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Designing an Artificial Intelligence-Based Digital Marketing Model Using the Grounded Theory Approach (Case Study: Companies Operating in the Steel Industry)

1. Seyed Mehdi. Mirahmadi Babaheidari: Department of Management Mo.C., Islamic Azad University, Isfahan, Iran
2. Seyed Hasan. Hosseini*: Associate Professor, Department of Management, Faculty Member, Imam Ali University, Tehran, Iran
3. Saeid. Landaran Isfahani: Department of Management Mo.C., Islamic Azad University, Isfahan, Iran

*corresponding author's email: hosseini@iamu.ac.ir

ABSTRACT

The present study aimed to design an artificial intelligence-based digital marketing model for companies operating in the steel industry using the grounded theory approach. In terms of approach, this study was qualitative, and in terms of purpose, it was exploratory-developmental. Data were collected through in-depth semi-structured interviews with 15 experts from the steel industry, senior managers, and university scholars familiar with the fields of artificial intelligence and digital marketing. Sampling was conducted purposively and theoretically, and the data collection process continued until theoretical saturation was achieved. Data analysis was performed using open, axial, and selective coding based on the paradigmatic model of grounded theory. The findings indicated that causal factors, including competitive pressure in the steel market, increasing complexity of industrial customer behavior, the need for demand forecasting, and the growth of digital technologies, provide the foundation for the emergence of artificial intelligence-based digital marketing. Contextual factors such as organizational culture, level of digital maturity, and top management support, as well as intervening factors including employee resistance, lack of digital skills, and infrastructural limitations, influence the implementation of this approach. The identified key strategies included intelligent data analytics, implementation of smart CRM systems, personalization of interactions, and automation of marketing processes, which lead to outcomes such as increased decision-making accuracy, improved customer acquisition and retention, cost reduction, and enhancement of competitive advantage. The proposed model can serve as a scientific and practical framework for managers in the steel industry in the process of digital transformation in marketing. By designing an artificial intelligence-based digital marketing model in the steel industry, the present study demonstrated that the transition from traditional marketing to intelligent marketing requires simultaneous attention to causal, contextual, and intervening factors, as well as strategies and consequences within an integrated system. The main practical implication of the findings for managers in the steel industry is the provision of an operational roadmap for the gradual implementation of intelligent data analytics, personalized interactions, and marketing process automation with the aim of improving decision-making accuracy, reducing costs, and strengthening competitive advantage in complex industrial markets.

Keywords: Digital Marketing, Artificial Intelligence, Grounded Theory, Companies Operating in the Steel Industry.

Introduction

The rapid advancement of artificial intelligence (AI), machine learning, and natural language processing (NLP) technologies has fundamentally transformed organizational decision-making processes across industries. In recent



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years, businesses have increasingly shifted from traditional operational and marketing models toward intelligent, data-driven systems capable of processing large volumes of structured and unstructured information in real time. This technological transition has significantly altered the strategic landscape of industrial markets, particularly in sectors characterized by high complexity, intense competition, and dynamic customer expectations. AI-based systems are no longer limited to operational automation; rather, they are now integrated into strategic forecasting, customer behavior analysis, investment planning, digital communication, and intelligent market management (1-3). The emergence of intelligent analytical systems has enabled firms to improve predictive capabilities, optimize marketing resource allocation, and generate sustainable competitive advantages through algorithmic decision-making. Consequently, organizations operating in industrial environments are increasingly recognizing AI as a transformative capability rather than merely a technological tool (4-6). This transformation is particularly relevant in industries such as steel, where market volatility, supply chain complexity, and industrial customer heterogeneity necessitate advanced analytical and adaptive marketing systems.

Digital marketing has evolved considerably from its initial role as an online communication mechanism into a sophisticated ecosystem driven by intelligent technologies and predictive analytics. Modern digital marketing systems increasingly rely on AI-powered algorithms to analyze consumer preferences, personalize interactions, forecast demand patterns, and optimize customer engagement strategies. The integration of AI into digital marketing has enhanced firms' abilities to interpret market signals and respond proactively to environmental changes (7, 8). In particular, NLP techniques have emerged as a critical component of intelligent digital marketing because they enable organizations to process textual and linguistic data generated through customer interactions, social media communications, online reviews, and industrial feedback systems (9, 10). Through NLP-driven sentiment analysis and semantic interpretation, firms can better understand customer attitudes, expectations, and purchasing behaviors. These capabilities allow organizations to transition from reactive marketing approaches toward predictive and adaptive marketing systems capable of continuously learning from data (11, 12). Furthermore, AI-driven digital marketing systems contribute to improved market transparency, reduced uncertainty, and more accurate strategic planning within highly competitive industrial sectors.

The importance of NLP and AI applications in business environments has expanded substantially due to the exponential growth of digital data. Industrial organizations increasingly generate massive amounts of information through enterprise systems, online transactions, customer communications, and operational networks. Traditional analytical methods are often incapable of effectively processing such large-scale and complex datasets. Consequently, AI-based analytical frameworks have become essential for extracting actionable insights from organizational data ecosystems (13, 14). NLP algorithms, clustering techniques, and machine learning models provide organizations with the ability to identify hidden patterns, classify customer preferences, and automate strategic decision-making processes (15, 16). These technologies are increasingly used to enhance customer relationship management systems, optimize product positioning, and improve communication effectiveness across digital channels. In addition, AI-based analytics facilitate more accurate market forecasting and enable organizations to develop agile responses to rapidly changing industrial conditions (17, 18). Such capabilities are particularly valuable in industrial sectors characterized by high uncertainty and global competition.

The steel industry represents one of the most strategically significant industrial sectors in many economies due to its direct relationship with infrastructure development, manufacturing, energy, transportation, and construction activities. However, the industry faces substantial challenges associated with fluctuating global demand, volatile

raw material prices, environmental pressures, and changing customer expectations. In recent years, the increasing complexity of industrial markets has compelled steel companies to reconsider their traditional marketing and customer management practices. Conventional marketing methods are often unable to address the growing demand for personalized communication, predictive market analysis, and data-driven strategic planning. As a result, AI-based digital marketing has emerged as a potentially effective solution for enhancing market responsiveness and organizational competitiveness within the steel sector (7, 8). Intelligent systems can assist steel companies in analyzing industrial customer behavior, forecasting purchasing trends, optimizing sales strategies, and identifying emerging market opportunities through advanced algorithmic analysis (6, 19). These developments suggest that digital transformation in industrial marketing is no longer optional but rather a strategic necessity for long-term organizational sustainability.

One of the major advantages of AI-driven digital marketing lies in its capacity to improve the quality and efficiency of organizational decision-making. Traditional managerial decision-making often relies heavily on personal experience, intuition, and limited information. In contrast, AI systems utilize predictive algorithms, machine learning techniques, and real-time data analytics to generate evidence-based insights that support more rational and accurate strategic decisions (2, 3). The use of intelligent data analytics enables organizations to reduce operational uncertainty, identify behavioral trends, and anticipate future market dynamics with greater precision. This capability is particularly important in industrial sectors where inaccurate forecasting can lead to significant financial losses and reduced competitive performance. AI-based predictive models have demonstrated substantial potential in improving forecasting accuracy within financial and industrial environments (17, 19). Moreover, AI systems facilitate faster responses to customer demands and market changes by automating analytical processes and reducing dependence on manual evaluations. Consequently, organizations that successfully integrate AI into their digital marketing strategies may achieve superior organizational agility and enhanced market adaptability.

Another critical dimension of AI-based digital marketing involves the role of social media analytics and sentiment analysis in shaping customer engagement strategies. Social media platforms generate large amounts of textual data reflecting customer opinions, perceptions, and emotional responses toward products and brands. NLP-based sentiment analysis enables organizations to systematically evaluate customer attitudes and identify emerging behavioral patterns (9, 20). These analytical capabilities support more personalized and targeted marketing campaigns, thereby improving customer acquisition and retention. In industrial markets, where long-term relationships and trust-based interactions are particularly important, intelligent sentiment analysis can significantly enhance communication effectiveness and customer relationship management. Furthermore, AI-driven personalization strategies contribute to more efficient allocation of marketing resources by enabling firms to tailor messages and offers according to customer-specific preferences and behaviors (11, 12). Such approaches not only improve marketing effectiveness but also strengthen brand positioning in highly competitive industrial environments.

Despite the growing significance of AI technologies in digital marketing, several organizational and structural barriers continue to hinder effective implementation. Employee resistance to technological change, lack of digital skills, limited technological infrastructure, and concerns regarding data security and ethical issues represent major challenges for organizations attempting to adopt AI-driven systems (13, 14). In many industrial organizations, traditional organizational cultures and centralized decision-making structures may further impede digital transformation processes. Moreover, the successful implementation of AI-based marketing systems requires substantial investments in technological infrastructure, data management capabilities, and employee training

programs. Ethical concerns related to algorithmic transparency, data privacy, and automated decision-making have also become increasingly important in discussions surrounding AI adoption (3, 12). These challenges highlight the need for comprehensive organizational models capable of integrating technological, managerial, and human dimensions within the digital transformation process.

Previous studies have extensively examined the applications of AI, NLP, and machine learning within financial forecasting, customer analytics, and digital business systems. Research has demonstrated the effectiveness of AI-driven financial modeling, intelligent forecasting systems, and predictive analytical frameworks in enhancing organizational performance and strategic planning (2, 5). Other studies have focused on NLP applications in business communication, online sentiment analysis, and intelligent customer engagement systems (9, 10). Additionally, several scholars have explored the transformative role of AI in digital marketing and organizational growth, emphasizing the importance of intelligent systems in improving customer experiences and operational efficiency (7, 8). Research has also highlighted the strategic implications of AI integration in organizational innovation, skill development, and future-oriented business transformation (16, 21). Nevertheless, despite the growing body of literature on AI and digital marketing, limited attention has been devoted to designing integrated and localized models specifically tailored to the steel industry. Existing studies have largely concentrated on financial markets, e-commerce environments, or general business applications, while the unique structural, technological, and competitive characteristics of industrial sectors such as steel remain underexplored.

Given the increasing importance of digital transformation and AI integration in industrial marketing, there is a critical need to develop a comprehensive model capable of explaining the causal conditions, contextual factors, intervening variables, strategic mechanisms, and organizational consequences associated with AI-based digital marketing in the steel industry. Grounded theory provides an appropriate methodological framework for exploring complex organizational phenomena and generating context-specific theoretical models based on the experiences and perceptions of industry experts. Through qualitative exploration and systematic conceptualization, grounded theory enables researchers to identify the underlying relationships among technological, managerial, and environmental dimensions of digital transformation. Therefore, the present study aims to design an artificial intelligence-based digital marketing model in companies operating in the steel industry using the grounded theory approach.

Methods and Materials

Considering the exploratory nature of the study and its primary objective, namely designing an artificial intelligence-based digital marketing model in the steel industry, the present research is developmental in terms of outcome, applied in terms of purpose, and qualitative in terms of data type. The research approach is qualitative and based on the grounded theory methodology. This approach enables the researcher to deeply explore the experiences and perceptions of industry experts and to systematically extract concepts, categories, and relationships among them in the form of a comprehensive and localized model.

The statistical population of the study consisted of elites and experts in the steel industry who possessed sufficient knowledge, experience, and expertise in digital marketing, emerging technologies, and industrial market management. Sampling was conducted purposively using a theoretical approach. Accordingly, experts were selected based on criteria such as having at least 10 years of managerial or senior expert experience in the steel industry, familiarity with digital marketing and information technology, participation in industrial product development

and sales projects, and willingness to participate in the research. The sampling process continued until theoretical saturation was achieved, which was anticipated to occur through 10 to 15 in-depth interviews.

The primary data collection tool in this study was semi-structured and in-depth interviews with steel industry experts. Interview questions were designed with a general and exploratory orientation in order to provide an opportunity for participants to express their viewpoints, experiences, and perceptions. In addition, the review of industrial documents and records was utilized to enrich the collected data.

The collected data were analyzed using the grounded theory method through three stages: open coding, axial coding, and selective coding. In the open coding stage, initial concepts were extracted from the interviews and categorized into preliminary categories based on semantic similarities. In the axial coding stage, relationships among categories were analyzed and interpreted according to the six dimensions of the paradigmatic model, including causal conditions, central phenomenon, contextual conditions, intervening conditions, strategies, and consequences. In the selective coding stage, the storyline of the research was identified and the final model was developed. MAXQDA software was used for data management and organization.

To ensure the validity and reliability of the qualitative findings, the four criteria proposed by Guba and Lincoln (1989), including credibility, transferability, dependability, and confirmability, were employed. To enhance credibility, techniques such as prolonged engagement with the data, member checking, and peer checking were applied. Transferability was achieved through rich and detailed descriptions of the research process and findings. Dependability was ensured through comprehensive documentation of all research stages and the decision-making process, while confirmability was established through process auditing and precise reporting of the study procedures.

Findings and Results

Using the grounded theory approach, this study identified causal factors, including competitive pressure, the need for demand forecasting, access to data, and technological growth; intervening factors, including employee resistance, lack of digital skills, and infrastructural limitations; and contextual factors, including organizational culture, digital maturity, and organizational structure. Furthermore, operational strategies such as intelligent data analytics, smart CRM, process automation, personalized interactions, and self-learning marketing were designed.

The implementation of these strategies generates tangible outcomes, including increased decision-making accuracy, improved customer acquisition and retention, reduced costs, enhanced competitive advantage, and the redefinition of marketers' roles. The validity of the model was confirmed using Structural Equation Modeling (SEM) and structural equations, demonstrating that artificial intelligence is the primary driver of digital marketing success in complex industries such as steel. This finding provides a significant scientific and practical contribution to theory development and managerial guidance. As noted earlier, approximately 15 experts from the steel industry, university faculty members, and experienced managers participated in this study. They were selected from the following groups:

- Managers of companies operating in the steel industry
- University faculty members specializing in artificial intelligence

The descriptive characteristics of the participants and the codes used for the analysis of their interviews are presented in Table 1.

Table 1. Distribution of Participant Groups in the Study and the Codes Used

Participant Code	Gender	Education	Age	Employment Status	Marital Status
P1	Male	Master's Degree	Over 40 years	Part-time	Married
P2	Male	PhD	Over 40 years	Full-time	Married
P3	Male	PhD	Over 40 years	Full-time	Married
P4	Male	PhD	Over 40 years	Full-time	Married
P5	Male	Master's Degree	Over 40 years	Full-time	Married
P6	Male	Master's Degree	Over 40 years	Full-time	Married
P7	Male	Master's Degree	30–40 years	Full-time	Single
P8	Male	Senior Manager	Over 40 years	Part-time	Married
P9	Male	Senior Manager	30–40 years	Part-time	Single
P10	Male	PhD	Over 40 years	Full-time	Married
P11	Male	Senior Manager	30–40 years	Full-time	Married
P12	Male	Senior Manager	30–40 years	Full-time	Married

Strauss and Corbin (1998) identified the first stage of data analysis in grounded theory as open coding. Breaking down and conceptualizing data means dividing an observation, sentence, or paragraph into smaller components and assigning a name or label to each event, idea, or occurrence that represents the phenomenon in question. To generate a concept, the researcher should ask what the data refer to and what they represent.

The name assigned to each category should be more abstract than the names of the concepts constituting that category, and the category should have the strongest relationship with those concepts in a way that immediately recalls what it represents. According to Strauss and Corbin, researchers do not need to exert excessive effort in selecting appropriate names during the initial stages of the study. What is important is assigning a label that the researcher can remember, reflect upon, and, most importantly, use to continue the analytical process.

At this stage, all sentences were carefully reviewed, and the concepts extracted from one or more sentences were recorded on the left side. To generate a concept, the researcher must examine the data and ask what the data indicate and what they represent.

After coding the data, all concepts were compared with one another, and semantically related concepts were grouped into categories and assigned an appropriate label. In fact, concepts that appeared to be related to a similar phenomenon formed a category, which greatly assisted the researcher in summarizing the data.

The data obtained from each interview determined the nature of the questions posed in subsequent interviews. In later interviews, participants sometimes answered several subsequent questions during the course of their discussions in addition to responding to the researcher's direct questions. Since semi-structured interviews involve open-ended rather than multiple-choice questions, participants may provide more extensive responses than the researcher initially anticipated. Consequently, additional questions continuously emerged for the researcher both during the interviews and after the analysis of the collected data.

In axial coding, the data that had been decomposed into concepts and categories during open coding were reconnected in new ways in order to reveal the relationships between a core category and its subcategories. At the axial coding stage, six questions were raised for each main category: What are the causal conditions, phenomenon, context, intervening conditions, action/interaction strategies, and consequences? The answers to these questions were extracted from the identified subcategories and recorded alongside the main categories. At this stage, the simultaneous process of data collection and analysis continued in order to further elaborate and refine the categories.

Causal conditions refer to events, incidents, and occurrences that lead to the emergence or development of a phenomenon. The phenomenon refers to the central idea, event, occurrence, or issue toward which a set of actions or reactions is directed for management or response purposes. It represents a specific set of characteristics related to the phenomenon, namely the location of events or incidents associated with a phenomenon along a dimensional continuum. Context refers to the specific set of conditions within which action/interaction strategies occur. Intervening conditions refer to structural conditions related to the action/interaction strategies associated with a phenomenon; these conditions either facilitate or constrain the strategies situated within a particular context. Action/interaction strategies are devised by actors to manage, handle, transfer, or respond to a phenomenon under a particular set of observed conditions. Consequences refer to the outputs or results of actions and interactions" (Strauss and Corbin, 1990).

"In grounded theory, during the final integration stage, there must be a close relationship among categories and subcategories based on the characteristics of the core paradigm—conditions, context, action/interaction (including strategies), and consequences. Furthermore, categories must reach theoretical saturation. In fact, the close integration of categories based on paradigm characteristics and their saturation provides the theory with explanatory power, without which the theory would possess lower acceptability". Table 2 presents the results of axial coding of the research codes based on the multiple grounded theory approach. According to this table, out of the 74 extracted codes, 63 codes were included in the axial coding stage.

Table 2. Axial Coding

Row	Dimensions	Initial Code
1	Causal Factors	Competitive pressure in the steel market
2		Declining effectiveness of traditional marketing
3		Increasing complexity of industrial customer behavior
4		Need for demand forecasting
5		Growth of digital technologies
6		Pressure from top management for productivity
7		Access to extensive customer data
8		Changes in customer communication channels
9		Necessity of personalizing sales offerings
10		Transition from reactive marketing to predictive marketing
11		Reduction of market uncertainty through algorithmic analysis
12		Transformation of value creation logic in industrial marketing
13		Redefinition of sustainable competitive advantage
14		Artificial intelligence as a driver of marketing paradigm change
15	Intervening Factors	Employee resistance to technology
16		Lack of digital skills
17		High implementation costs
18		Poor data quality
19		Lack of specialized industrial consultants
20		IT infrastructure problems
21		Information security concerns
22		External regulations and restrictions
23		Cognitive gap between humans and intelligent systems
24		Limited algorithmic rationality
25		Ethical considerations of algorithms in marketing
26		Institutionalization of algorithm-based decision-making
27	Contextual Factors	Traditional organizational culture
28		Centralized decision-making structure
29		Company size and scale
30		Level of organizational digital maturity
31		History of information systems usage
32		Conditions of the domestic steel market

33		Support from top management
34		Collaboration with knowledge-based companies
35		Co-evolution of technology and marketing strategy
36		Digital path dependency
37		Marketing as data architecture
38		Market as a data network
39		Artificial intelligence as a dynamic capability
40	Influential Strategies	Use of intelligent data analytics
41		Implementation of smart CRM
42		Personalization of marketing messages
43		Automation of marketing processes
44		Predictive market analysis
45		Use of industrial social networks
46		Employee training
47		Collaboration with AI specialists
48		Gradual implementation of the project
49		Artificial intelligence as a marketing decision-making logic
50		Marketing as an adaptive intelligent system
51		Self-learning marketing
52		Transfer of analytical power from individuals to systems
53	Influential Consequences	Increased accuracy of marketing decision-making
54		Improved customer acquisition and retention
55		Reduced marketing costs
56		Increased targeted sales
57		Enhanced competitive advantage
58		Increased market transparency
59		Improved digital branding
60		Increased organizational agility
61		Readiness for the digital future
62		Redefinition of the marketer's role in the age of algorithms
63		Replacement of managerial intuition with computational rationality

In selective coding, the process of storytelling, discovering the core category, relating it to other categories according to the paradigmatic model, validating relationships against the data, and filling gaps and refining subcategories that require revision, elaboration, and expansion are carried out. In practice, these stages are not necessarily performed in the exact order described, nor are they completely distinguishable from one another, and the researcher constantly moves back and forth among them. In selective coding, the researcher must integrate and interpret the findings generated throughout the study, which is perhaps the most difficult task of the researcher, and even experienced researchers struggle with this issue.

In selective coding, the researcher describes their inner understanding of the subject by writing a narrative about the analysis. The narrative explains the processes existing within the data, the relationships among categories, the emergence of the core category, and the manner in which other categories become connected to it. In fact, the narrative presents an account of a sequence of events and incidents that occurred in the past and provides a descriptive narration regarding the central phenomenon (Strauss and Corbin, 2006, p. 118). At this stage, as in previous stages, the processes of questioning, modification, deletion, and expansion of categories continue. In reality, the iterative movement among the three coding procedures persists throughout the study process. Even after writing the narrative, identifying the core category, and establishing relationships between the core category and other categories, the researcher may return to the field to collect specific data in order to fill theoretical gaps in the emerging theory. This process may be conducted for any category that appears weak in terms of elaboration and development or raises unresolved questions.

The primary objective in grounded theory is the discovery of a central category that integrates and unifies all dimensions of the theory. The outcome of this narrative process is the final conceptualization of the core category, for which an appropriate label is assigned. The conceptual label given to the core category must adequately reflect the data expressed by the participants. Finally, through coding of the interviews using the multiple grounded theory method, the two models illustrated in Figure 1 were extracted.

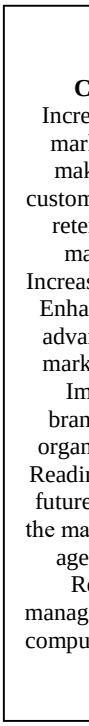


Figure 1. Final Model of the Present Study

Discussion and Conclusion

The findings of the present study demonstrated that the development of artificial intelligence-based digital marketing in companies operating in the steel industry is influenced by a complex network of causal, contextual, and intervening factors that collectively shape organizational strategies and outcomes. The grounded theory analysis revealed that competitive pressure in the steel market, declining effectiveness of traditional marketing approaches, increasing complexity of industrial customer behavior, growth of digital technologies, and the need for

demand forecasting were among the most influential causal drivers behind the transition toward AI-driven marketing systems. These findings indicate that industrial organizations are increasingly recognizing the limitations of conventional marketing mechanisms in environments characterized by market volatility, data complexity, and rapidly changing customer expectations. The results align with previous studies emphasizing that AI technologies have transformed organizational decision-making processes and enabled firms to develop predictive and adaptive strategic capabilities (1, 2). Similarly, research by (4) highlighted that organizations increasingly rely on AI-driven analytical systems to create data-oriented strategic infrastructures capable of improving operational and market performance.

The study further demonstrated that AI-based digital marketing is not merely a technological innovation but rather a paradigm shift in the logic of industrial marketing. The identified causal dimensions showed that organizations are moving from reactive marketing systems toward predictive and intelligent marketing ecosystems. This transition reflects the increasing importance of algorithmic analysis, personalized communication, and data-driven forecasting in industrial markets. These findings are consistent with the arguments presented by (8) and (7), who argued that AI technologies fundamentally alter marketing structures by enabling organizations to process customer information more effectively and create adaptive communication strategies. Furthermore, the findings support the perspective of (11), who emphasized that social media algorithms and NLP technologies significantly enhance marketing decision-making accuracy through large-scale analysis of customer-generated content and behavioral signals.

One of the significant findings of the study was the identification of contextual factors influencing the implementation of AI-driven digital marketing. Traditional organizational culture, centralized decision-making structures, organizational digital maturity, collaboration with knowledge-based firms, and support from top management emerged as critical contextual dimensions. These findings suggest that technological adoption in industrial environments depends heavily on organizational readiness and strategic alignment between digital capabilities and managerial structures. Organizations characterized by rigid managerial systems and low digital maturity may encounter greater difficulties during digital transformation processes. These results are consistent with studies indicating that organizational culture and leadership support play a central role in successful AI adoption and digital innovation (1, 3). The findings also reinforce the conclusions of (21), who demonstrated that AI implementation requires institutional adaptability and continuous organizational learning to support intelligent strategic systems.

The findings additionally revealed that several intervening factors constrain the successful implementation of AI-based digital marketing in the steel industry. Employee resistance to technological change, lack of digital skills, infrastructural limitations, information security concerns, high implementation costs, and the absence of specialized consultants were identified as major barriers. These results highlight the reality that technological transformation is not solely dependent on software and digital systems but also requires human acceptance, technical competencies, and infrastructural readiness. Similar findings have been reported in previous literature examining the organizational challenges of AI integration. For example, (13) argued that the effectiveness of NLP and AI systems depends significantly on organizations' ability to overcome technical and human resource barriers. Likewise, (14) emphasized that machine learning and NLP systems require skilled personnel and appropriate organizational infrastructure to produce reliable strategic outcomes. The findings of the current study also support the argument of (12), who highlighted that ethical concerns, data quality issues, and algorithmic transparency remain critical challenges in AI-based marketing systems.

Another important finding of the study involved the operational strategies organizations employ to implement AI-based digital marketing. Intelligent data analytics, implementation of smart CRM systems, predictive market analysis, marketing process automation, employee training, collaboration with AI specialists, and personalization of marketing messages were identified as the core strategic mechanisms. These findings indicate that AI-driven digital marketing operates through interconnected technological and managerial processes designed to improve organizational adaptability and customer engagement. The implementation of smart CRM systems and intelligent data analytics reflects the increasing role of algorithmic systems in customer relationship management and industrial market forecasting. These findings correspond with previous studies emphasizing the importance of AI-enabled customer analytics and intelligent communication systems in digital business environments (9, 10). Moreover, the findings support the conclusions of (20), who demonstrated that sentiment analysis and deep learning techniques significantly improve organizations' understanding of customer perceptions and online behavioral patterns.

The results of the study also demonstrated that AI-based digital marketing contributes to several important organizational outcomes, including increased decision-making accuracy, improved customer acquisition and retention, reduced marketing costs, increased targeted sales, improved digital branding, and enhanced competitive advantage. These findings indicate that intelligent marketing systems provide substantial strategic value for organizations operating in complex industrial environments. The use of AI algorithms and predictive analytics enables firms to reduce uncertainty and optimize strategic planning through more accurate market forecasting and customer analysis. These results align with studies conducted by (6) and (19), which demonstrated that AI-based predictive systems improve forecasting capabilities and facilitate more effective organizational decision-making. The findings are also consistent with the conclusions of (5), who emphasized that AI-driven systems significantly enhance strategic investment and market analysis through real-time data processing and intelligent forecasting.

One of the notable conceptual contributions of the present study is the identification of artificial intelligence as a dynamic organizational capability and as a new logic of marketing decision-making. The findings suggest that AI has shifted the analytical power of organizations from individual managerial intuition toward computational rationality and intelligent systems. This transformation reflects a broader structural evolution in industrial marketing, where organizations increasingly rely on algorithmic intelligence to interpret market conditions and customer behavior. Such findings support the theoretical perspectives proposed by (4) and (2), who argued that AI systems are reshaping organizational strategic architectures by embedding intelligent analytics into core managerial processes. In this context, AI no longer functions merely as a supporting technological instrument but rather as a strategic infrastructure capable of redefining organizational competitiveness and market positioning.

The study further highlighted the growing importance of NLP technologies in digital marketing systems. NLP-driven systems enable organizations to process unstructured textual information generated through social media, customer feedback, industrial communication platforms, and digital interactions. The integration of NLP into digital marketing allows organizations to identify customer sentiment, evaluate communication effectiveness, and improve personalization strategies. These findings are strongly supported by previous research demonstrating the strategic role of NLP in business analytics and digital communication systems (9, 10). Similarly, (15) emphasized that NLP and clustering techniques significantly improve organizations' understanding of market demands and behavioral segmentation patterns. Furthermore, the findings align with (16), who argued that AI-driven information extraction systems facilitate dynamic knowledge generation and strategic adaptability within organizations.

The grounded theory framework used in this study provided a comprehensive understanding of the multidimensional nature of AI-based digital marketing in the steel industry. Unlike many previous studies that primarily focused on technological dimensions, the present research integrated organizational, strategic, contextual, and behavioral dimensions into a unified conceptual framework. This integration represents a significant theoretical contribution because it demonstrates that digital transformation in industrial marketing cannot be understood solely through technological adoption. Instead, successful implementation requires simultaneous alignment between organizational culture, strategic management, human resources, technological infrastructure, and intelligent analytical systems. The findings therefore extend the existing literature on AI-driven marketing by providing a context-specific and industry-oriented model applicable to industrial sectors characterized by operational complexity and competitive uncertainty.

The present study also contributes practical insights for managers and policymakers operating within the steel industry. The findings indicate that organizations seeking to implement AI-based digital marketing systems should prioritize digital maturity development, employee skill enhancement, and gradual implementation strategies. Furthermore, organizations should establish collaborative relationships with AI specialists and knowledge-based firms to improve technological adaptability and analytical capabilities. These findings support prior research emphasizing that organizational growth in the era of digital transformation depends significantly on strategic learning, technological flexibility, and intelligent adaptation mechanisms (7, 8). In addition, the findings reinforce the conclusions of (18), who highlighted the importance of AI-driven analytics and data visualization systems in improving real-time organizational responsiveness and strategic planning efficiency.

Another important implication of the findings relates to the future role of marketers in AI-driven industrial environments. The results suggest that AI technologies are redefining the traditional functions of marketers by automating analytical tasks and increasing reliance on computational intelligence. Consequently, marketing professionals are increasingly expected to possess interdisciplinary competencies combining technological literacy, analytical reasoning, and strategic communication skills. These findings align with prior studies emphasizing that AI integration requires continuous skill development and organizational learning (16, 21). Moreover, the emergence of self-learning marketing systems and adaptive intelligent platforms indicates that future industrial marketing structures will become increasingly autonomous, predictive, and data-centered.

One limitation of the present study was its qualitative nature and reliance on a relatively limited number of expert participants within the steel industry, which may restrict the generalizability of the findings to other industrial sectors or geographical contexts. In addition, the study focused primarily on managerial and expert perspectives, while the viewpoints of operational employees and industrial customers were not directly incorporated into the analysis. Another limitation relates to the rapidly evolving nature of AI technologies, which may lead to continuous changes in digital marketing practices over time.

Future research could examine the proposed model quantitatively using larger samples and structural equation modeling techniques across different industrial sectors. Comparative studies between industries with varying levels of digital maturity may also provide valuable insights into contextual differences in AI adoption. Moreover, future studies could investigate the role of organizational learning, ethical governance, cybersecurity readiness, and employee digital competencies in shaping the effectiveness of AI-driven marketing systems. Longitudinal studies examining the evolution of intelligent marketing systems over time would also contribute significantly to the literature.

From a practical perspective, managers in the steel industry should adopt a gradual and strategic approach toward AI-based digital marketing implementation. Organizations should invest in employee digital training, strengthen technological infrastructure, and develop integrated data management systems to support intelligent decision-making. Furthermore, companies should establish collaborative partnerships with AI specialists and technology firms to improve innovation capacity and reduce implementation barriers. Managers should also pay careful attention to ethical considerations, data security, and algorithmic transparency to ensure sustainable and responsible digital transformation in industrial marketing environments.

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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

All ethical principles were adheried in conducting and writing this article.

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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