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The Effect of Artificial Intelligence Components on Improving Customer Experience: The Mediating Role of Social Media Marketing and the Moderating Role of Response Strategy

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ABSTRACT

This study aimed to investigate the effect of artificial intelligence components on customer experience improvement at Iran Khodro Company, considering social media marketing as a mediating variable and response strategy as a moderating variable. This applied, quantitative study employed a descriptive, cross-sectional, correlational design based on structural equation modeling. The statistical population comprised managers, experts, and specialists employed at Iran Khodro Company in Tehran who were directly involved in product design, production, marketing, sales, and related organizational processes. Using Cochran's formula for an unlimited population, 384 participants were selected through stratified random sampling. Data were collected using a nine-item Artificial Intelligence Components Questionnaire, the 33-item Customer Experience Questionnaire, the nine-item Social Media Marketing Questionnaire, and the 11-item organizational strategy instrument adapted to measure response strategy. Face and content validity were evaluated by the academic supervisor and 13 organizational experts. Cronbach's alpha coefficients for the constructs ranged from 0.76 to 0.85. Data were analyzed using SPSS and SmartPLS 3 through partial least squares structural equation modeling, bootstrapping, measurement-model assessment, and direct, indirect, and moderation analyses. Artificial intelligence components had a significant direct effect on customer experience improvement ($t = 8.155$, $p = 0.001$) and social media marketing ($t = 468.240$, $p = 0.001$). Social media marketing also significantly affected customer experience improvement ($t = 7.857$, $p = 0.026$). The indirect effect of artificial intelligence components on customer experience improvement through social media marketing was significant ($t = 8.160$, $p = 0.049$), confirming the mediating role of social media marketing. However, response strategy did not significantly moderate the relationship between artificial intelligence components and customer experience improvement because its interaction t-value was below the critical threshold ($t = 1.292$). Artificial intelligence can improve customer experience both directly and indirectly by strengthening social media marketing; however, response strategy did not significantly alter this relationship, suggesting that effective integration of intelligent technologies with customer-oriented social media activities is more influential than general strategic orientation.

Keywords: Artificial intelligence, customer experience, social media marketing, response strategy, structural equation modeling, automotive industry.

Introduction

The rapid expansion of artificial intelligence has transformed the foundations of contemporary marketing and customer relationship management. Organizations increasingly use artificial intelligence to collect, process, and interpret extensive volumes of customer data, automate interactions, predict preferences, personalize communications, and improve the speed and accuracy of managerial decision-making. These capabilities have shifted artificial intelligence from a primarily technical resource to a strategic mechanism for creating value throughout the customer journey. In highly competitive markets, customer experience is no longer determined solely by product quality or price; rather, it emerges from the totality of customers' cognitive, emotional, behavioral, sensory, and relational encounters with an organization across multiple channels and touchpoints. Consequently, companies are under growing pressure to integrate artificial intelligence into customer-facing processes in ways that produce consistent, timely, personalized, and responsive experiences. Recent studies have accordingly emphasized the capacity of artificial intelligence to improve customer experience through data-driven personalization, automated communication, intelligent recommendation, real-time analysis, and more precise alignment between organizational offerings and customer expectations [1, 2].

Artificial intelligence contributes to customer experience improvement through several interrelated components. Machine-learning systems can identify behavioral patterns that are difficult to detect through conventional analytical methods, while natural language processing can extract customer sentiments, needs, complaints, and intentions from textual data. Recommendation systems can generate individualized product and service suggestions, predictive analytics can anticipate future behaviors, and automated agents can provide immediate responses to routine inquiries. From a marketing perspective, these capabilities enable organizations to replace generalized communication with more individualized and context-sensitive interactions. Artificial intelligence can also strengthen market segmentation, campaign optimization, customer churn prediction, sentiment analysis, content creation, and customer-service automation. Comparative analyses of machine-learning approaches in digital marketing show that artificial intelligence and social media analytics can improve targeting, campaign performance, and resource allocation by identifying the models most suitable for different marketing objectives [3, 4]. Similarly, the combined use of social media data algorithms and natural language processing can assist organizations in converting large quantities of unstructured user-generated content into actionable knowledge for marketing decisions [5].

Despite these advantages, the effect of artificial intelligence on customer experience does not occur automatically. Artificial intelligence technologies create potential value, but that value must be transmitted through organizational processes and customer-facing communication channels. Social media has become one of the most influential of these channels because it allows organizations to communicate continuously with customers, distribute content rapidly, observe reactions, respond publicly to inquiries and complaints, and facilitate interaction among customers themselves. Social media marketing therefore represents more than the online dissemination of promotional messages. It includes relationship building, interactive communication, content management, community formation, electronic word of mouth, influencer collaboration, social listening, and the management of customer engagement across digital platforms. The evolution of social media affordances has increasingly enabled customers to participate in brand-related activities, share experiences, produce content, and shape the meaning and reputation of brands through networked interactions [6].

The growing strategic importance of social media marketing is closely connected to its ability to shape customer perceptions before, during, and after purchase. Social platforms expose customers to organizational content, peer evaluations, influencers, brand communities, customer-service exchanges, and public responses to consumer concerns. These encounters contribute to the formation of expectations and influence how customers interpret subsequent experiences with the organization. Research has shown that social media marketing communication can strengthen consumer loyalty by sustaining interaction, reinforcing familiarity, and providing relational value beyond the immediate transaction [7].

Social media marketing activities have also been associated with brand experience, brand loyalty, willingness to pay a premium, brand awareness, and purchase decisions, suggesting that their effects extend across attitudinal and behavioral dimensions of consumer response [8-10]. These findings indicate that social media marketing can act as a central mechanism through which technological capabilities are translated into meaningful customer outcomes.

The mediating role of social media marketing is particularly relevant in the relationship between artificial intelligence and customer experience. Artificial intelligence improves an organization's capacity to analyze digital behavior, predict customer interests, produce personalized messages, optimize posting schedules, automate responses, and monitor emerging issues. However, customers experience these capabilities through the content, conversations, recommendations, services, and responses delivered across social media platforms. In this sense, social media marketing operationalizes artificial intelligence by converting analytical insights into visible and interactive customer encounters. Artificial intelligence may, for example, identify customer segments and predict preferred content, while social media marketing delivers that content in an accessible and engaging format. Likewise, sentiment analysis may detect dissatisfaction, but the customer experience improves only when the organization uses that information to communicate appropriately, resolve concerns, or adapt its offering. Accordingly, social media marketing may explain how and through what process artificial intelligence contributes to customer experience improvement [1, 2].

The effectiveness of social media marketing also depends on its capacity to foster interaction, co-creation, electronic word of mouth, and dynamic brand experiences. Customers increasingly participate in the construction of brand meaning by commenting on organizational content, sharing experiences, recommending products, criticizing service failures, and engaging with other users. Co-created experiences and electronic word of mouth can strengthen consumer equity when organizations facilitate meaningful participation and respond constructively to customer contributions [11]. Structural modeling research has likewise demonstrated that social media influence, brand reputation, and electronic word of mouth jointly shape consumer purchase decisions, highlighting the interconnected nature of social communication and marketplace behavior [12]. These mechanisms are relevant to customer experience because customers evaluate not only their direct interactions with the organization but also the experiences and judgments communicated by others within digital networks.

Influencer marketing represents another major dimension of social media marketing. Influencers can humanize marketing communication, provide product demonstrations, reduce perceived uncertainty, and connect brands with specialized or highly engaged audiences. However, influencer effectiveness varies according to credibility, expertise, attractiveness, congruence with the brand, content quality, audience characteristics, and the interaction among these conditions. Meta-analytic evidence indicates that influencer marketing effectiveness depends on a broad configuration of source, message, audience, and platform-related factors rather than on a single universal predictor [13]. Configurational analysis has similarly shown that different combinations of influencer characteristics and content features may produce high marketing effectiveness, meaning that several alternative pathways can generate successful outcomes [14]. Studies of influencer engagement and social media appropriation further suggest that audience attentiveness and platform-use patterns affect the ways in which consumers engage with influencer-based fashion communication [15]. Influencer marketing can therefore enrich customer experience when it supports relevance, authenticity, trust, and interaction, but it can weaken experience when communication is perceived as artificial, intrusive, or poorly aligned with consumer expectations.

Viral and guerrilla marketing techniques further illustrate the strategic potential of social media. Social media-driven viral marketing can accelerate message diffusion through influencers, social sharing, emotional appeals, and network effects, thereby increasing visibility and engagement at relatively low marginal cost [16]. The integration of guerrilla marketing techniques with social media applications can also create surprise, memorability, and intensified consumer participation within digital campaigns [17]. Nevertheless, the effects of such techniques on customer experience depend on whether the organization manages them coherently and responsibly. A campaign may generate attention without improving the customer's overall evaluation of the organization. For this reason, the strategic use of artificial intelligence in social media marketing should be directed not merely toward maximizing reach or virality but toward delivering relevant, credible, and customer-centered interactions.

The importance of such alignment is evident across different sectors. In online fashion retailing, social media marketing has been linked to brand loyalty through mediating mechanisms such as brand consciousness, showing that social communication affects loyalty by shaping how consumers perceive and relate to brands [18]. In the luxury-goods market, social media marketing interacts with the symbolic, experiential, and identity-related dimensions of consumer behavior, requiring organizations to balance exclusivity with digital accessibility [19]. In sports marketing, even non-professional clubs use social media as a marketing communication tool to develop stakeholder relationships, enhance visibility, and strengthen engagement despite limited resources [20]. In architecture and professional services, social media-based marketing frameworks have been proposed as mechanisms for sustaining communication and market presence during economic downturns [21]. These sectoral findings demonstrate that social media marketing can support customer experience across a variety of organizational settings, but its implementation must reflect the characteristics of the industry, target audience, service process, and competitive environment.

Generational differences are also relevant to the effectiveness of digital and social media marketing. Members of Generation Z commonly interact with brands through visually rich, mobile, participatory, and socially connected environments. Strategies intended to engage this group often emphasize authenticity, entertainment, social proof, personalization, rapid communication, and opportunities for participation. Social media marketing strategies can therefore shape the purchase behavior of Generation Z by aligning brand communication with the interaction patterns and content preferences of younger consumers [22]. Yet the personalization of communication for different generations increasingly depends on artificial intelligence, which can analyze behavioral data and adapt messages at scale. The combination of artificial intelligence and social media marketing may thus enable organizations to address diverse customer expectations without relying on undifferentiated communication strategies.

In addition to enhancing routine marketing performance, artificial intelligence and social media can strengthen the flexibility and resilience of digital marketing during crises. Periods of economic instability, supply disruption, reputational risk, or rapid shifts in customer demand require organizations to detect emerging signals and adjust their communication quickly. Artificial intelligence can support real-time monitoring and scenario analysis, while social media allows organizations to communicate directly with customers and respond to rapidly changing expectations. Their integration may therefore improve the adaptability of marketing systems during crises [23]. This flexibility is especially important in industries characterized by complex products, long purchase cycles, extensive after-sales interactions, and high levels of public scrutiny, such as the automotive industry.

However, the relationship between artificial intelligence and customer experience may depend not only on social media marketing but also on the organization's response strategy. A response strategy refers to the pattern through which an organization interprets environmental signals and decides when, how, and to what extent it should act. Some organizations respond proactively by anticipating emerging customer needs and investing early in new technologies. Others adopt an analytical orientation, combining innovation with careful evaluation of market evidence. Still others respond defensively or reactively, introducing changes only after competitors, customers, or external pressures make action unavoidable. These orientations can influence whether artificial intelligence capabilities produce timely and customer-centered outcomes. A technologically advanced system may fail to improve customer experience when the organization delays action, ignores customer feedback, or lacks coordination among technical, marketing, and service units.

The moderating role of response strategy is therefore theoretically significant. When response strategy is proactive and analytically informed, organizations may use artificial intelligence insights to redesign customer journeys, personalize communication, resolve complaints rapidly, and coordinate responses across channels. Under reactive or defensive conditions, the same artificial intelligence capabilities may remain underused or may be applied only after customer dissatisfaction has intensified. Response strategy can thus strengthen or weaken the effect of artificial intelligence on customer experience by influencing the translation of technological information into organizational action. This interpretation is consistent with the broader strategic-management view that organizational outcomes depend not only on resources but also on the organization's capacity to balance exploration and exploitation, integrate knowledge, and respond adaptively to environmental change. Organizational ambidexterity, for example, has been identified as a mediating capability connecting knowledge infrastructure and strategic practices to sustainable performance [24]. Although this evidence concerns sustainable performance rather than customer experience directly, it reinforces the principle that organizational capabilities and strategic response patterns shape the value ultimately derived from technological and knowledge-based resources.

The automobile industry provides an especially important context for examining these relationships. Automotive customers encounter companies through advertising, digital research, dealership contacts, financing processes, product customization, purchase, maintenance, warranty services, complaint management, and online brand communities. The complexity and duration of this journey mean that customer experience is formed through multiple interconnected episodes rather than a single transaction. Artificial intelligence can potentially improve this journey through predictive maintenance, intelligent product recommendations, personalized offers, conversational agents, demand forecasting, sentiment analysis, and automated service routing. Social media marketing can extend these capabilities by creating interactive communication, distributing customized content, monitoring electronic word of mouth, and managing customer concerns in public digital spaces.

At the same time, automotive companies face particular risks when artificial intelligence, social media marketing, and organizational response are poorly coordinated. Automated responses that appear impersonal, inaccurate targeting, delayed handling of complaints, inconsistent messages across departments, or failure to respond to negative electronic word of mouth can damage customer trust. Conversely, a well-integrated system can identify dissatisfaction early, route complaints to the appropriate unit, provide transparent updates, and maintain continuity across online and offline touchpoints. The quality of response strategy may consequently determine whether artificial intelligence-supported social media activities are interpreted as convenient and attentive or as intrusive and superficial.

Customer experience is also closely associated with subsequent behavioral outcomes, including purchase intention, loyalty, positive word of mouth, willingness to pay, and continued engagement. Empirical research in consumer markets has shown that social media marketing can influence purchase decisions through customer experience, demonstrating that experience may function as a central mechanism linking online marketing exposure to behavioral choice [25]. Studies of brand revitalization similarly show that interaction on social media can renew customer relationships with established or heritage brands by transforming communication into processes of restoration, reinterpretation, and renewed relevance [26]. These findings are particularly relevant to long-established automotive brands seeking to preserve brand heritage while responding to new technological expectations.

The effectiveness of social media marketing should nevertheless be evaluated beyond immediate purchasing outcomes. Brand loyalty, customer equity, relational quality, perceived authenticity, and long-term engagement represent equally important consequences. Research on consumer loyalty indicates that social media marketing communication can support enduring relationships when it provides value, facilitates interaction, and maintains consistent brand meaning [7]. Similarly, studies of influencer marketing effectiveness emphasize that engagement depends on the credibility and strategic fit of the communication rather than exposure alone [27]. These considerations reinforce the need to examine customer experience as a broad evaluative outcome that reflects the quality of the customer–organization relationship across multiple interactions.

Despite the growing literature on artificial intelligence, social media marketing, and customer experience, several research gaps remain. Many studies investigate artificial intelligence as a direct predictor of marketing effectiveness or customer outcomes, while others focus on social media marketing as an independent determinant of purchase decisions, loyalty, brand awareness, or brand experience. Fewer studies have examined social media marketing explicitly as the mechanism through which artificial intelligence improves customer experience. Moreover, existing research often concentrates on retail, fashion, beauty products, sports organizations, luxury goods, or professional services, with comparatively less evidence from major industrial and automotive organizations. The strategic conditions under which artificial intelligence capabilities become more or less effective have also received insufficient attention. In particular, the moderating role of response strategy has not been adequately integrated into models combining artificial intelligence, social media marketing, and customer experience.

Addressing these gaps is important because the adoption of artificial intelligence does not guarantee customer value. Organizations may invest extensively in intelligent technologies without achieving meaningful improvement in customer experience when marketing processes are fragmented or response strategies are poorly aligned with customer needs. A model that simultaneously examines the direct effect of artificial intelligence components, the mediating role of social media marketing, and the moderating role of response strategy can provide a more comprehensive explanation of how technological capabilities are converted into experiential outcomes. Such a model also offers practical value by distinguishing technological investment from the organizational and communicative mechanisms required to realize its benefits.

Accordingly, the aim of the present study was to examine the effect of artificial intelligence components on customer experience improvement at Iran Khodro Company, with social media marketing as a mediating variable and response strategy as a moderating variable.

Methodology

The present study was applied in terms of its objective and quantitative in terms of its methodological approach. A descriptive, cross-sectional, survey-based correlational design was employed to examine the effect of artificial intelligence components on customer experience, with social media marketing considered as a mediating variable and response strategy as a moderating variable. Because the proposed conceptual framework included several direct, indirect, and interaction effects among latent constructs, the relationships were investigated through structural equation modeling. This design was considered appropriate because it enabled the simultaneous assessment of the measurement properties of the research instruments and the structural relationships among artificial intelligence, social media marketing, customer experience, and response strategy without manipulating the study variables.

The statistical population consisted of managers, experts, and specialists employed at Iran Khodro Company in Tehran who were directly involved in the company's key product design, production, marketing, sales, customer communication, or related decision-making processes. These occupational groups were selected because their professional responsibilities provided them with relevant knowledge of organizational applications of artificial intelligence, social media marketing practices, customer experience management, and organizational responses to customers. The target population was treated as large or statistically unlimited because no precise and stable figure was available for all eligible employees and stakeholders at the time of the study. Therefore, Cochran's formula for an unlimited population was used to estimate the required sample size. With a 95% confidence level, a 5% margin of error, and the maximum assumed variability in the population, the minimum sample size was determined to be 384 participants.

Participants were selected through stratified random sampling. The eligible population was first divided into occupational strata, including managers, experts, and specialists working in the areas of design, production, marketing, sales, and other relevant organizational functions. Participants were then randomly selected from each stratum to provide adequate representation of the principal occupational groups involved in the company's value-creation and customer-related activities. The inclusion criteria were current employment at Iran Khodro Company in Tehran, direct involvement in at least one of the relevant organizational processes, sufficient familiarity with the company's technological or marketing activities, and willingness to participate in the research. Questionnaires with substantial missing data, patterned responses, or evidence of incomplete completion were considered unsuitable for analysis. Participation was voluntary, and respondents were informed that their information would be analyzed anonymously and used exclusively for research purposes. They were also assured that participation or nonparticipation would have no effect on their employment status or organizational evaluation.

Data were collected using a structured questionnaire comprising demographic questions and four standardized measurement instruments. The demographic section gathered information such as participants' occupational position, organizational department, educational level, work experience, and other characteristics relevant to describing the sample. The main section of the questionnaire assessed artificial intelligence components, social media marketing, customer experience, and response strategy. Unless otherwise specified by the original instruments, the items were rated on a five-point Likert scale ranging from very low or strongly disagree to very high or strongly agree. Higher scores represented a stronger presence or more favorable evaluation of the construct being measured.

Artificial intelligence components were assessed using the nine-item questionnaire developed by Abu et al. in 2019. The instrument was used to evaluate the extent to which artificial intelligence-related capabilities and practices were present in the organization and contributed to its customer-oriented operations. The items addressed participants' perceptions of the application of intelligent technologies in relevant organizational processes, including the processing and use of customer information, support for decision-making, improvement of interactions, personalization of organizational services, and enhancement of responsiveness to customer requirements. The total score was obtained by aggregating the responses to the nine items, with higher scores indicating a greater level of artificial intelligence capability and application. In the present study, the instrument demonstrated satisfactory internal consistency, with a Cronbach's alpha coefficient of 0.85.

Customer experience was measured using the 33-item Customer Experience Questionnaire developed by Sanderson and Lian in 2011. This instrument evaluated respondents' perceptions of the quality and effectiveness of the organization's interactions with customers across different stages of the customer journey. The items covered the experiential outcomes associated with organizational communications, product and service encounters, accessibility of information, responsiveness to customer expectations, perceived value, and the overall quality of the relationship between the company and its customers. The questionnaire was used to provide a comprehensive assessment of customer experience rather than limiting the construct to customer satisfaction or a single transactional encounter. A higher total score reflected a more favorable and improved customer experience. The Cronbach's alpha coefficient obtained for this questionnaire in the present study was 0.82, indicating an acceptable level of internal reliability.

Social media marketing was evaluated using the nine-item Social Media Marketing Questionnaire developed and validated by Yang et al. in 2014. The questionnaire consisted of three dimensions: social media capabilities, technological factors, and organizational factors. The social media capabilities dimension assessed the organization's capacity to use social media platforms for communicating with customers, disseminating information, creating engagement, and supporting interactive relationships. The technological factors dimension examined the availability, suitability, and effective use of the technological infrastructure required for social media marketing. The organizational factors dimension evaluated the organizational support, resources, competencies, and managerial arrangements necessary for implementing social media marketing activities. The instrument used closed-ended items scored on a five-point Likert scale. Higher scores indicated stronger social media marketing capabilities and more effective integration of social media into the organization's marketing activities. The Cronbach's alpha coefficient for the social media marketing scale was 0.76, demonstrating acceptable internal consistency.

Response strategy was assessed using an adapted version of the 11-item Organizational Strategy Questionnaire developed by Miles and Snow in 1978. The original instrument distinguishes among prospective or pioneering, analytical, and reactive or defensive strategic orientations. For the purposes of the present study, the items were interpreted in relation to the organization's strategic response to technological developments, social media conditions, market changes, and customer expectations. The prospective orientation represented proactive efforts to anticipate customer needs and emerging market developments, the analytical orientation reflected the systematic evaluation of information before selecting an organizational response, and the reactive or defensive orientation represented responses adopted primarily after environmental changes or customer demands had already occurred. The items were scored on a five-point Likert scale ranging from very low to very high. Higher scores indicated a stronger and more clearly developed strategic response orientation. The Cronbach's alpha coefficient for the response strategy questionnaire was 0.79, confirming acceptable internal consistency.

The face and content validity of the complete research questionnaire were examined before the main data collection process. Face validity was evaluated to determine whether the items were understandable, clearly worded, relevant to the respondents' professional context, and apparently appropriate for measuring the intended constructs. Content validity was assessed to ensure that the items provided sufficient and balanced coverage of artificial intelligence, customer experience, social media marketing, and response strategy. The questionnaire was reviewed by the academic supervisor and a panel of 13 experts and production managers from Iran Khodro. The reviewers evaluated the clarity, appropriateness, relevance, and comprehensiveness of the items. Their comments were used to correct ambiguous expressions, improve the wording of selected items, and enhance the contextual compatibility of the instruments with the automotive manufacturing environment.

The reliability of the instruments was examined through Cronbach's alpha as an indicator of internal consistency. The coefficients were 0.85 for artificial intelligence components, 0.82 for customer experience, 0.76 for social media marketing, and 0.79 for response strategy. Because all coefficients exceeded the commonly accepted threshold of 0.70, the measurement instruments were considered sufficiently reliable for the main analysis. In addition to Cronbach's alpha, the measurement model was subsequently assessed through the reliability and validity criteria available in partial least squares structural equation modeling, including indicator loadings, composite reliability, convergent validity, and discriminant validity.

The collected data were analyzed at descriptive and inferential levels. Before the principal analyses, the dataset was screened for incomplete questionnaires, missing values, response irregularities, and potential data-entry errors. Descriptive statistics were used to summarize the demographic characteristics of the participants and describe the distribution of the principal study variables. Frequencies and percentages were calculated for categorical variables, while means and standard deviations were computed for continuous variables and the scores of the research constructs. Skewness and kurtosis indices were also examined to assess the distributional characteristics of the observed variables and identify serious deviations from normality. These preliminary analyses, along with the calculation of Cronbach's alpha coefficients, were conducted using SPSS software.

The hypothesized model was tested using partial least squares structural equation modeling in SmartPLS 3. This variance-based approach was selected because the study aimed to predict customer experience and simultaneously estimate multiple direct, mediating, and moderating relationships among latent constructs. The analytical procedure was conducted in two stages. First, the measurement model was examined to determine whether the observed indicators adequately represented their corresponding latent variables. Indicator reliability was evaluated through outer loadings, and internal consistency was examined using Cronbach's alpha and composite reliability. Convergent validity was assessed using the average variance extracted, while discriminant validity was evaluated by examining the degree to which each construct was empirically distinct from the other constructs in the conceptual model.

After establishing the adequacy of the measurement model, the structural model was evaluated. Collinearity among the predictor constructs was examined before estimating the structural paths. The direct effect of artificial intelligence components on customer experience was then tested, together with the effect of artificial intelligence on social media marketing and the effect of social media marketing on customer experience. The coefficient of determination was used to evaluate the proportion of variance explained in the endogenous constructs, and effect-size indices were considered to determine the practical contribution of the predictor variables. Predictive relevance was also examined to evaluate the model's capacity to predict the endogenous constructs. Path coefficients were interpreted according to their direction, magnitude, and statistical significance.

The mediating role of social media marketing in the relationship between artificial intelligence components and customer experience was examined by estimating the indirect path from artificial intelligence to customer experience through social media marketing. The significance of this indirect effect was assessed through the bootstrapping procedure available in SmartPLS 3. Bootstrapping was performed using a large number of resamples to generate standard errors, t-values, p-values, and confidence intervals for the estimated paths. Mediation was supported when the indirect effect was statistically significant and its confidence interval did not include zero. The direct and indirect effects were considered together to determine whether social media marketing produced partial or full mediation.

The moderating role of response strategy was examined by constructing an interaction term between artificial intelligence components and response strategy. This interaction term was entered into the structural model as a predictor of customer experience. A statistically significant interaction effect indicated that the strength or direction of the relationship between artificial intelligence and customer experience varied according to the organization's response strategy. The moderating effect was interpreted by examining the sign and magnitude of the interaction coefficient and, where necessary, comparing the relationship between artificial intelligence and customer experience at lower and higher levels of response strategy. All hypotheses were evaluated at a significance level of 0.05, and the final interpretation of the model was based on the combined assessment of statistical significance, effect magnitude, explanatory power, predictive relevance, and overall theoretical consistency.

Findings and Results

A total of 384 managers, experts, and specialists employed at Iran Khodro Company in Tehran participated in the study. Regarding age, 63 participants were younger than 30 years, representing 16.4% of the sample; 145 participants were between 30 and 35 years old, representing 37.8%; 48 participants were between 35 and 40 years old, representing 12.5%; and 128 participants were older than 45 years, representing 33.3%. Thus, the largest age group consisted of participants aged 30–35 years. Regarding gender, 229 participants were women, representing 59.6% of the sample, and 155 were men, representing 40.4%. In terms of educational attainment, 34 participants held a high-school diploma, representing 8.9% of the sample; 87 held an associate degree, representing 22.7%; 184 held a bachelor's degree, representing 47.9%; 59 held a master's degree, representing 15.4%; and 20 held a doctoral degree, representing 5.2%. Accordingly, participants with a bachelor's degree constituted the largest educational group.

Descriptive statistics were calculated to summarize the distributions of response strategy, artificial intelligence components, customer experience improvement, and social media marketing. As presented in Table 1, artificial intelligence components had the highest mean score among the research variables, with a mean of 4.586 and a standard deviation of 3.521. Customer experience improvement had a mean of 3.366 and a standard deviation of 2.267, while social media marketing had a mean of 2.972 and a standard deviation of 2.485. Response strategy had the lowest mean score, with a mean of 2.807 and a standard deviation of 3.050. The reported skewness values ranged from 0.260 to 1.770, and the kurtosis values ranged from −2.790 to −1.890. These indices were examined as preliminary indicators of the distributions of the research variables before the structural equation modeling analysis.

Table 1

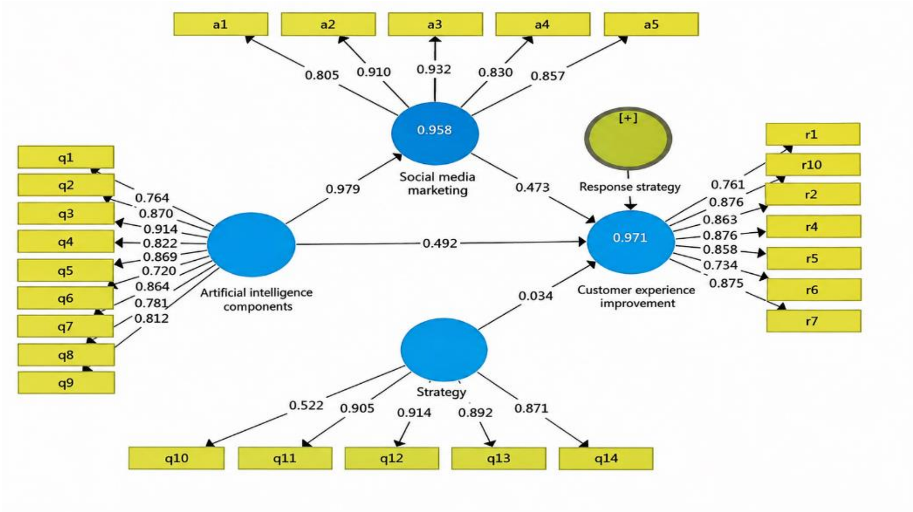
Descriptive Statistics of the Research Variables

Variable	Mean	Standard Deviation	Skewness	Kurtosis
Response strategy	2.807	3.050	1.018	−2.010
Artificial intelligence components	4.586	3.521	1.770	−2.790
Customer experience improvement	3.366	2.267	0.260	−1.890
Social media marketing	2.972	2.485	1.460	−1.930

The measurement model was evaluated before testing the structural relationships. The first stage involved examining the outer loadings of the observed indicators on their corresponding latent constructs. Factor loadings reflect the correlation between each observed indicator and the latent construct that it is intended to measure. A loading of 0.40 or higher was adopted as the minimum acceptable threshold. The results showed that the factor loadings of most indicators exceeded 0.40, indicating that the majority of the questionnaire items adequately represented their intended constructs.

Figure 4

Path Coefficients in the Conceptual Model



The internal consistency reliability of the constructs was evaluated using Cronbach’s alpha, rho_A, and composite reliability. Convergent validity was assessed through the average variance extracted. As shown in Panel A of Table 2, Cronbach’s alpha coefficients were 1.000 for response strategy, 0.791 for social media marketing, 0.932 for customer experience improvement, and 0.941 for artificial intelligence components. Composite reliability coefficients were 1.000, 0.852, 0.946, and 0.951, respectively. All reported composite reliability coefficients exceeded the recommended threshold of 0.70, indicating satisfactory internal consistency reliability.

The average variance extracted values were reported as 1.000 for response strategy, 0.538 for social media marketing, 0.714 for customer experience improvement, and 0.982 for artificial intelligence components. Because all reported values exceeded the minimum threshold of 0.50, the constructs were considered to demonstrate acceptable convergent validity. The AVE results indicated that each latent variable explained more than half of the variance in its associated indicators.

Discriminant validity was assessed using the Fornell–Larcker criterion. According to this criterion, the square root of the AVE for each latent construct should exceed its correlations with the other constructs. The supplied Fornell–Larcker matrix is reproduced in Panel B of Table 2. Based on the original analysis, the measurement model was reported to possess acceptable discriminant validity because the diagonal values were considered greater than the relevant interconstruct correlations.

Table 2

Reliability, Convergent Validity, and Discriminant Validity of the Measurement Model

Panel A. Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted
Response strategy	1.000	1.000	1.000	1.000
Social media marketing	0.791	0.876	0.852	0.538
Customer experience improvement	0.932	0.936	0.946	0.714
Artificial intelligence components	0.941	0.946	0.951	0.982

Panel B. Reported Fornell–Larcker Discriminant-Validity Matrix

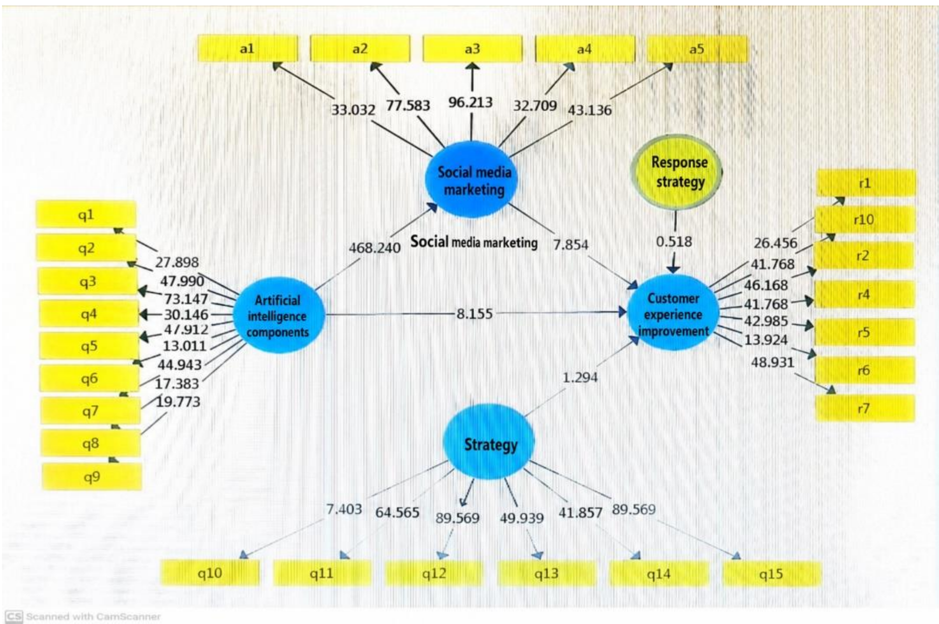
Latent Construct	Response Strategy	Social Media Marketing	Customer Experience Improvement	Artificial Intelligence Components
Response strategy	0.1000			
Social media marketing	0.097	0.539		
Customer experience improvement	0.062	0.158	0.988	
Artificial intelligence components	0.053	0.150	0.845	0.826

The numerical values in the supplied Fornell–Larcker matrix were retained as originally reported. However, some diagonal values do not correspond mathematically to the square roots of the AVE values reported in Panel A. Therefore, the original SmartPLS output should be rechecked before publication to ensure that the AVE values and the Fornell–Larcker diagonal coefficients have been transcribed correctly.

After confirming the reported adequacy of the measurement model, the structural model was evaluated. Unlike the measurement model, which examines relationships between latent constructs and their observed indicators, the structural model evaluates the relationships among the latent variables. The statistical significance of the structural paths was assessed using bootstrapped t-statistics and p-values. At the 95% confidence level, a path was considered statistically significant when its absolute t-value exceeded 1.96.

Figure 2

Significance Coefficients in the Conceptual Model



As reported in Panel A of Table 3, the direct path from artificial intelligence components to social media marketing was statistically significant, with a t-value of 468.240 and a reported p-value of 0.001. The direct effect of artificial intelligence components on customer experience improvement was also significant, with a t-value of 8.155 and a p-value of 0.001. In addition, social media marketing had a statistically significant direct effect on customer experience improvement, with a t-value reported as 7.854 and a p-value of 0.026. By contrast, the direct path from response strategy to customer experience improvement had a t-value of 1.294 and therefore did not reach the critical value of 1.96. On the basis of the t-statistic, this path was classified as nonsignificant.

The indirect effect of artificial intelligence components on customer experience improvement through social media marketing was statistically significant. The indirect path produced a t-value of 8.160 and a reported p-value of 0.049. Because the t-value exceeded 1.96, the mediating effect of social media marketing was supported at the 95% confidence level. This finding indicated that artificial intelligence components were associated with improved customer experience not only directly but also indirectly through the enhancement of social media marketing.

The explanatory power of the structural model was evaluated using the coefficient of determination. As reported in Panel B of Table 3, the R^2 value for social media marketing was 0.022, with an adjusted R^2 of 0.020. Thus, artificial intelligence components explained approximately 2.2% of the variance in social media marketing. The R^2 value for customer experience improvement was reported as 0.997, with an adjusted R^2 of 0.977. Accordingly, the predictors included in the model collectively explained approximately 99.7% of the variance in customer experience improvement, although the discrepancy between the unadjusted and adjusted coefficients and the exceptionally high explanatory value should be examined for possible model overfitting, construct overlap, or transcription error.

Predictive relevance was evaluated through the Q^2 criterion. Positive Q^2 values indicate that a structural model has predictive relevance for an endogenous construct. The reported Q^2 values were 0.130 for response strategy, 0.137 for social media marketing, and 0.069 for customer experience improvement. On the basis of these positive reported values, the model was interpreted as possessing predictive relevance for the endogenous variables. No Q^2 value was reported for artificial intelligence components because it functioned as an exogenous construct in the conceptual model.

Table 3

Structural-Model Results, Explanatory Power, and Predictive Relevance

Panel A. Direct and Indirect Structural Effects

Structural Path	t-Statistic	p-Value	Result
Response strategy → customer experience improvement	1.294	0.005	Nonsignificant based on the t-statistic
Social media marketing → customer experience improvement	7.854	0.026	Significant
Artificial intelligence components → social media marketing	468.240	0.001	Significant
Artificial intelligence components → customer experience improvement	8.155	0.001	Significant
Artificial intelligence components → social media marketing → customer experience improvement	8.160	0.049	Significant indirect effect

Panel B. Coefficients of Determination

Endogenous Variable	R^2	Adjusted R^2
Social media marketing	0.022	0.020
Customer experience improvement	0.997	0.977

Panel C. Predictive-Relevance Indices

Construct	SSO	SSE	Reported Q^2
Response strategy	172.035	196.697	0.130
Social media marketing	96.560	100.119	0.137
Customer experience improvement	346.442	322.489	0.069
Artificial intelligence components	267.200	267.200	—

The reported Q^2 values were retained from the supplied results. Nevertheless, for response strategy and social media marketing, the reported SSE values exceed their corresponding SSO values. Under the stated formula, $Q^2 = 1 - SSE/SSO$, this would ordinarily yield negative rather than positive Q^2 coefficients. The original blindfolding output should therefore be verified before final submission.

The study examined the effects of artificial intelligence components on customer experience improvement, the mediating role of social media marketing, and the moderating role of response strategy. The results of the hypothesis tests are summarized in Table 4.

The main mediation hypothesis proposed that artificial intelligence components significantly affected customer experience improvement through social media marketing. The indirect effect had a t-value of 8.160 and a reported p-value of 0.049. Because the t-value exceeded 1.96, the mediation hypothesis was supported. Thus, social media marketing transmitted part of the effect of artificial intelligence components to customer experience improvement.

The first subsidiary hypothesis proposed that artificial intelligence components had a significant effect on customer experience improvement in Iran Khodro. The path produced a t-value of 8.155 and a p-value of 0.001. Therefore, the first subsidiary hypothesis was supported. This result demonstrated that greater use and development of artificial intelligence components were significantly associated with improvement in customer experience.

The second subsidiary hypothesis proposed that artificial intelligence components significantly affected social media marketing. The corresponding path had a t-value of 468.240 and a p-value of 0.001. Consequently, the second subsidiary hypothesis was supported. This finding indicated that artificial intelligence components had a statistically significant association with the organization’s social media marketing activities.

The third subsidiary hypothesis proposed that social media marketing had a significant effect on customer experience improvement. The hypothesis-specific results reported a t-value of 7.857 and a p-value of 0.026. Because the t-value was greater than 1.96, the third subsidiary hypothesis was supported. Thus, stronger social media marketing was significantly associated with a more favorable customer experience.

The fourth subsidiary hypothesis restated the proposed mediating relationship and predicted that artificial intelligence components would significantly affect customer experience improvement through social media marketing. The indirect effect had a t-value of 8.160 and a p-value of 0.049. Therefore, the fourth subsidiary hypothesis was supported, confirming the mediating role of social media marketing.

The fifth subsidiary hypothesis proposed that response strategy moderated the relationship between artificial intelligence components and customer experience improvement. The interaction effect had a reported t-value of 1.292, which was below the critical threshold of 1.96. Accordingly, the moderating hypothesis was not supported. Therefore, the results did not provide sufficient evidence that the relationship between artificial intelligence components and customer experience improvement changed significantly at different levels of response strategy.

Table 4

Results of the Research Hypotheses

Hypothesis	Proposed Relationship	t-Statistic	p-Value	Decision
Main mediation hypothesis	Artificial intelligence components significantly affect customer experience improvement through social media marketing.	8.160	0.049	Supported
Subsidiary hypothesis 1	Artificial intelligence components significantly affect customer experience improvement.	8.155	0.001	Supported
Subsidiary hypothesis 2	Artificial intelligence components significantly affect social media marketing.	468.240	0.001	Supported
Subsidiary hypothesis 3	Social media marketing significantly affects customer experience improvement.	7.857	0.026	Supported
Subsidiary hypothesis 4	Artificial intelligence components indirectly affect customer experience improvement through social media marketing.	8.160	0.049	Supported
Subsidiary hypothesis 5	Response strategy moderates the relationship between artificial intelligence components and customer experience improvement.	1.292	0.001	Not supported based on the t-statistic

Overall, the results supported the direct effect of artificial intelligence components on customer experience improvement, the direct effect of artificial intelligence components on social media marketing, and the direct effect of social media marketing on customer experience improvement. The indirect effect of artificial intelligence components on customer experience improvement through social media marketing was also statistically significant, confirming the mediating role of social media marketing. However, the proposed moderating role of response strategy was not supported because the reported t-value for the interaction effect was below 1.96. Therefore, the findings supported the mediation component of the conceptual model but did not support its moderation component.

Several supplied p-values are inconsistent with their corresponding t-statistics and reported decisions. In particular, a t-value of approximately 1.29 would ordinarily not correspond to $p = 0.005$ or $p = 0.001$ in a two-tailed test. The decisions concerning response strategy were therefore based on the supplied t-values and the stated critical value of 1.96. The bootstrapping output from SmartPLS should be reviewed to correct these inconsistencies before the findings are submitted for publication.

Discussion and Conclusion

The present study examined the effect of artificial intelligence components on customer experience improvement, considering social media marketing as a mediating mechanism and response strategy as a moderating variable among managers, experts, and specialists working at Iran Khodro Company. The findings supported most of the proposed relationships in the conceptual model. Artificial intelligence components had a significant direct effect on customer experience improvement, artificial intelligence significantly influenced social media marketing, and social media marketing significantly predicted customer experience improvement. In addition, the indirect effect of artificial intelligence on customer experience through social media marketing was significant, confirming the mediating role of social media marketing. However, the proposed moderating role of response strategy in the relationship between artificial intelligence components and customer experience improvement was not supported. Taken together, the findings suggest that artificial intelligence can improve customer experience both directly and through the development of more effective social media marketing, whereas the strategic response orientation measured in this study did not significantly alter the strength of this relationship.

The significant direct effect of artificial intelligence components on customer experience improvement indicates that greater organizational use of intelligent technologies is associated with more favorable customer-related outcomes. This result can be explained by the capacity of artificial intelligence to process extensive customer data, detect behavioral patterns, forecast customer needs, automate routine interactions, and personalize products, services, and communications. In the automotive industry, the customer journey extends from information search and product comparison to purchase, delivery, maintenance, warranty services, and complaint management. Artificial intelligence can support each of these stages by providing timely recommendations, intelligent service routing, predictive support, automated responses, and more precise customer segmentation. Therefore, the observed effect suggests that artificial intelligence is not merely a technical infrastructure but a customer-experience capability that enables the organization to make interactions faster, more relevant, and more responsive.

This finding is aligned with studies emphasizing the role of artificial intelligence in improving customer experience through customer-data analysis, personalized communication, intelligent automation, and better marketing decisions. Ebrahimi and Ebrahimi directly reported that artificial intelligence contributes to improved customer experience and that social media marketing can serve as an important channel through which this improvement occurs [1, 2]. Similarly, Talha showed that the integration of artificial intelligence and social media analytics can optimize digital marketing campaigns through more accurate targeting, predictive modeling, and algorithmic evaluation of customer behavior [3, 4]. Fang and Meng also demonstrated that social media algorithms and natural language processing can convert unstructured digital data into actionable marketing knowledge, thereby improving the quality of organizational decision-making [5]. These studies collectively support the interpretation that artificial intelligence improves customer experience by increasing the organization's capacity to understand customers and provide appropriate responses at different touchpoints.

The effect of artificial intelligence on customer experience may also be explained by the growing importance of real-time responsiveness. Customers increasingly expect companies to recognize their needs quickly, provide accurate information, and ensure continuity across digital and physical channels. Artificial intelligence can reduce delays in customer service, prioritize urgent requests, analyze complaints, and assist employees in selecting suitable responses. In this way, intelligent systems can reduce customer effort and improve perceptions of competence and convenience. Artificial intelligence is particularly valuable in environments characterized by large customer bases and complex information flows, because conventional human-centered systems may be unable to analyze all relevant customer data rapidly. The reported result therefore reflects the strategic value of combining analytical intelligence with customer-facing service processes.

The second major finding showed that artificial intelligence components had a significant effect on social media marketing. This finding indicates that organizations with stronger artificial intelligence capabilities are better positioned to manage social media communication, content distribution, customer targeting, engagement analysis, and campaign optimization. Artificial intelligence supports social media marketing by identifying audience segments, determining suitable content, selecting appropriate communication times, analyzing online sentiment, monitoring electronic word of mouth, and predicting customer reactions. Automated systems can also help organizations generate content, identify emerging trends, and respond to frequently asked questions. Thus, the significant relationship observed in this study suggests that artificial intelligence provides the analytical and operational foundation required for more systematic and data-driven social media marketing.

This result is consistent with research indicating that artificial intelligence has become increasingly integrated into digital marketing processes. Talha found that machine-learning algorithms and social media analytics can improve campaign optimization and marketing efficiency by allowing firms to compare predictive methods and select those with higher performance [3, 4]. Fang and Meng similarly highlighted the role of natural language processing and social media data algorithms in analyzing user-generated content and supporting marketing decisions [5]. Hassanzadeh and Sheikh Hosseini further argued that artificial intelligence and social media jointly increase the flexibility of digital marketing, especially during crises that require rapid interpretation of market signals and accelerated communication [23]. These findings confirm that artificial intelligence strengthens not only isolated marketing activities but also the organization's broader capacity to adapt social media communication to changing market conditions.

The significant effect of artificial intelligence on social media marketing can also be understood in relation to the evolving affordances of digital platforms. Social media platforms provide multiple forms of interaction, including commenting, sharing, rating, live communication, community participation, and user-generated content. However, the volume and speed of these interactions create substantial managerial challenges. Artificial intelligence enables organizations to extract meaningful information from these interactions and distinguish important patterns from digital noise. Hu emphasized that changes in social media affordances have altered the landscape of digital marketing by expanding opportunities for customer participation and interactive brand communication [6]. Artificial intelligence helps organizations use these affordances more effectively by determining which interactions are most relevant, what type of content should be delivered, and how engagement patterns should influence future communication strategies.

The third finding showed that social media marketing had a significant effect on customer experience improvement. This result demonstrates that social media platforms are important customer-experience environments rather than merely promotional channels. Customers use social media to obtain information, compare products, observe the experiences of others, communicate with organizations, express complaints, and participate in brand communities. Therefore, the quality of social media marketing can influence customers' expectations, emotions, trust, perceived accessibility, and overall evaluation of the organization. When social media communication is responsive, informative, interactive, and personalized, it can strengthen the customer's sense of connection with the organization and improve the continuity of the customer journey.

The finding is consistent with Gad's study, which showed that social media marketing influences purchase decisions through customer experience, indicating that customer experience functions as a key mechanism connecting digital communication with behavioral outcomes [25]. Leung also found that social media marketing communication can strengthen consumer loyalty by maintaining interaction and creating relational value [7]. Zare and colleagues reported that social media marketing affects brand experience among customers of sportswear brands on Instagram, supporting the idea that digital communication contributes directly to experiential evaluations [10]. Pashazadeh and Abdi similarly showed that social media marketing activities influence brand loyalty and willingness to pay a higher price through brand-related mechanisms [8]. These studies support the present finding that effective social media marketing contributes to customer experience by shaping both immediate perceptions and longer-term relational outcomes.

The influence of social media marketing on customer experience may also derive from co-creation and electronic word of mouth. Social media allows customers to move beyond passive message reception and participate actively in creating brand meaning. Customers share product experiences, respond to corporate content, recommend brands, and publicly evaluate service quality. Qadri emphasized that co-creation and electronic word of mouth contribute to dynamic brand experience and consumer equity in social media marketing [11]. Juaton and colleagues also demonstrated that social media influence, brand reputation, and electronic word of mouth jointly affect consumer purchase decision-making [12]. These findings suggest that customer experience on social media is produced through a network of interactions involving the organization, customers, influencers, and other users. Consequently, companies that effectively manage these interactions can improve customer experience even before direct purchase or service encounters occur.

Influencer-based communication may further explain the positive relationship between social media marketing and customer experience. Influencers can reduce uncertainty by presenting products in relatable contexts, demonstrating their use, and providing interpretations that customers perceive as more personal than conventional advertising. However, influencer effectiveness depends on credibility, content quality, audience compatibility, and brand fit. Spörl-Wang and colleagues found that influencer marketing effectiveness is shaped by multiple source, message, audience, and platform factors [13]. Ma and colleagues similarly showed that different combinations of influencer and content characteristics can produce high effectiveness [14]. Rajeshwari also emphasized the role of influencer marketing in strengthening social media campaign effectiveness [27]. In the context of customer experience, these results imply that influencer communication can enhance experience when it is perceived as credible and relevant, but its effectiveness requires careful strategic alignment.

The significant mediating role of social media marketing was one of the most important findings of the study. This result indicates that artificial intelligence improves customer experience partly because it enhances the quality and effectiveness of social media marketing. In other words, artificial intelligence provides analytical capabilities, but social media marketing translates these capabilities into visible customer interactions. Artificial intelligence can identify customers' preferences, predict their needs, analyze sentiments, and optimize communication; nevertheless, customers experience these capabilities through personalized content, relevant recommendations, rapid responses, and interactive communication on social media. Therefore, social media marketing represents a transmission mechanism linking technological capacity to customer-related outcomes.

This mediating effect is strongly aligned with the work of Ebrahimi and Ebrahimi, who specifically examined the effect of artificial intelligence on customer experience through social media marketing and concluded that social media marketing plays a meaningful intermediary role [1, 2]. The finding is also indirectly supported by research showing that artificial intelligence improves digital campaign optimization [3, 4], while social media marketing influences customer experience, loyalty, brand awareness, and purchasing outcomes [7, 9, 25]. The combination of these two bodies of evidence supports the mechanism identified in this study: artificial intelligence strengthens the organization's social media marketing capability, and this improved capability contributes to a better customer experience.

The mediation finding can also be interpreted through the logic of personalization. Artificial intelligence enables the organization to analyze differences among customers and adapt messages accordingly. Social media provides the delivery environment in which personalized communication can occur at scale. This is particularly relevant for customer segments with distinct digital behaviors. Eandhizhai and colleagues emphasized that social media strategies aimed at Generation Z should reflect this group's preference for authenticity, participation, social proof, and interactive content [22]. Lee and colleagues also showed that fashion attentiveness and patterns of social media appropriation influence engagement with social media influencers [15]. Accordingly, artificial intelligence can identify such audience characteristics, while social media marketing can translate those insights into segment-specific content and interaction.

Social media marketing also enables artificial intelligence-supported insights to influence broader brand relationships. Karunarathne and Wanninayake found that social media marketing affects brand loyalty through brand consciousness in online fashion retailing [18]. Simamora reported that social media marketing influences purchase decisions through brand awareness [9]. Zhou and Li showed that social media interaction can revitalize heritage brands by restoring relevance and strengthening customer relationships [26]. These findings indicate that social media marketing does not merely deliver artificial intelligence-generated messages; it shapes brand meaning and helps integrate technological personalization into broader customer perceptions of the organization.

The result also has relevance for marketing adaptability. Gündüzyeli showed that the integration of guerrilla marketing techniques with social media can increase engagement and create memorable digital interactions [17]. Kaur similarly discussed social media-driven viral marketing as a strategic approach to increasing message diffusion through influencer communication and network effects [16]. Such strategies may be made more effective through artificial intelligence, which can identify content with higher viral potential and select audiences likely to engage with it. However, the present findings suggest that the ultimate value of these techniques should be evaluated in terms of their contribution to customer experience rather than attention alone.

In contrast to the supported direct and mediating relationships, response strategy did not significantly moderate the relationship between artificial intelligence components and customer experience improvement. This means that the strength of the relationship between artificial intelligence and customer experience did not vary significantly according to the measured level of response strategy. One possible explanation is that the direct effect of artificial intelligence was sufficiently strong and broadly distributed across the organization, reducing the additional influence of response strategy. Intelligent systems may improve customer experience through automation, personalization, and information processing regardless of whether the organization’s strategic orientation is primarily proactive, analytical, or reactive.

Another possible explanation concerns the operationalization of response strategy. The strategy measure was adapted from a broader organizational-strategy framework, whereas the proposed moderating effect concerned responsiveness in customer-facing and technology-related processes. A general strategic orientation may not fully capture the specific capabilities required to convert artificial intelligence insights into customer responses. More focused constructs, such as digital agility, customer-response speed, data-driven decision-making, crisis responsiveness, or cross-functional coordination, might produce different results. Pazhoohan and colleagues emphasized that organizational outcomes depend on intermediate capabilities such as knowledge infrastructure and organizational ambidexterity [24]. Their findings suggest that broad strategy alone may be insufficient and that the mechanisms connecting organizational resources to performance may be more specific and capability-based.

The nonsignificant moderation result may also reflect relatively limited variation in response strategy among participants from a single large organization. Employees working within the same corporate system may be exposed to similar policies, procedures, and decision structures, thereby reducing the statistical variance required to detect a moderating effect. Moreover, response strategy may operate as a direct predictor, mediator, or contextual condition rather than as a moderator. Research across sectors indicates that organizations adapt their social media communication according to resource constraints, stakeholder expectations, and environmental conditions. Marthinus and colleagues showed that non-professional sports clubs adopt social media in different ways depending on organizational resources and communication needs [20]. Othman and Maarek proposed a social media-based framework for architectural firms operating during economic downturns, emphasizing the importance of context-sensitive strategic adaptation [21]. These studies suggest that strategic response may influence the design of marketing activities more directly than it changes the relationship between artificial intelligence and customer experience.

The results therefore support a model in which artificial intelligence contributes directly to customer experience and indirectly through social media marketing, while response strategy does not significantly change this effect. This pattern highlights the practical importance of social media marketing as the primary organizational mechanism connecting artificial intelligence to the customer. It also suggests that organizations should not assume that possessing a particular strategic orientation will automatically amplify the value of artificial intelligence. Instead, they may need specific implementation capabilities, including integration of customer databases, coordinated digital communication, employee training, rapid feedback systems, and continuous evaluation of customer responses.

The study had several limitations that should be considered when interpreting the findings. First, the cross-sectional correlational design does not permit definitive causal conclusions, even though the conceptual model specified directional relationships. Second, the data were collected through self-report questionnaires, which may have been influenced by common-method variance, social desirability, or differences in participants' familiarity with artificial intelligence and customer-management processes. Third, the participants were selected from a single automotive company in Tehran, limiting the generalizability of the findings to other companies, industries, regions, and customer-service environments. Fourth, managers, experts, and specialists evaluated organizational constructs, whereas actual customers were not included in the sample. Consequently, customer experience was assessed from an organizational perspective rather than through customers' direct reports. Finally, the measurement of response strategy was based on an adapted general strategy instrument, which may not have captured all dimensions of technology-specific and customer-oriented responsiveness.

Future studies should employ longitudinal or experimental designs to examine whether the implementation of artificial intelligence produces changes in social media marketing and customer experience over time. Researchers should replicate the model in other automotive firms, service industries, retail organizations, financial institutions, and digital businesses to assess its external validity. Multisource studies could combine employee questionnaires with customer surveys, objective social media indicators, complaint records, engagement metrics, and customer-retention data. Future research should also distinguish among artificial intelligence applications, such as chatbots, recommendation systems, predictive analytics, sentiment analysis, and automated content generation, because their effects may differ. The moderating role of more specific organizational capabilities, including digital agility, response speed, customer orientation, data quality, organizational readiness, and cross-functional integration, should also be tested. Comparative analyses across customer segments and generational groups could clarify whether the model functions differently according to age, digital literacy, purchase involvement, or previous experience with the brand.

Managers should integrate artificial intelligence with social media marketing rather than implementing intelligent technologies as isolated technical systems. Iran Khodro and similar organizations should use artificial intelligence to analyze customer conversations, identify recurring concerns, personalize content, prioritize complaints, and provide timely responses across social platforms. Social media teams should receive access to relevant customer insights and should coordinate closely with sales, after-sales service, technical support, and product-development units. Organizations should establish clear standards for the use of chatbots and automated responses so that efficiency does not reduce perceived empathy or authenticity. Managers should continuously evaluate customer reactions to artificial intelligence-supported communication and combine automated systems with human intervention for complex or emotionally sensitive issues. Because response strategy did not significantly strengthen the relationship between artificial intelligence and customer experience, priority should be given to concrete implementation capabilities, including data integration, employee competence, real-time monitoring, service coordination, and measurable customer-experience objectives.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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References

[1] A. Ebrahimi and N. Ebrahimi, "Investigating the effect of artificial intelligence on improving customer experience through social media marketing," *Management, Education and Development in the Digital Age*, vol. 9, pp. 1-13, 2025.

[2] A. Ebrahimi and N. Ebrahimi, "The impact of artificial intelligence on improving customer experience through social media marketing," *Management, Education and Development in the Digital Age*, vol. 2, no. 4, pp. 1-13, 2025, doi: 10.61838/kman.jpdot.2.1.1.

[3] M. Talha, "Optimizing Digital Marketing Campaigns Using Artificial Intelligence (AI) and Social Media Analytics: A Comparative Study of Machine Learning Algorithms," *International Journal of Scientific Research in Engineering and Management*, vol. 9, no. 3, pp. 1-9, 2025, doi: 10.55041/ijsrem42691.

[4] M. Talha, "Optimizing Digital Marketing Campaigns Using Artificial Intelligence (AI) and Social Media Analytics: A Comparative Study of Machine Learning Algorithms," *Interantional Journal of Scientific Research in Engineering and Management*, vol. 09, no. 03, pp. 1-9, 2025, doi: 10.55041/ijsrem42691.

[5] Z. Fang and C. Meng, "Application of Social Media Data Algorithms and NLP in Marketing Decision-Making," p. 51, 2025, doi: 10.1117/12.3082754.

[6] R. Hu, "The Evolution of Social Media Affordances and the Changing Landscape of Digital Marketing," *Advances in Economics Management and Political Sciences,* vol. 189, no. 1, pp. 136-141, 2025, doi: 10.54254/2754-1169/2025.bl23889.

[7] L. Leung, "The influence of social media marketing communication on consumer loyalty," *Journal of Promotion Management,* vol. 31, no. 2, pp. 109-127, 2025. [Online]. Available: https://www.emerald.com.

[8] Y. Pashazadeh and R. Abdi, "Analysis of the Impact of Social Media Marketing Activities on Willingness to Pay a Higher Price and Brand Loyalty in Mobile Electronic Technologies with the Mediating Role of Brand Equity (Case Study: Urmia University)," *Consumer Behavior Studies*, 2025.

[9] E. C. Simamora, "The Influence of Social Media Marketing on Purchase Decisions With Brand Awareness as Mediation (Study on Truffle Belly Jimbaran)," *Dinasti International Journal of Economics Finance & Accounting,* vol. 6, no. 2, pp. 1520-1531, 2025, doi: 10.38035/dijefa.v6i2.4471.

[10] M. A. Zare, A. R. Omidi, and S. Safari Kohanki, "The effect of social media marketing on brand experience among customers of selected sportswear brands on Instagram: A case study of Iranian Instagram users," in *Second International Conference on Educational Sciences, Psychology, Sport Sciences and Physical Education,* Sari, 2025.

[11] M. H. Qadri, "Exploring Dynamic Brand Experience Through Co-Creation and E-Wom: Implications for Consumer Equity in Social Media Marketing," *Ijss,* vol. 3, no. 2, pp. 712-732, 2025, doi: 10.59075/ijss.v3i2.1518.

[12] E. J. Juaton, A. Enaga, J. M. B. Lazaro, and H. B. Carmona, "Social Media Influence, Brand Reputation, and Electronic Word-of-Mouth Marketing: A Structural Equation Model on Consumer Purchase Decision Making on Apparel Businesses," *International Journal of Research and Innovation in Social Science,* vol. 9, no. 5, pp. 1519-1537, 2025, doi: 10.47772/IJRISS.2025.905000121.

[13] K. Spörl-Wang, F. Krause, and S. Henkel, "Predictors of social media influencer marketing effectiveness: A comprehensive literature review and meta-analysis," *Journal of Business Research,* vol. 186, p. 114991, 2025, doi: 10.1016/j.jbusres.2024.114991.

[14] C. Ma, B. W. Wang, L. Dai, X. Guan, and Z. Yang, "What determines the effectiveness of social media influencer marketing? An fsQCA-based study of influencer characteristics and content features' configurational effects," *Journal of Business Research*, vol. 189, p. 115170, 2025, doi: 10.1016/j.jbusres.2024.115170.

[15] S. K. Lee, S. Sugiyama, J. Park, H. Lee, and J. E. Katz, "Fashion Attentiveness and Influencer Engagement: Exploring Social Media Appropriation in South Korea," *Journal of Fashion Marketing and Management: An International Journal,* vol. 30, no. 2, pp. 258-274, 2025, doi: 10.1108/JFMM-01-2025-0033.

[16] A. Kaur, "Social Media-Driven Viral Marketing: A Strategic Approach to Leveraging Influencer Marketing for Enhanced Virality," *Cana,* pp. 2215-2224, 2025, doi: 10.52783/cana.v32.5617.

[17] B. Gündüzyeli, "The Effects of Integrating Guerrilla Marketing Techniques with Social Media Applications in Digital Marketing," (in English), *Businesses,* vol. 5, no. 4, p. 47, 2025, doi: 10.3390/businesses5040047.

[18] P. D. A. I. Karunarathne and W. M. C. B. Wanninayake, "Impact of Social Media Marketing on Brand Loyalty in Online Fashion Retail Industry in Sri Lanka (SDG 09): The Mediating Role of Brand Consciousness," *JLSDGR,* vol. 5, no. 8, p. e6049, 2025, doi: 10.47172/2965-730x.sdgsreview.v5.n08.pe06049.

[19] A. Hamidnia and A. R. Shekarchizadeh, "Consumer behavior and social media marketing in the luxury goods market: A review of related models," in *Second Conference on Economics, Management, and Accounting*, 2025.

[20] J. Marthinus, R. G. Duffett, and B. Knott, "Social Media Adoption as a Marketing Communication Tool by Non-Professional Sports Clubs: A Multiple Case Study Approach," *International Journal of Sports Marketing and Sponsorship,* vol. 26, no. 6, pp. 14-31, 2025. [Online]. Available: https://doi.org/10.1108/IJSMS-04-2024-0082.

[21] A. A. E. Othman and Y. A. Maarek, "A Social Media-Based Framework for Marketing Architectural Design Firms in Egypt During Global Economic Downturn," *International Journal of Architectural Research Archnet-Ijar,* 2025, doi: 10.1108/arch-08-2024-0340.

[22] P. G. Eandhizhai, K. B. N.A, and R. Yuvaraj, "Strategies for Social Media Marketing to Engage and Shape the Purchase Behavior of Gen Z," *JoMW,* vol. 2024, no. 5, pp. 36-41, 2025, doi: 10.53935/jomw.v2024i4.692.

[23] N. Hassanzadeh and M. Sheikh Hosseini, "A Revolution in the Role of Social Media and Artificial Intelligence (AI) in Enhancing the Flexibility of Digital Marketing during Crises," 2025. [Online]. Available: https://www.noormags.ir/view/en/articlepage/2282715.

[24] A. Pazhoohan, P. Akbari, and M. A. Nouri, "Analyzing the Effect of Corporate Social Responsibility and Knowledge Management Infrastructure on Sustainable Performance Considering the Mediating Role of Organizational Ambidexterity," *Quarterly Journal of New Approaches in Management and Marketing*, vol. 5, no. 1, 2026.

[25] K. Gad, "The Impact of Social Media Marketing on Purchase Decision through Customer Experience: An Empirical Study on Skin and Hair Care Products in Egypt," *Arab Journal of Administration*, vol. 46, no. 1, 2026. [Online]. Available: https://aja.journals.ekb.eg/article_306639.html.

[26] Y. Zhou and Y. Li, "From interaction to restoration: How social media marketing revitalizes heritage brands," *Journal of Interactive Marketing*, vol. 63, pp. 21-39, 2025.

[27] R. Rajeshwari, "The effectiveness of influencer marketing in social media networks," *International Journal of Advertising*, vol. 44, no. 1, pp. 180-195, 2025. [Online]. Available: https://pubsonline.informs.org/doi/abs/10.1287/ijoc.2022.1246.