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

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ABSTRACT

Artificial intelligence (AI) has become a strategic enabler for redesigning marketing practices, particularly for small and medium-sized enterprises (SMEs) in the food industry, where firms face intense competition, resource constraints, heterogeneous customer preferences, and infrastructural limitations. This study developed a context-specific model for improving marketing strategies in food-sector SMEs by integrating Deep Q-Network (DQN) and DistilBERT algorithms. A mixed-methods design was used. In the qualitative phase, semi-structured interviews were conducted with 12 experts and analyzed through thematic network analysis. In the quantitative phase, a questionnaire developed from 25 organizing themes was administered to 384 managers and specialists. Reliability was acceptable to excellent (Cronbach's alpha = 0.78-0.88), and normality was confirmed using the Kolmogorov-Smirnov test (Sig. = 0.08-0.19). The highest mean scores were found for senior management technology adoption (4.25) and marketing-strategy personalization capability (4.25). DQN achieved accuracy of 0.94, MSE of 0.15, F1-score of 0.92, and mean cumulative reward of 98.5. DistilBERT achieved accuracy of 0.91, cross-entropy loss of 0.12, precision of 0.89, and recall of 0.90. The findings suggest that DQN is better suited to dynamic marketing optimization, whereas DistilBERT is more appropriate for text-based customer analytics. The proposed framework provides a practical AI-driven model tailored to Iranian food-industry SMEs. The algorithmic analyses were based on structured questionnaire-derived features and coded textual materials from expert and managerial narratives; therefore, the reported performance should be interpreted as internal model validation rather than evidence from deployed real-time marketing campaigns.

Keywords: *Artificial intelligence; Marketing strategy; Small and medium-sized enterprises; Food industry; Deep Q-Network; DistilBERT.*

1. Introduction

Rapid digital transformation has made artificial intelligence a strategic tool for redesigning marketing models, especially in SMEs that operate under resource scarcity and strong competitive pressure. In marketing, AI can support customer segmentation, prediction, personalization, pricing, and campaign optimization when it is embedded in managerial decision-making rather than treated as a purely technical add-on (Davenport et al., 2020;

Huang & Rust, 2021; Magableh et al., 2024). This issue is particularly important in food-industry SMEs, where consumer preferences, seasonality, price sensitivity, and supply-chain complexity require adaptive and data-driven marketing decisions.

Prior research shows that AI and digital marketing can improve customer engagement, targeting, and firm performance, yet SMEs often face weaker data infrastructure, limited digital maturity, and insufficient technical expertise (Kshetri et al., 2024; Oecd, 2021; Sharabati et al., 2024). Data-driven marketing can improve the speed and precision of managerial decisions, but its effectiveness depends on the quality, availability, and interpretability of data (Varian, 2014). Therefore, models developed for large corporations cannot be transferred mechanically to SMEs without considering local market conditions and organizational limitations.

The main gap addressed in this study is the lack of an integrated and locally adapted model that combines qualitative market understanding with advanced AI algorithms for food-industry SMEs. The study focuses on two complementary algorithmic functions: DQN for dynamic marketing optimization and DistilBERT for semantic analysis of customer-related textual data. DQN is theoretically appropriate because marketing decisions can be framed as sequential actions evaluated through reward feedback (Mnih et al., 2015; Sutton & Barto, 2018). DistilBERT is appropriate because customer comments, complaints, and managerial narratives are text-based data that can be analyzed using transformer-based language models (Devlin et al., 2019; Sanh et al., 2019; Vaswani et al., 2017).

The central research question is: how can AI algorithms be used to design an effective model for improving marketing strategies in food-industry SMEs? The study further examines the factors that influence AI adoption, the optimization of marketing strategies through DQN, the analysis of customer behavior through DistilBERT, and the comparative performance of the two algorithms.

2. Methods and Materials

2.1. Research Design

This study used an applied-developmental mixed-methods design. The qualitative phase explored expert views regarding AI adoption in food-industry SME marketing, while the quantitative phase validated the extracted themes and supported algorithmic modeling. The mixed-methods logic followed established research design principles for integrating qualitative exploration with quantitative validation (Creswell & Creswell, 2023). The qualitative validation approach was informed by procedures for credibility, dependability, and interpretive trustworthiness in qualitative inquiry (Creswell & Poth, 2018).

The study was cross-sectional. Data were collected through semi-structured interviews, structured questionnaires, and literature review. Thematic network analysis was used to extract basic, organizing, and global themes from the interviews (Attride-Stirling, 2001). The questionnaire sample size was determined using Cochran's formula for an unknown population (Cochran, 1977). Internal consistency was assessed using Cronbach's alpha, with values above 0.70 interpreted as acceptable according to common psychometric guidance (Nunnally & Bernstein, 1994). Descriptive and reliability analyses followed standard multivariate data-analysis principles (Hair et al., 2019).

2.2. Qualitative and Quantitative Phases

The qualitative population consisted of managers, marketing specialists, and owners of SMEs operating in the Iranian food industry who had experience in evaluating or applying AI technologies in marketing activities. Purposive sampling was used. Twelve expert interviews were conducted, with theoretical saturation reached after the first ten interviews and confirmed through two additional interviews. Interviews lasted approximately 45-75 minutes and were audio-recorded with informed consent.

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Table 1

Demographic Characteristics of Qualitative Experts

No.	Position	Industry	Education	Age	Experience	Area of expertise
1	Chief executive officer	Dairy	M.Sc. Management	45	15	Digital marketing
2	Marketing manager	Confectionery	Ph.D. Marketing	38	12	AI in marketing
3	Senior marketing expert	Dairy	M.Sc. Information Technology	42	10	Data analytics
4	Production manager	Food packaging	M.Sc. Management	50	20	Production and marketing
5	IT specialist	Confectionery	M.Sc. Industrial Engineering	35	12	Information technology
6	Sales manager	Protein products	M.Sc. Economics	40	13	Sales and distribution
7	Chief executive officer	Dairy	Ph.D. Management	48	18	Strategic management
8	Marketing expert	Food packaging	M.Sc. Marketing	36	11	Content marketing
9	Finance manager	Protein products	M.Sc. Accounting	44	16	Financial marketing
10	R&D specialist	Confectionery	Ph.D. Research and Development	39	11	Market research
11	Operations manager	Food packaging	M.Sc. Operations Management	47	19	Operations and supply chain
12	Digital marketing specialist	Dairy	M.Sc. Digital Marketing	41	14	Digital marketing and AI

The quantitative instrument was developed from the organizing themes extracted in the qualitative phase. Items were measured on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Because the exact size of the population was unknown, the Cochran formula for an infinite population was used, resulting in 384 respondents. Reliability was assessed using Cronbach's alpha, and normality was examined using the Kolmogorov-Smirnov test.

2.3. AI Modeling

Two AI models were evaluated. DQN was used to optimize marketing strategies by formulating market conditions as states, marketing actions as actions, and sales growth, customer engagement, and cost control as reward components. Experience replay and target-network mechanisms were used to improve training stability, consistent with deep reinforcement learning and later refinements addressing overestimation bias (Mnih et al., 2015; Van Hasselt et al., 2016). DistilBERT was used for natural language processing of customer opinions and managerial narratives. Textual data were tokenized and transformed into semantic embeddings, allowing the model to detect customer preferences and behavioral patterns with lower computational cost than full BERT-based models (Devlin et al., 2019; Goodfellow et al., 2016; Sanh et al., 2019; Vaswani et al., 2017).

Modeling data construction and validation procedure. To address reproducibility, the structured DQN input matrix was constructed from the 25 organizing themes measured in the questionnaire. Each case represented one respondent-level marketing scenario, with normalized theme scores used as state features. The action set consisted of alternative marketing-policy options derived from the qualitative phase, including personalization, targeted promotion, customer-segment prioritization, channel selection, and cost-control actions. The reward function combined three components: expected sales improvement, customer-engagement potential, and marketing-cost reduction. Because no longitudinal sales log or deployed campaign data were available, reward values were computed from expert-coded scenario scores and should be interpreted as an internally validated decision-support simulation.

For DQN, the dataset was divided into training, validation, and test subsets using a 70/15/15 split. Model stability was checked through repeated random splits. The model used experience replay, a target network, epsilon-greedy exploration, mini-batch training, and mean squared error as the optimization loss. The state representation, action alternatives, and reward components were kept

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identical across validation runs to avoid post-hoc adjustment.

For DistilBERT, the textual dataset consisted of anonymized interview excerpts, managerial narratives, and customer-oriented marketing statements coded during the qualitative phase. Texts were cleaned, tokenized with the DistilBERT tokenizer, truncated or padded to a fixed sequence length, and divided into training, validation, and test sets using the same 70/15/15 logic. The model was fine-tuned for classification of marketing-relevant themes. Accuracy, precision, recall, F1-score, and cross-entropy loss were calculated on the held-out test subset.

3. Findings and Results

The qualitative analysis produced 25 organizing themes grouped into broader domains. These domains and themes are summarized in Table 2.

Table 2

Main Factors Affecting AI Adoption in Food-Industry SMEs

Domain	Key organizing themes
Technological infrastructure	Access to IT infrastructure; access to advanced data-analysis platforms; technical support and after-sales services
Human resources and knowledge	Employees' AI-related knowledge and skills; access to AI specialists
Financial and economic resources	AI implementation costs; R&D investment; financial resources for technology investment
Organizational factors	Senior management technology adoption; business size and scale; compatibility with existing marketing processes; integration with CRM systems
Data and analytics	Existing data quality; availability of analyzable data patterns
Market factors	Competition intensity; target-customer behavior and preferences; market digitalization; food-industry supply-chain complexity
Legal and ethical factors	Data-privacy regulations; customer trust in AI technologies
Strategic factors	Awareness of AI's competitive advantages; marketing personalization capability; advertising-cost reduction; collaboration with technology firms and AI startups

Table 3 reports the selected descriptive findings. Respondents generally agreed that the identified factors are important for AI adoption in food-industry marketing. Mean scores ranged from 3.45 to 4.25.

Table 3

Selected Descriptive Results for Key Variables

Variable	Mean	SD	Variance	Interpretation
Senior management technology adoption	4.25	0.70	0.49	Highest-rated driver
Marketing-strategy personalization capability	4.25	0.70	0.69	Highest-rated strategic capability
Awareness of AI's competitive advantages	4.20	0.70	0.61	Strong strategic awareness
Compatibility with existing marketing processes	4.15	0.80	0.64	Strong operational relevance
Innovative organizational culture	4.15	0.80	0.37	Strong organizational enabler
AI implementation costs	3.45	0.95	0.90	Main financial barrier
R&D investment	3.55	0.95	0.90	Weak investment capacity
Access to AI specialists	3.60	0.95	0.90	Human-resource limitation

The Kolmogorov-Smirnov test confirmed that all 25 variables followed a normal distribution, with significance values ranging from 0.08 to 0.19. Therefore, the data were suitable for parametric analyses. Reliability analysis using Cronbach's alpha showed acceptable to excellent internal consistency, with coefficients ranging from 0.78 to 0.88. Selected reliability results are shown in Table 4.

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Table 4

Reliability Summary for Selected Variables

Variable	Cronbach's alpha
Marketing-strategy personalization capability	0.88
Senior management technology adoption	0.87
Awareness of AI's competitive advantages	0.87
Innovative organizational culture	0.86
Compatibility with existing marketing processes	0.86
Existing data quality	0.83
Advertising-cost reduction through AI	0.83
AI implementation costs	0.78
R&D investment	0.78

Table 5 compares the performance of DQN and DistilBERT. DQN achieved the strongest overall performance for marketing-strategy optimization, while DistilBERT performed strongly in textual customer analysis.

Table 5

Frequency of Characterization Indicators

Indicator Code	Characterization Indicator	Frequency	Percentage
P1	Antihero	78	78
P2	Pessimistic psychological characteristics	64	64
P3	Character's social position	52	52
P4	Femme fatale	74	74
P5	Complex interpersonal relationships	63	63

To investigate the interaction among structural indicators, Phi (Φ) correlation coefficients were calculated. The strongest relationships are presented in Table 5. High-contrast lighting showed a strong positive association with dark urban production design (Φ = .61) and frame composition (Φ = .54), indicating that these visual components frequently co-occur to construct the distinctive visual atmosphere of noir. Within the narrative dimension, narrative structure demonstrated substantial correlations with flashback (Φ = .58) and narrative suspense (Φ = .52), reflecting the central role of nonlinear storytelling and suspense in noir narratives. Among the characterization variables, the antihero exhibited the strongest relationship with the femme fatale (Φ = .63), while its association with moral tension was also considerable (Φ = .56). Furthermore, the relationship between the femme fatale and narrative suspense (Φ = .47) suggests that this character type plays an essential role in generating narrative uncertainty.

Table 6

Comparison of DQN and DistilBERT Performance

Metric	DQN	DistilBERT
Accuracy	0.94	0.91
Main error metric	MSE = 0.15	Cross-entropy = 0.12
MAE	0.35	-
Precision	-	0.89
F1-score	0.92	0.87
Recall	-	0.90
Mean total reward	98.5	-
Main use	Dynamic marketing optimization	Textual customer analysis

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Table 6 shows the top five factors by model-based importance. Both models identified senior management technology adoption and marketing-strategy personalization as the most important factors.

Table 7

Top Five Factors by Model-Based Importance

Factor	DQN Q-value	DistilBERT attention weight
Senior management technology adoption	20.4	0.65
Marketing-strategy personalization capability	19.1	0.58
Financial resources for investment	17.8	0.52
Innovative organizational culture	16.5	0.48
Existing data quality	15.2	0.44

The error-distribution results further indicated that DQN had fewer large errors than DistilBERT, with only one case above the highest error threshold compared with three cases for DistilBERT. DistilBERT produced more low-error cases in textual prediction, but DQN demonstrated greater stability across the full error distribution. Therefore, DQN was identified as the more appropriate model for optimizing marketing strategies in resource-constrained SMEs that require rapid and flexible decision-making, whereas DistilBERT was more suitable for SMEs with rich textual customer data and a need for customer-feedback interpretation (see Table 7).

Table 8

Error-Distribution Summary for DQN and DistilBERT

Error range	DQN (count)	DistilBERT (count)	Interpretation
0.00-0.30	134	145	Lowest-error predictions
0.30-0.60	45	35	Moderate low-error predictions
0.60-0.90	15	12	Moderate-error predictions
0.90-1.20	5	5	High-error predictions
>1.20	1	3	Largest-error predictions

4. Discussion

The findings indicate that AI can support marketing-strategy development in food-industry SMEs, but its value depends on managerial commitment, data quality, organizational readiness, and financial feasibility. Senior management technology adoption emerged as the strongest factor in both the descriptive results and the model-based rankings. This finding is consistent with the AI-marketing literature, which emphasizes that AI creates business value when it is embedded in strategic decision-making rather than treated as a purely technical tool (Davenport et al., 2020; Huang & Rust, 2021; Magableh et al., 2024). In SMEs, where decision authority is often concentrated in senior managers, leadership commitment becomes a necessary condition for successful implementation.

The superior performance of DQN suggests that reinforcement learning is particularly suitable for marketing environments requiring sequential and adaptive decision-making. DQN learns optimal actions through reward feedback and is designed for dynamic environments in which present decisions affect future outcomes (Mnih et al., 2015; Sutton & Barto, 2018). The inclusion of target networks and experience replay is also consistent with evidence that stabilizing Q-learning improves performance and reduces instability in deep reinforcement learning (Van Hasselt et al., 2016). In this study, DQN achieved higher overall accuracy than DistilBERT and produced stronger results for dynamic marketing optimization, implying that SMEs may benefit from AI systems that continuously adjust marketing actions based on sales, customer engagement, and cost-related outcomes.

DistilBERT also showed strong performance, particularly for customer-text analysis. This result is coherent with the development of transformer architectures and BERT-based language representation models (Devlin et al., 2019; Vaswani et al., 2017). DistilBERT reduces computational requirements while preserving much of

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BERT's language-understanding capacity, making it relevant for SMEs with limited infrastructure (Sanh et al., 2019). Its practical value lies in analyzing customer reviews, complaints, comments, and social-media feedback, while DQN is better suited to policy optimization.

Personalization was another central finding. Marketing-strategy personalization received one of the highest mean scores and was ranked as a major factor in both AI models. This is consistent with studies showing that digital and AI-enabled marketing can improve engagement through segmentation, targeted communication, and individualized value propositions (Kshetri et al., 2024; Sharabati et al., 2024). However, personalization depends on reliable data. The importance assigned to existing data quality confirms that incomplete or fragmented customer data can limit AI performance, a point also consistent with the broader literature on data-driven decision-making (Varian, 2014).

The results further show that financial constraints remain a major barrier. AI implementation costs and R&D investment received lower mean scores than managerial adoption and personalization capability. This suggests that even when SMEs recognize the strategic value of AI, they may struggle to implement it due to limited budgets, lack of specialists, and insufficient infrastructure. This interpretation aligns with research on the digital transformation of SMEs, which stresses that adoption depends on absorptive capacity, organizational readiness, and access to affordable digital infrastructure (Oecd, 2021). Therefore, gradual implementation is recommended, beginning with low-cost cloud tools, pilot campaigns, and narrowly defined use cases such as customer-feedback analysis or seasonal promotion optimization.

Finally, the ethical and legal dimensions should not be treated as secondary. Since AI marketing depends on customer data, privacy, transparency, and customer trust directly influence adoption. AI-driven personalization may increase engagement, but opaque or excessive data use may undermine trust. SMEs should therefore combine technical implementation with clear data-governance rules, transparent communication with customers, and human oversight. Overall, the study supports a dual-model approach: DQN for dynamic optimization of marketing strategies and DistilBERT for semantic analysis of customer feedback.

5. Conclusion

This study proposed and evaluated a context-specific AI-based model for improving marketing strategies in food-industry SMEs. The findings showed that senior management technology adoption, marketing-strategy personalization, awareness of AI's competitive advantages, compatibility with existing marketing processes, and innovative organizational culture are central factors in AI adoption. DQN outperformed DistilBERT in dynamic marketing optimization, whereas DistilBERT showed strong performance in analyzing textual customer data. The proposed framework suggests that SMEs can improve marketing effectiveness by combining reinforcement learning for adaptive decision-making with NLP tools for customer insight extraction. The study focused on food-industry SMEs in Iran and used cross-sectional questionnaire and interview data. Therefore, generalization to other industries or national markets should be made cautiously. Future research should test the model using longitudinal data, real sales records, customer-platform behavioral data, and experimental marketing campaigns. Further studies may also compare DQN and DistilBERT with alternative models such as gradient boosting, large language models, or hybrid reinforcement-learning and NLP architectures. However, the framework should be regarded as a validated analytical prototype rather than a fully deployed commercial system. Its practical effectiveness should be tested with longitudinal sales records, live customer-platform data, and controlled marketing experiments before strong managerial claims are made.

Authors' Contributions

Jafar Taherzadeh: conceptualization, data collection, formal analysis, software/modeling, and writing-original draft. Hasan Vahedi: methodology, validation, supervision, and writing-review and editing. Seyed Hossein Hosseini: data interpretation, investigation, and writing-review and editing. Mehdi Sanei: resources, project administration, and writing-review and editing. All authors reviewed and approved the final manuscript.

Declaration

Artificial intelligence (AI)-assisted tools were used to improve the linguistic quality, readability, and grammatical accuracy of the manuscript. The authors retained full responsibility for the study design, data collection, data analysis, interpretation of the findings, and final content. All AI-assisted outputs were reviewed, verified, and edited by the authors before submission. No AI tool was used as an author of the manuscript.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

The study was conducted in accordance with ethical principles for research involving human participants. All interviewees and survey respondents were informed about the purpose of the study, participation was voluntary, and informed consent was obtained before data collection. Participants were assured that their responses would remain confidential and would be reported only in aggregate form. No personally identifiable information was reported in the manuscript.

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