asset.

However, market competition also played a crucial role in driving AI adoption. The study found that in highly competitive markets, SMEs were more likely to adopt AI technologies to gain a competitive advantage. This is supported by research by Stancu and Panait (2025), who argued that businesses operating in competitive environments tend to seek out innovative solutions, such as AI, to maintain market positioning and enhance customer relationships (Stancu & Panait, 2025). The pressure to outperform competitors in the food industry encourages SMEs to adopt AI-driven marketing strategies to stay ahead of the curve. Therefore, competitive dynamics can serve as both a motivator and a barrier to AI adoption, depending on the specific resources available to SMEs.

##### Consumer Insights and Personalization

AI's ability to analyze consumer data and provide actionable insights was also a major theme in the study. Participants noted that AI tools that could analyze consumer behavior and predict preferences were highly valued. This finding supports the work of Aghababaei et al. (2025), who highlighted the importance of AI in improving customer engagement and enhancing personalization (Aghababaei et al., 2025). Personalized marketing, enabled by AI-driven insights, allows SMEs to offer tailored experiences that can increase customer satisfaction and loyalty. As consumer expectations evolve, particularly with the rise of digital technologies, SMEs must adapt their marketing approaches to meet the demand for personalized interactions (Żyminkowska & Zachurzok-Srebrny, 2025). Failure to leverage AI for personalization may result in SMEs losing their competitive edge, as consumers

increasingly expect brands to cater to their individual preferences.

### **Theoretical and Practical Contributions**

The findings of this study contribute to the literature by addressing a significant gap in the research on AI adoption in the food industry, particularly in SMEs. Most existing studies have focused on large organizations with substantial resources, neglecting the unique challenges faced by SMEs (Shaik, 2023). This research extends the understanding of AI adoption in SMEs by providing a localized framework that considers the economic, cultural, and operational realities of food industry businesses in emerging markets like Iran. By incorporating local market factors, such as the availability of resources, consumer behaviors, and regulatory concerns, the study offers a tailored approach for SMEs to adopt AI technologies in a way that aligns with their specific needs and constraints.

In addition, the study emphasizes the importance of data utilization in driving marketing strategies. With AI tools, SMEs can analyze large datasets to gain valuable insights into customer preferences, behavior, and buying patterns. This capability is essential for businesses in the food industry, where consumer tastes can change rapidly. The ability to quickly adapt marketing strategies based on data-driven insights can lead to more effective customer engagement, higher conversion rates, and increased profitability (Rosário & Raimundo, 2025).

## **5. Conclusion**

In conclusion, the findings of this study underscore the multifaceted challenges and opportunities that SMEs in the food industry face in adopting AI-driven marketing strategies. While AI presents significant potential for improving marketing effectiveness and competitiveness, SMEs must overcome challenges related to technology infrastructure, financial constraints, and human resources. Management support, a competitive market environment, and the effective use of consumer data are key factors that drive AI adoption and success. The study's localized framework for AI adoption offers practical insights for SMEs in emerging markets, highlighting the need for tailored strategies that consider the unique constraints and opportunities of the food industry. Future research could explore the longitudinal effects of AI adoption on SME performance and examine the role of government and industry partnerships in facilitating AI integration.

### **Authors' Contributions**

All authors contributed substantially to the study and to manuscript development, and all approved the final version.

### **Declaration**

Artificial intelligence was used only for language polishing and editorial support during manuscript preparation. No AI tool was used for data collection, statistical analysis, or generation of the study results. The authors reviewed, verified, and take full responsibility for the final content of the manuscript.

### **Transparency Statement**

Data are available from the corresponding author upon reasonable request.

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### **Declaration of Interest**

The authors report no conflict of interest.

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### **Ethics Considerations**

This study was conducted after obtaining approval from the Research Committee of the Department of Management, Shahrud Branch, Islamic Azad University, Shahrud, Iran. All data were collected and analyzed in accordance with ethical research principles, ensuring confidentiality, responsible data use, and academic integrity.

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