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RESEARCH ARTICLE

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Role of artificial intelligence in marketing strategies and performance

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Abstract

This study examines the role of artificial intelligence (AI) as a marketing strategy and explains its contribution to firms and the factors influencing their development. The study tests an empirical model based on the research variables and constructs identified using structural equation modeling and the fuzzy set qualitative comparative analysis (FsQCA) approach. Data were collected from 278 food firms. The findings indicate that the implementation of an AI marketing strategy affects performance. Additionally, this study shows that marketing capabilities, customer value co-creation, and market orientation are positively related to performance. Finally, the results highlight that marketing capabilities, customer value co-creation, and market orientation affect the development of AI marketing strategies. The research results of FsQCA find that causal conditions of marketing capabilities, customer value co-creation, market orientation, and AI marketing strategy are necessary and sufficient recipes for higher firm performance.

KEYWORDS

AI marketing strategy, artificial intelligence (AI), FsQCA, market orientation, performance

1 | INTRODUCTION

The number of artificial intelligence (AI) start-ups is growing rapidly, and many big high-technology companies invest huge amounts of money in AI development, including deep learning, machine learning, and data analytics. AI applications emerge in a broad range of industries, such as solutions in logistics, medicine, industrial production processes, transportation, and digital marketing (Agarwal et al., 2020; Chen et al., 2020; Grewal et al., 2020; Longoni et al., 2019) as well as financial advising (i.e., Méndez-Suárez et al., 2019), future work (i.e., Autor, 2015), digital social museums (i.e., Mas & Monfort, 2021), augmented reality, and virtual reality (Hilken et al., 2022; Ibáñez-Sánchez et al., 2022) among many others.

AI plays an increasingly important role in marketing research because the development and application of AI data-driven approaches to collect and provide valuable information is increasingly used for brand or company marketing (Huang & Rust, 2021; Wang et al., 2021). Thus, the role of AI in improving marketing decision-making is huge and involves several fields (Rust, 2020; Saura, 2021), such as processing data, analyzing data, detecting fraudulent responses and voice-activated devices (Parry et al., 2016; Schneider et al., 2018; Simester et al., 2020), developing marketing management support systems (Coelho et al., 2020; Grewal et al., 2020; Hartmann et al., 2019; Letheren et al., 2021; Rai, 2020) as well and marketing intelligent systems (Jarrahi, 2018; Martínez-López & Casillas, 2009).

The food industry includes fast food, coffee shops, restaurants, beverages, and food sales. Marketing strategies continue to evolve rapidly. The important role of supporting marketing decisions, such as product, pricing, distribution, and promotion, consumers' food consumption and purchase intention has been widely examined in the marketing field. Consumers perceive that a company is developing AI strategies that may attract more customers, creating a mutually beneficial relationship between the consumer and the firm. Therefore, however, there are many unanswered questions regarding the potential for AI to be successful in influencing strategy choice and performance.

However, some marketing problems within AI strategic decisions are ill-defined or under-structured (Huang & Rust, 2021). Dealing with the problems of marketing information and data is one of the greatest challenges in marketing research (Dekimpe, 2020; Lehmann, 2020). AI advances analytical methods and information systems to manage marketing issues of firms (Simester et al., 2020). However, literature on AI in marketing applications remains fragmented. While some studies show that the implementation of AI for marketing innovation affects performance (Berg et al., 2018; Wu et al., 2020), others suggest that marketing actions must consider the various effects of the different strategies and channels (i.e., Méndez-Suárez & Monfort, 2020, 2021). The effects on the performance of the application of AI marketing strategies, such as those that argue that marketing capabilities are crucial to the performance of AI marketing strategies (i.e., Bruni & Verona, 2009; Falasca et al., 2017; Pimentel Claro & Oliveira Claro, 2010; Vorhies & Morgan, 2005) and enable companies to obtain competitive advantages (i.e., Dzyabura & Hauser, 2019). However, there is a lack of studies that connect marketing capabilities with AI marketing strategies. A similar approach applies to the concept of co-creation. Numerous studies have mentioned the importance of co-creating with consumers for performance. (i.e. Ranjan & Read, 2016; Yi & Gong, 2013), either through increased satisfaction (Payne et al., 2008) or the desire to show identity in the processes (Pera et al., 2016)

Therefore, few marketing studies provide a comprehensive strategic framework for AI for marketing decisions at the strategic level. This deficiency in AI needs to be conceptualized, as AI marketing remains an untested paradigm. Thus, this study attempts to answer the following questions: (a) How does an AI marketing strategy impact the performance of organizations? (b) What are the key factors affecting AI marketing strategies?

This study applies theory-building, qualitative, and quantitative approaches to develop an AI strategic framework that examines the AI marketing environment, strategy, and performance in the food franchise and chain firm contexts. The research tests an empirical model for a practical situation based on research variables and constructs identified by employing structural equation modeling (SEM) and the fuzzy set qualitative comparative analysis (FsQCA) This empirical study collected data from food firms.

The remainder of this article is structured as follows: First, a brief review of the literature and the suggested research hypotheses is detailed. The research methodology and data analysis are described. Finally, the results are explained, and a discussion and main conclusions are presented.

2 | LITERATURE REVIEW

AI is a technology that learns and adapts behavior based on previous experience and attempts to simulate humans (Glikson & Woolley, 2020). AI is a decision-maker in complex and diverse contexts (Jarrahi, 2018). These solutions can learn, process, plan, and predict (Letheren et al., 2021), overtaking humans to accomplish computable approaches for decision-making (Moriuchi, 2019; Parry et al., 2016). Some authors argue that AI techniques can indeed reduce the need for human expertize because they can extract patterns and optimize the identification of critical assets (Nedjah et al., 2022).

Thus, AI achieves superior knowledge of the business environment and is important for firms (Dekimpe, 2020; Zhao & Priporas, 2017) because the input-output ratio of knowledge has a positive influence on the different incentives for companies (Cheng et al., 2022) and organizations achieve performance by acquiring and identifying resources for the development of strategic decisions to capture and retain customers (Barney et al., 2011).

AI has motivated the development of analytical methods to manage marketing information and problems (Zhao & Priporas, 2017). AI solutions can be applied to marketing strategies as part of their digital transformation, which implies using digital technologies to trigger business improvements and improve customer experience, or creating new business models (Fitzgerald et al., 2014; Marinko Škare & Małgorzata porada-Rochon', 2021). The question to be answered is whether the implementation of AI marketing strategies has an impact on company performance and overall marketing strategies.

Additionally, organizational culture generates capabilities that exhibit a certain market orientation (Ngo & O'Cass, 2012; Smirnova et al., 2011). De Luca et al. (2010) explored market orientation to produce a positive link between market orientation and performance. However, the link between market orientation and firm performance remains debatable (Kumar et al., 2011). Nevertheless, despite the scarcity of studies, it seems appropriate to argue that AI marketing strategies and market orientation is an important antecent for company performance. This can be empirically tested as follows.

H1: *Market orientation has a positive effect on organizational performance.*

Few studies examine the impact of AI marketing strategies on firm performance. Some studies have emphasized that when firms adopt AI applications for marketing innovation, this has a positive impact on firm performance (Berg et al., 2018; Davenport & Kirby, 2016). In fact, understood as innovation, the application of AI marketing strategies could improve performance since innovation is a driver of a firm's performance in enhancing its customer equity (Santos-Vijande et al., 2022; Wu et al., 2020). Other studies have also shown that value proposition innovation is positively related to performance in digital start-ups (Guo et al., 2022) and in digital public services and the value of trade in the green goods sector (Ha & Thanh, 2022). However, recent studies have also shown that measuring the value of the return on marketing actions must consider the simultaneous cross effects of different initiatives; otherwise, marketing professionals that may make incorrect decisions infer attribution from misleading calculations (Méndez-Suárez & Monfort, 2020, 2021). Therefore,

H2: *AI marketing strategy has a positive impact on performance.*

The resource-based view (RBV) theory explains how company resources drive a firm's performance and create a competitive advantage

(Barney et al., 2011; Morgan et al., 2009; Sok & O'Cass, 2011; Vorhies et al., 2011). Specifically, RBV demonstrates the ability to gain or improve a competitive advantage (Barney et al., 2011; Bruni & Verona, 2009). In the context of marketing, capability refers to a firm's ability to coordinate its marketing strategies to plan and implement successful marketing strategies (Falasca et al., 2017) and represents a firm's ability to understand and predict customers' needs by using technology tools (Jin & Cho, 2018; Sung et al., 2022)

The literature argues that there are two types of innovation capabilities: strategic and operational (Adamides & Karacapilidis, 2020). A firm's strategic decision and development involve possessing its resources through specific operational or marketing capabilities for market success (Le Meunier-FitzHugh et al., 2011; Sok & O'Cass, 2011). In this sense, marketing capabilities can determine firms' competitive advantage and performance (Bruni & Verona, 2009; Pimentel Claro & Oliveira Claro, 2010) and meet customers' demands to respond to competitive pressure in products and markets by integrating internal and external firms' resources, skills, and competencies (Kim & McMillan, 2008; Smirnova et al., 2011). Thus, AI marketing strategy implementation is based on marketing capabilities with scarcity, value, inimitability, and nonsubstitutability to achieve competitive advantage (Vorhies et al., 2011). Therefore, marketing capabilities may be an important determinant of competitive strategy choice (Falasca et al., 2017). Consequently, the stronger a firm's marketing capability is, the more likely it is that the firm will use an AI marketing strategy.

Competitors cannot easily develop or acquire capabilities by implementing AI marketing strategies (Zhao & Priporas, 2017) since implementing an AI marketing strategy uses marketing capabilities, including monitoring products and markets, carrying out customer tests of products, and launching new products. Furthermore, marketing capabilities allow firms to understand market dynamics and changing markets (Falasca et al., 2017) and achieve sustainable competitive advantages (Dzyabura & Hauser, 2019; Mu et al., 2018). For this reason, it seems clear that all companies are bound by their marketing capabilities, which influences AI marketing strategies.

H3: *Marketing capabilities influence AI marketing strategy positively*.

Marketing capabilities are the management and development of market information and marketing strategies (Rai, 2020; Schneider et al., 2018) and enhanced performance (Mu et al., 2018) in the AI marketing context. Vorhies and Morgan (2005) propose that marketing capabilities are positively related to business performance. Marketing skills and knowledge enable a firm to understand customer preferences and competitors' actions with better performance than competitors (Vorhies et al., 2011; Yalcinkaya et al., 2007). Marketing capabilities can also coordinate resources to implement successful marketing plans (Falasca et al., 2017; Morgan et al., 2009) and achieve better performance (Vorhies & Morgan, 2005). Furthermore, marketing capabilities and performance may have a positive association, but future empirical research needs to explore the relationship between AI marketing capabilities and performance.

H4: *Marketing capabilities influence organizational performance positively*.

Following this argument, another company resource is value co-creation. Jin and Cho (2018) asserted that value co-creation is a process of mutual value that works with customers. It is a concept closely related to stakeholder engagement, which involves an interactive, experiential process based on actors' engagement with a focal organization (Viglia et al., 2018). In the B2B context, customers can improve their product/service innovation capability and obtain higher product quality and services by participating in product/service production or delivery (Kumar et al., 2019). Moreover, customers participating in value co-creation activities enhance the exchange relationship (Kumar et al., 2019; Yi & Gong, 2013), provide suppliers with feedback, and increase repurchase rates (Lehmann, 2020. This can be empirically tested as follows.

H5: *Customer value co-creation influences AI marketing strategy positively*.

In the field of communication and marketing, recent studies have shown that companies should design tools and platforms that can trigger consumers' desire to express their individuality (Pera et al., 2016), and efforts should be made to communicate what is of interest to their audiences (Monfort et al., 2019; Rangel-Pérez et al., 2022). Ranjan and Read (2016) examined the effects of customer value co-creation on AI management and marketing. These studies suggest that a firm's customer value co-creation can influence its AI marketing strategy to encourage research and development. Thus, it is proposed that value co-creation positively affects AI marketing strategy since firms need to be aware of the increasing importance of digital experience in tailoring marketing campaigns (Micu et al., 2019). Additionally, Payne et al.(2008), Ranjan and Read (2016), and Yi and Gong (2013) suggest that engaging customers may have higher levels of satisfaction, so customer value co-creation can enhance a firm's performance. Therefore, it can be argued that customer value co-creation is a condition for positive AI marketing strategy and company performance. Therefore,

H6: *Customer value co-creation influences performance positively*.

3 | RESEARCH METHODOLOGY

The research tests an empirical model for the practical situation based on research variables and constructs identified by employing SEM and the FsQCA approach. The research objective was to develop an empirical model to study and measure research constructs in the food industry context. The research methods were as follows:

3.1 | Sampling

Taiwan was chosen as the country of study as it increasingly uses AI marketing strategies. The Taiwanese government has focused on the development of AI. Taiwanese firms are under pressure to develop AI to achieve better performance. The study uses food franchises and chain stores to obtain information on the selected firms, and AI development is an important criterion to consider. This study uses questionnaire data from a survey of CEO and marketing managers in Taiwan between March and August 2020 received survey questionnaires. The sample is obtained by gathering information from food firms in the Taiwan Annual Chain Store and Franchise Guide (2020), yielding a sample database of 842 companies included in the survey. The unit of analysis is the firm's headquarters determined by research objectives because the AI marketing decision is at the senior managers or the head of the headquarters.

After finishing a literature review and personal interviews on AI strategies for marketing applications, the empirical study collected data from senior marketing executives of food firms. This study tests the theory to be generalizable to AI marketing strategies in the context of food franchises and chain store firms. The research employed a self-administered questionnaire for data collection and had a follow-up procedure. The research chooses senior managers, sales, or the CEO of the headquarters as key informants because of their knowledge and expertize in examining AI marketing strategies and performance issues.

3.2 | Survey development

The research measures market orientation using five items adapted from Kumar et al. (2011) and Murray et al. (2011). The research measures marketing capabilities using four items adapted from Morgan et al. (2009) and O'Cass and Ngo (2012). Customer value co-creation is measured by developing four items from the work of Pimentel Claro et al. (2010) and Payne et al. (2008). The research measures performance using four items adapted from Rego et al. (2013) and Stewart (2009). Finally, the research measures AI marketing strategy using 11 items adapted from Casillas and Martínez-López (2009) and Davenport (2016).

Pretests were conducted to detect any weaknesses in wording and improve the clarity of the questionnaire. The research conducted a pretest with approximately 20 marketing managers to refine the measures and finalize the questionnaire. All questionnaire items were closed-ended. Before the final distribution, the questionnaires were pretested to clarify misleading or ambiguous questions. Finally, the questionnaire data were collected using a mail questionnaire.

3.3 | Data analysis

The research employs the AMOS 19, SPSS 18.0, and FsQCA statistics packages to test the research hypotheses. Cronbach's α test reliability and confirmatory factor analysis (CFA) were used to test the validity of each instrument. The measurement model assessed convergent validity (average variance extracted [AVE], internal consistency [composite reliability], and discriminant validity). Measurement validation consisted of internal consistency, convergent validity, and discriminant validity. Cronbach's alpha values were calculated for each research construct in the proposed model (Nunnally, 1978).

Statistical analysis tests whether a good fit of CFA is the theoretical model. This study used SEM analysis to test the hypotheses after testing the validity of the measurement model. The AVE of constructs exceeded the minimum criterion of 0.50 and is acceptable for testing validity.

This study used the fuzzy set qualitative comparative analysis (fsQCA) method to compare the SEM analysis. Calibration can convert variables into fuzzy variables and assign values between 0.0 and 1.0 according to their degree of membership (Woodside, 2013; Woodside et al., 2013). Woodside (2013) recommended that the fsQCA method embraces complex causality to test asymmetrical relations between research observations or constructs. Ragin (2008) and Woodside (2013) emphasize fsQCA analysis to supplement SEM or regression analysis. FsQCA can identify patterns of multiple causations by testing various antecedent conditions to examine sufficient or necessary conditions for an outcome.

This study's coverage and consistency can be used to evaluate sufficient and necessary conditions. Fuzzy sets have the advantage of addressing the concern that crisp sets QCA use dichotomies (Woodside, 2013; Woodside et al., 2013). Ragin (2008) stressed the importance of using cases with theoretical and substantive knowledge in this process. In summary, fsQCA methods assess sufficiency and necessity, which are debated (Woodside, 2013; Woodside et al., 2013). Four research constructs (marketing capabilities, customer value co-creation, market orientation, and AI strategy) predicted firms' marketing performance.

4 | EMPIRICAL RESULTS

Measures capture CEO and marketing managers' perceptions of the relationship with their marketing environment, AI marketing strategy, and performance. Table 1 presents the survey's firm characteristics. Most firms are under 5 years of age (26%), with job titles such as marketing managers (44.96%) and sales (27.7%). Twenty six percentage of food firms had company experience between 5 and 10 years, while most food firms had an AI experience of less than 1 year.

The final sample size was 278 participants, with a response rate of 33.01%. Table 2 shows all the mean values, standard deviations, and standardized loading measures. Twenty six standardized loadings with 0.7 or higher are acceptable for testing the validity. Table 2 tests the empirical relationships among the research constructs.

4.1 | Overall model fit

This study measures the validity and reliability of research constructs using AMOS 9. Cronbach's alpha was used to estimate each research construct (Cronbach, 1951). The AVE from each research construct exceeded the minimum requirement of 0.50, and the lowest value for

TABLE 1 Firm demographics of respondents

	Responses	Percentage
Job title		
CEO	47	16.91%
Marketing managers	125	44.96%
Sales	77	27.7%
Technical engineering	25	8.99%
Other	4	1.44%
Total	278	100%
Company type		
Fast food	23	8.27%
Coffee shop	98	35.25%
Restaurant	89	32.01%
Beverage	36	12.95%
Food sales	32	11.51%
Total	278	100%
Company size		
Under 10 persons	57	20.50%
11–50 persons	17	6.12%
51–100 persons	48	17.27%
101–150 persons	74	26.62%
151–200 persons	56	20.14%
Above 201 persons	26	9.35%
Total	278	100%
Company experience		
Under 5 years	65	23.38%
5–10 years	73	26.26%
11–15 years	57	20.50%
16–20 years	55	19.78%
21+ years	28	10.07%
Total	100	100%
AI experience		
Under 1 year	82	29.50%
1–2 years	69	24.82%
3–4 years	60	21.58%
5–6 years	52	18.71%
6+ years	15	5.40%
Total	100	100%

AVE was 0.76. Reliability estimates for each construct using composite reliabilities exceeded the threshold of 0.70. Convergent validity and discriminant validity are acceptable for all research constructs, as shown in Table 3.

4.2 | Measurement model fit

This study measures the relevant overall model fit indices in Table 4. The chi-squared test yielded chi-squared values of 472.65 with 265 degrees of freedom, $p = 0.00$. Fit indices yield values including the comparative fit index (CFI) (0.93), root mean square error of approximation (RMSEA) (0.061), normed fit index (NFI) (0.92), and goodness of fit index (GFI) (0.94). These values support a good model-measurement fit for the sample data set.

4.3 | Structural model fit

The research used CFA and path analysis on all research constructs to test the theoretical model. The analysis of the causal paths in the structural model is presented in Table 5. The structural model fit supports all six proposed research hypotheses: market orientation has a positive effect on organizational performance (H1); AI marketing strategy has a positive effect on organizational performance (H2); marketing capabilities positively influence AI marketing strategy (H3); marketing capabilities positively influence organizational performance (H4); customer value co-creation positively influences AI marketing strategy (H5); and customer value co-creation positively influences organizational performance (H6).

4.4 | The fsQCA model

The fsQCA was calibrated in the first step. Ragin (2008) and Woodside and Zhang (2013) used fuzzy set theory and performed calibrations in fsQCA. Following the suggestions of Fiss (2011) and Pappas, Mikalef, et al. (2017), the scale measures calibrates into fuzzy sets with values ranging from 0 to 1 for three cut points (0 = no set membership, 0.5 = crossover point, and 1 = full set membership). The research calibrates the data to the values of 0.95, 0.50, and 0.05 as the three breakpoints or thresholds. The fsQCA program is employed to transform the variables into calibrated sets, including full nonmembership, crossover point, and six full memberships. Ordanini et al. (2014) and Pappas, Kourouthanassis, et al. (2017) suggest that the values of 6, 4, and 2 can be used as the thresholds. The results of the variable calibration are listed in Table 6.

In an empirical study, FsQCA involves a necessity analysis (or configurational element analysis) (Schmitt et al., 2017). The necessary analysis was a condition with a consistency score above 0.9 (Ragin, 2008). Table 7 shows that marketing capabilities, customer value co-creation, and AI marketing strategies are necessary to achieve a high level of performance. However, these are insufficiently independent. A low-performance analysis confirmed the assertion that the absence of the above conditions yielded a lower score for performance (consistency score < 0.80). (Figure 1)

The fsQCA analysis describes how marketing capabilities, customer value co-creation, market orientation, and AI marketing strategies are necessary conditions or sufficient elements for the

TABLE 2 Mean value, standard deviation, and standardized loadings of measures in the measurement model

Construct and scale items	Mean	SD	Standardized loadings
Marketing capabilities (7-point scales with anchors *strongly disagree* and *strongly agree*)			
1. Our firm has incorporates customer needs into marketing of products and services.	4.6	1.7	0.87
2. Our firm implements a great of marketing activities.	4.9	1.4	0.82
3. Our firm has advertising management and creative skills.	5.3	1.6	0.86
4. Our firm has skills to segment and target markets.	5.2	1.3	0.89
Customer value co-creation (7-point scales with anchors *strongly disagree* and *strongly agree*)			
5. Our customers participate in the process of production or service with my firm.	5.6	1.3	0.84
6. Our customers provide us with opinions on our product or service.	4.8	1.6	0.79
7. Our firm shares long-term plans for our product or service with our customers.	4.9	1.7	0.84
8. Our firm deals with problems that arise in customer relationship management.	4.9	1.6	0.82
Market orientation (7-point scales with anchors *strongly disagree* and *strongly agree*)			
9. My firm carries out house market research	5.3	1.6	0.81
10. My firm meets with customers to find out what products or services they need.	5.4	1.5	0.83
11. My firm reviews the future product or service innovations for customers.	5.2	1.6	0.85
12. My firm usually discusses market trends and development.	4.8	1.4	0.75
13. In my firm, my department shares other departments when one department finds out information about competitors' actions.	4.9	1.5	0.78
AI Marketing strategy (7-point scales with anchors *low* and *high*)			
14. Segmenting, positioning, and targeting business markets	4.9	1.8	0.87
15. Managing customers' relationships	4.6	1.5	0.73
16. Marketing channel relationships	5.1	1.6	0.83
17. Organizational buying and supply chain management processes	5.5	1.4	0.82
18. Pricing strategies	4.3	1.9	0.86
19. Product development and innovation	4.7	1.4	0.81
20. To conduct marketing research	4.9	1.7	0.82
21. To communicate with customers interaction	5.2	1.6	0.77
22. Receive customer feedback on my firm's product or services	5.1	1.4	0.81
Performance (7-point scales with anchors *low* and *high*)			
Please compare your firm's performance to your competitors' performance over the last 5 years			
23. Profit	5.2	1.8	0.87
24. Satisfaction of customers	5.4	1.5	0.91
25. Sales growth	4.9	1.6	0.86
26. Quality of service/product	5.3	1.4	0.83

Abbreviations: Mean, mean value; SD, standard deviation.

outcome of performance. Furthermore, it appears that marketing capabilities, customer value co-creation, market orientation, and AI marketing strategy are necessary and sufficient for predicting firm performance. In Table 8, the solutions of the higher-performance firms sample exhibit high consistency and coverage of the solutions. The overall solution coverage indicates that causal conditions account for 93% of the membership in the higher-performance firms' solutions (see Table 8). The study also examines the outcome condition of low performance with 79% membership in the low-performance firms' solution. The current results provide additional support for the research hypotheses. The results reinforce the findings and compare them with the SEM. Thus, causal conditions, including marketing capabilities, customer value co-creation, market orientation, and AI marketing strategy, are necessary and sufficient for higher performance. When marketing capabilities, customer value co-creation, market orientation, and AI marketing strategy increase, firm performance increases. Finally, the research model tests predictive validity, and the findings are reliable and valid, as shown in Table 8.

5 | DISCUSSION AND CONCLUSIONS

The research objectives shed light on a topic in which there is scarce literature, and different variables collide. Therefore, this study has obtained results that answer two key questions: whether AI marketing strategies affect the performance of organizations, and what are some of the factors that improve the results of AI marketing strategies? The research findings show that AI marketing strategies affect performance. Additionally, this study shows that marketing capabilities, customer value co-creation, and market orientation are positively related to performance. Finally, the results highlight that

TABLE 3 Construct measurement in the survey

Measures construct	Cronbach's α	AVE
Marketing capabilities	0.86	0.82
Customer value co-creation	0.83	0.78
Market orientation	0.87	0.84
AI marketing Strategy	0.83	0.76
Performance	0.93	0.85

Abbreviation: AVE, average variance extracted.

TABLE 4 Overall model fit

Chi-square	472.65
d.f.	265
p value	0.000
RMSEA	0.061
CFI	0.93
NFI	0.92
GFI	0.94

Abbreviations: CFI, comparative fit index; GFI, goodness of fit index; NFI, normed fit index; RMSEA, root mean square error of approximation.

TABLE 6 Data calibration

Configuration element (range)	Fully-in (95%)	Crossover (50%)	Fully-out (5%)
Marketing capabilities	6	4	2
Customer value co-creation	6	4	2
Market orientation	6	4	2
AI marketing strategy	6	4	2
Performance	6	4	2

Note: Calibration thresholds: fully in = top quartile, crossover = median, fully out = bottom quartile.

TABLE 5 Path analysis results

Path	Standardized path estimate	*t*-value	Significant
H1: Market orientation→ Performance	0.48**	5.92	s
H2: AI marketing strategy→ Performance	0.62**	6.75	s
H3: Marketing capabilities →AI marketing strategy	0.76**	7.47	s
H4: Marketing capabilities → Performance	0.62*	7.62	s
H5: Customer value co-creation →AI marketing strategy	0.82*	8.15	s
H6: Customer value co-creation →Performance	0.65**	7.23	s

Note: All *t*-values are significant at $^{*}p < 0.05$; $^{**}p < 0.01$.
Abbreviation: s, significant.

TABLE 7 Analysis of necessary conditions for predicting performance

Configuration element	High-performance Consistency	Coverage	Low performance Consistency	Coverage
Marketing capabilities	0.9223	0.8857	0.7546	0.2285
Customer value co-creation	0.9508	0.8983	0.7427	0.2165
Market orientation	0.8659	0.9357	0.7106	0.2345
AI marketing strategy	0.9474	0.9175	0.7423	0.2068

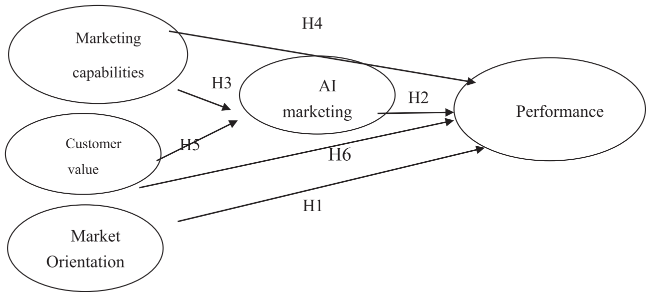

FIGURE 1 Research framework

marketing capabilities, customer value co-creation, and market orientation affect AI marketing strategies.

First, regarding the impact of AI marketing strategy, the results show that AI marketing strategy positively impacts organizational performance in terms of increase in profits, quality of service/products, sales growth, and customer satisfaction. This result is consistent with previous studies claiming that AI application positively impacts firm performance (Berg et al., 2018; Davenport & Kirby, 2016). AI marketing strategy is an innovation and a driver for performance improvement (Guo et al., 2022; Santos-Vijande et al.,

TABLE 8 Sufficiency analysis for high performance and low performance

	Raw coverage	Unique coverage	Consistency
(a) Sufficiency analysis for high performance[a]			
Marketing capabilities (MC)	0.543245	0.047515	0.895920
Customer value co-creation (CVC)	0.387282	0.013183	0.915397
Market orientation (MO)	0.345030	0.038553	0.929875
AI marketing strategy (AIMS)	0.248482	0.004268	0.934496
~ MC • CVC • ~ MO	0.249102	0.049149	0.753257
MC • ~ MO • ~ AIMS • CVC	0.307365	0.017365	0.733158
MC • MO • AIMS • ~ CVC	0.213748	0.027839	0.759210
MC • CVC • MO • AIMS	0.328314	0.032506	0.941538
MC • CVC • MO • ~ AIMS	0.224095	0.026187	0.904085
(b) Sufficiency analysis for low performance[b]			
Marketing capabilities (MC)	0.328235	0.065882	0.725087
Customer value co-creation (CVC)	0.202941	0.040588	0.748490
Market orientation (MO)	0.367846	0.017654	0.714322
AI marketing strategy (AIMS)	0.264218	0.072174	0.832869
MO • ~ AIMS	0.284597	0.084597	0.826408
~ MC • ~ CVC • ~ MO	0.246455	0.046455	0.923954
~ MO • ~ CVC •~ MC •AIMS	0.374328	0.074328	0.934734

Note: The symbol "~" stands for "absence of."

[a]Solution coverage: 0.9345; solution consistency: 0.8746.

[b]Solution coverage: 0.7948; solution consistency: 0.8134.

2022; Wu et al., 2020). Thus, the results are in line with those of others who argue that AI is important for business because it offers a better understanding of the environment (Dekimpe, 2020; Zhao & Priporas, 2017) and enables the development of decisions to maintain and attract customers (Barney et al., 2011). Similarly, the study sheds light on the debate about the relationship between market orientation and firm performance (Kumar et al., 2011), as it strengthens previous results in this line, which argue that market orientation does have an effect on performance (De Luca et al., 2010).

Second, in terms of which factors positively influence AI marketing strategy, the study has shown that the marketing capabilities and customer co-creation of the organization positively influence AI marketing strategy and performance. This strengthens the RBV theory, arguing that capabilities can improve competitive advantage (Barney et al., 2011; Bruni & Verona, 2009; Dzyabura & Hauser, 2019; Mu et al., 2018). The results are consistent with other studies (i.e., Bruni & Verona, 2009; Pimentel Claro & Oliveira Claro, 2010) (2005), which showed that marketing capabilities could determine firms' competitive advantage and performance. The marketing mix can be coordinated with developing and implementing successful marketing plans (Falasca et al., 2017; Morgan et al., 2009). This study also revealed that customer co-creation impacts AI marketing strategy and performance along with marketing capabilities. These results shed new light on the research conducted by Ranjan and Read (2016) and Yi and Gong (2013) since they show that they affect performance and that a firm's customer value co-creation can influence its AI marketing strategy to encourage AI research and development.

To predict performance, this study employs fsQCA to examine the combined conditions of marketing capabilities, customer value co-creation, market orientation, and AI marketing strategy. The empirical findings of the fsQCA show that marketing capabilities, customer value co-creation, market orientation, and AI marketing strategy are necessary to enhance organized performance. Further, the research findings demonstrate that marketing capabilities, customer value co-creation, market orientation (internal environment), and AI marketing strategy are necessary and sufficient to improve performance. This finding supports resource-based view theories. Accordingly, this study demonstrates that a firm's internal environment in the form of marketing capabilities, customer value co-creation, market orientation, and AI marketing strategy would be necessary and sufficient for organizational performance. Consistent with our fsQCA results, firms should focus on integrating their internal resources into AI marketing efforts. AI marketing strategies should be integrated with marketing capabilities, customer value co-creation, and market orientation to improve performance.

The paper reveals a clear visual figure explaining how SEM and fsQCA complement each other in offering added value. This study contributes to existing literature. First, examining the antecedents of performance through SEM and fsQCA provides comprehensive findings demonstrating the subject. Some previous studies in the body of literature analyze the subject matter using a symmetric approach (Ragin, 2008; Saridakis et al., 2016). The same outcome (performance) can be obtained using alternative methods. Adopting the SEM and fsQCA methodology, we comprehensively examine the variables' relationships. The combination of these two models allows researchers to obtain more comprehensive information. Previous studies have achieved comprehensive results using two different methodologies to explain performance (Kaya et al., 2020; Skarmeas et al., 2016). In summary, SEM can identify net effects, while fsQCA can identify asymmetric models (Woodside, 2013). The fsQCA results provide detailed and important information on how internal resources and AI marketing strategy choices can be shaped. Decision-makers should particularly explore why there is a difference in performance among firms.

From a methodological perspective, this study combines SEM and fsQCA. SEM analysis observes the strength of the relationships between variables in the model, while fsQCA yields configurations between variables that lead to an outcome in this study. Both research methods recognize the importance of adopting AI marketing strategies in highly competitive business environments. Empirically, the fsQCA results are more informative than the SEM results because they provide detailed insights into the alternative combinations (configurational paths) of marketing capabilities, customer value co-creation, market orientation, and AI marketing strategies lead to high performance. Using SEM and fsQCA enriches the understanding of how marketing capabilities, customer value co-creation, market orientation, and AI marketing strategy explain a firm's performance. While SEM research finds that marketing capabilities, customer value co-creation, market orientation, and AI marketing strategy positively affect performance, the fsQCA findings show that these factors should always be combined with core resources, including marketing capabilities, customer value co-creation, and market orientation. The results also indicate that marketing capabilities, customer value co-creation, market orientation, and AI marketing strategy are not individually relevant; they must be combined to enhance performance.

This is because of the existing debate on AI applications. Therefore, this study provides an original concept for applying AI and marketing research on COVID-19. The research process indicated that the sample data were collected from March to August 2020 in Taiwan. The COVID-19 pandemic strongly affected the entire world economy during that period. The research findings show that AI marketing strategy positively impacts firm performance in terms of increase in profits, quality of service/product, sales growth, and customer satisfaction by COVID-19. This study demonstrates that firms' performance can be improved through an AI marketing strategy in the food industry sector through COVID-19. Identifying impact factors enables CEO and marketing managers to understand AI marketing applications during and after COVID-19. This study also helps them make decisions regarding the effective use of AI marketing strategies to improve firm performance. The study's findings motivate CEO or marketing managers to support AI marketing strategies in food service by COVID-19 and after COVID-19.

Regarding practical implications, the results obtained through the different scales used help us understand that firms can conduct product, price, channel, promotion, marketing research, and communication with their customers easily from their conversations by using AI strategies and applications, such as chatbots. Firms may also gather market information about market trends and customer needs from AI, which can be used to strengthen their strategy, according to the results. The study has shown that AI marketing strategies help firms enhance customer satisfaction, improve customer service, and increase profits and sales. It also enables organizations to have easier access to information about customers and competitors. Similarly, AI marketing strategy improves customer satisfaction and product/service quality since the interactive nature of AI can create interactive communication between firms and consumers, which helps them to enhance customers' relationships and has better performance.

The limitations and future research directions are as follows. First, this study examines food firms in Taiwan. Future studies should empirically investigate companies in other countries and industries. Second, although the sample in this study is large enough for SEM and fsQCA analysis to yield valid empirical results, future research should conduct a broader study to obtain a larger sample set. Third, the research design calibrates only four performance impactor indicators; other internal or external environmental factors may impact organizational performance. Future studies should examine other research constructs and variables to evaluate the performance impact indicators. Finally, this study used a cross-sectional design to conduct the empirical research. Future research may conduct a longitudinal study to investigate the causal relationship between AI marketing strategy and performance at different times over a long period. Another issue to consider is the simultaneous cross-effects of the company's different initiatives (Méndez-Suárez & Monfort, 2020, 2021) and that, in the future, other research should include the activities carried out through the inclusion of these AI technologies.

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DATA AVAILABILITY STATEMENT

Research data are not shared.

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