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RECOGNIZING AND RANKING THE MOST IMPORTANT AI APPLICATIONS IN ONLINE MARKETING

The application of artificial intelligence (AI) in online marketing has garnered significant attention from investors and marketing professionals. Despite this interest, limited research has been conducted on this topic. Therefore, the objective of this study is to identify and rank the diverse applications of AI in various aspects of online marketing. This study employs a mixed-method approach, utilizing qualitative data gathered through semi-structured interviews with experts in online marketing, AI, and electronic marketing. Subsequently, forty AI applications in online marketing are identified and categorized into four groups, based on a mixed marketing approach. In the quantitative phase, a questionnaire is utilized to prioritize the identified applications. The opinions of industry experts and students in Iran with knowledge of AI and online marketing are analyzed. The research identifies four general areas where AI can be applied effectively in online marketing: product design and value creation, pricing and cost design, advertising and customer communication, and product distribution. Personalized advertising, based on user behavior, and analysis of customer emotions regarding advertising are deemed the highest priority applications. Finally, the study ranks the most significant and least significant applications. Among the identified applications, the distribution of distribution forces in branches proportional to the predicted workload of each branch is ranked as having the least priority.

Keywords: Artificial Intelligence, Online Marketing, Prioritization, Ranking

Introduction. The utilization of artificial intelligence (AI) solutions, in conjunction with data science and business analytics tools such as big data business information systems and data mining, has become increasingly critical in the management of modern organizations (Cheng, Cho, & Tasi, 2020). These technologies offer numerous advantages, including improved management processes, decision-making, and task automation resulting in optimization across various sectors (Lee et al., 2019). The significant focus on investing in AI technologies such as facial recognition, video content recognition, fraud detection, and financial affairs is evidenced by the $70 billion global investment in 2019 (Johnson & Crample, 2019). Furthermore, Tingano, Chan, and Lequier (2020) predict that the global investment in artificial intelligence will reach J150 billion by 2025.

Recent research has also highlighted the substantial influence of new technologies, including the Internet, social media, and AI, on marketing. By automating tedious and time-consuming tasks, AI frees up resources for more creative and strategic endeavors, emphasizing the importance of detailed analysis and competitive advantage (Mazurek, 2019). This issue has made developing new skills in the AI marketing group require the combination of skills of data specialists and also understanding the possibilities of the new technology in the marketing group. Therefore, it is crucial to discuss the impact of AI on marketing and how it is changing the field.

The rapid growth of the use of emerging technologies such as artificial intelligence in enterprises has led to numerous applications in the field. Many companies are seeking success in their businesses, leading to online marketing's adoption of these same tools (Sun, Lee, & Zhou, 2006). Advances in data collection, analytics, and the digital economy have enabled marketers to implement and streamline ad personalization tactics, reducing ineffective efforts and allowing for more investment in customer-generating methods (Kitzman et al., 2018). Personalized marketing can also be automated, increasing the effectiveness of a company's marketing strategy (Kim et al., 2001).

While the use of artificial intelligence (AI) in online marketing can bring significant benefits, many businesses are not aware of its applications and do not prioritize its use. Furthermore, the use of AI tools in marketing can pose data risks for customers and users. Despite the increasing commonality of AI use in marketing, there remains a lack of understanding of how organizations can plan and prioritize based on these tools. Therefore, it is crucial to conduct research to identify and prioritize AI applications in online marketing based on expert knowledge and experience (Mana, Singapore, & Masumdar, 2020).

To address this issue, this study examines the commercial importance of AI and its application in online marketing. The research method section explains the use of the best-worst method to classify and prioritize different indicators based on expert opinion. This method provides high accuracy and allows for classification that accurately reflects expert opinion. The study presented in this article aims to provide a comprehensive picture of the audience in the entire chain of online marketing, including sales persuasion and after-sales services. This approach has not been extensively explored in previous research. The article presents the results of the study, along with conclusions and suggestions for future research.

In conclusion, while the use of AI in online marketing has significant potential benefits, many businesses are not aware of its applications or do not prioritize its use. Conducting research to identify and prioritize AI applications based on expert knowledge and experience can help organizations better understand all available tools and plan accordingly. Additionally, a comprehensive approach that considers all aspects of the online marketing chain can provide a more complete picture of its audience and improve overall effectiveness.

Literature review

Artificial intelligence and business. The literature review presented in this article highlights the availability of machine learning services and the increasing use of cloud services by organizations that lack the necessary hardware to access these capabilities. These solutions are rapidly gaining popularity in the digital ecosystem, and their widespread adoption has transformed the market in a short period of time into introducing new technologies. The use of artificial intelligence emphasizes the importance of creative and strategic activities, and the detailed analyses performed by AI can increase the role of these activities in creating a competitive advantage (Jarek & Mazurek, 2019).

The next section of this article will discuss in detail the various applications of machine learning in the customer and marketing areas. However, it should be noted that machine learning has numerous other applications in business, such as logistics clamp automation by line, automated production by integrating industrial robots into the workflow and training them to perform difficult tasks (Lee, Hu, Yu, Lu, & Yang, 2017; Sadha et al., 2016), security monitoring (Yin, Zhu, Fei, & Hey, 2017), fraud detection and prevention (Setamsdal, 2019), and organizational performance prediction (Save, Kim, Casey, & Singh, 2015). Therefore, artificial intelligence can interpret information more effectively than ever before, allowing for the identification and analysis of unstructured data from customers (Bavana et al., 2020) to provide a sales perspective and analyze customer behavior and emotions (Shukla et al., 2020).

The role of artificial intelligence in online marketing. Artificial intelligence is one of the most important tools in online marketing, with various applications across the field. One of the most fundamental areas where AI is utilized is in intelligent market segmentation, which leads to more efficient marketing costs in the short term and a competitive advantage in the long run (Lilin & Rangaswami, 2004; Dolnikar, 2008). Another basic application of AI in marketing is the recommendation engine and recommender system for customers. The recommender system is a type of information filtering system that predicts a user's classification or preference for an item (Mehra, Ritika, & Mahitlayer, 2020).

Retailers use continuum analysis to perform shopping basket analysis, which helps them understand customer purchasing behavior in order to influence sales promotion, store design, loyalty programs, and discount schemes (Gutierrez, 2019). Market basket analysis is also used to maintain sales growth (Ray et al., 2020), while pricing strategies are being revolutionized with the help of artificial intelligence (Fang et al., 2020). Researchers in the field of combating fraud on the Internet are exploring the use of artificial neural networks to detect fraudulent transactions. However, regulations of countries in combating fraud are incomplete, and companies themselves must take measures to identify these frauds (Kaya, Kavdaroglu, & Sansoy, 2020; Stafford & Rosepach, 2020).

Another application of artificial intelligence in online marketing is the analysis of customer sentiments (Shukla et al., 2020). This technology is used to extract emotional tendencies in texts and helps large companies evaluate public opinion, conduct market research, monitor brand and product reputation, and understand customer experiences. Data mining in this field has received a unique reception in recent years (Chang, Chu, & Tasi, 2020). While research has sporadically discussed the applications of artificial intelligence in online marketing, no comprehensive study has yet categorized them simultaneously. However, recent years have seen a significant increase in research on the applications of artificial intelligence in business, including online marketing.

Empirical research background. In recent years, research on the applications of artificial intelligence in business has increased, and as a result, research in the field of artificial intelligence in marketing has also increased. Below are some of the studies in this area that have been mentioned.

Table 1-

Previous researches in the field of using artificial intelligence in online marketing

Proposed application	Title	Author
Pricing personalized dynamics	Personalized Dynamic Pricing Using Machine Learning: High Dimensional Features and Heterogeneous Elasticity	Ben & Kaskin, 2020

Personalization of the offer engine in marketing	Personalized digital marketing recommendation engine	Bahra, Ganaskaran, Gapta, Cambodia, & Bala, 2020
Personalization of ads	Using artificial intelligence to personalize advertisements from an emotional aspect	Mugaji, Olalia, & Akpabi, 2020
sentiment analysis	Keywords in online video advertising marketing campaigns: analysis	Femandes, 2020
Categorize customers and predict their churn rate	Customer segmentation and churn prediction in online retailing	Jera, Parekh, & Makar, 2020
Predicting the buying behavior of customers	Predictive model for diagnosing customer buying behavior using data mining	Viloria, Kiliari, & Hose, 2020
Predicting the buying behavior of customers	Analyzing customer-based sequential data: Application of attentional neural networks for sales forecasting	Canco, 2019
Organization redesign based on artificial intelligence strategies	Data Strategy and Artificial Intelligence: A Conceptual Enterprise Metadata Architecture for Enabling Market-Oriented Organizations	Moreno, Caio, Alberto Carrasco, Ramon, Herravidma, Enrique, 2019
The macro effect of artificial intelligence on the world	Artificial intelligence: scope, players, markets and geography	Paul Simon, & Jean, 2019
The macro effect of artificial intelligence on the world labor market	Artificial intelligence: the ambiguous effect of artificial intelligence on the job market with self-employment	Agrawal, Ganz, Joshua, Goldfarb, Avi, 2019
Investigating the sales market of artificial intelligence systems in the world	Development of the global market of artificial intelligence systems	Smirnov, Lukyanov, 2019
Automation of agricultural processes	Automated pastures and the digital divide: how agricultural technologies are shaping rural workers and communities	Roots, Groyley, Musby, Duncan, Phoenix, Horgan, LeBlanc, Martin, Nofeld, Hannah, Nixon, Shala, Fraser, & Ivan, 2019
The effect of artificial intelligence on learning	Reception and digitalization: learning and new technologies	Crittenden, Bill, Isabella, & William, 2019

Previous research on the applications of artificial intelligence has largely focused on the technical layer, with few studies exploring its management layers. Table 1 shows that only the second, third, and fifth cases consider the management and human aspects of the matter. In a specific field of marketing, there is a tendency to focus more on technical aspects and overlook the comprehensive management and human aspects. On the other hand, some researches only consider artificial intelligence as a black box that will make things easier and have an impact in the future world.

The second and third articles in Table 1 do not provide a detailed analysis of the dimensions of using artificial intelligence in online marketing. Instead, they analyze the effects of emerging technologies, including artificial intelligence, on the business environment and provide suggestions for the future of the business space. A small group of researches examine the existing trends in the use of emerging technologies such as artificial intelligence from a management point of view and describe the applications of these technologies in detail. The fifth article in Table 1 is an example of such research. While the view of these articles is closer to the present study than the previous two categories, their comprehensive approach to multiple technologies is a disadvantage, as they tend to overlook the details of individual applications.

One of the shortcomings of many AI application research studies in the field of marketing is the lack of a well-established framework for categorizing and prioritizing the applications found. Most studies do not provide any special classification or ranking, which can make it difficult for readers to understand the importance of each application. However, some studies, such as the one by Muller and Kristandel (2019), have highlighted the importance of certain aspects of content marketing, including recommendation marketing (Yutz, Karkhov, & Vandebos, 2012), personalization of content (Sandar, Jia, Waddle, & Huang, 2015), and even celebrity-oriented marketing (Kang, 2018), particularly for smaller celebrities (Tagtamir, 2018). It is important to note that different applications of AI in online marketing have varying levels of importance and impact, and a well-established framework can help prioritize them effectively.

Integrated marketing is an important aspect of online marketing (Berman & Telen, 2018). To achieve this, intelligent market segmentation is necessary (Ernest & Dolniar, 2018), which can be done using different methods such as classification based on geography, price, demographics, or purchase behavior. In addition to market segmentation, a recommendation engine for customers is also crucial (Ricky, Rocach, & Shapira, 2011). Collaborative filtering (Ghazanfar & Zadmak, 2012), content-based suggestion (Stephanie, 2015), multi-criteria recommender systems, risk-aware recommender systems, mobile recommender systems, hybrid recommender systems (Gomez Oribe, Carlos, Hunt, & Ney, 2015), product classification and shopping cart creation system (Gutierrez, 2019), product pricing system, dynamic pricing (Vahuda & Santosa, 2015), and product image search by the audience (Tautkote, Trinsginsgi, Scorapa, Brooki, & Mrask, 2019) are all important components of recommendation engines. Additionally, intelligent advertising engines can be designed for personalized purposes, and they can also help create productive content and detect fraud in digital advertising. Sentiment analysis is another application that can be used to analyze user sentiments from text (Talk Walker, 2019; Media DM News, 2019).

Methodology. In this section, we will outline the procedures involved in conducting the research, the instruments utilized, the approach to gathering data, and an evaluation of both the best and worst methods.

Research steps and data collection. To identify and rank the applications of artificial intelligence in online marketing, a mixed exploratory research approach was utilized. The data collection method aimed to achieve practical research. Firstly, a comprehensive literature review was conducted on artificial intelligence in online marketing. This was followed by semi-structured interviews with experts in the commercial applications of artificial intelligence, specifically in online marketing. Thematic analysis was employed to analyze the interviews and obtain a list of all existing applications of artificial intelligence in the online marketing sector. Thematic analysis is a process for analyzing textual data and recognizing patterns in qualitative data. It transforms scattered and diverse data into rich and detailed data. In the second stage, the methods and applications were ranked using the best-worst method. This helped to determine the areas of focus for the application of artificial intelligence in online marketing. Further details regarding this method are discussed in subsequent sections.

To collect data, a questionnaire was used in addition to interviews to weigh applications based on the best-worst method. In this step, experts were consulted to identify the most and least important criteria among all indicators through pairwise comparisons on a scale of 1 to 9 with the use of two matrices. After conducting a comprehensive review of the theoretical foundations of intelligence and commercial applications of AI in marketing, the first stage involved a qualitative approach and content analysis of semi-structured interviews with experts.

To obtain detailed information from an academic expert in the field of information technology management, the manager of an online advertising company was interviewed to improve the depth of the discussion. Statistical population for this study included data miners, programmers, and other experts with experience in developing artificial intelligence systems for advertising, with a judgmental sampling method. Ten people were selected as the sample size. As the research aimed to gather knowledge to understand the phenomenon, a judgmental approach was used to select the statistical population for both sectors. The criteria for selection were experience and knowledge of the field of research.

To determine the statistical population for the interview portion, the researchers prepared a list of active experts in the field of marketing and artificial intelligence based on their initial knowledge. After conducting interviews with each expert, a refined list of individuals meeting the researchers' desired criteria was obtained. The interview process continued until theoretical saturation was reached, which occurred after conducting the 10th interview. The researchers ultimately concluded the study with 9 interviews.

The selection criteria for these individuals included having a formal education in the field of artificial intelligence, authoring a minimum of three scientific research articles on the subject, having experience managing multiple large-scale marketing projects, and at least two years of programming experience within the artificial intelligence field. These conditions served as the primary factors in selecting participants for the study.

In the second stage, the researchers prepared a list of experts in the field of artificial intelligence using the best-worst method, and also sought input from the interviewees to complete the list. The primary research question asked during the interviews was, "What are the applications of artificial intelligence in online marketing?" Based on the research goals and assumptions, appropriate questions were formulated for the interview sessions. These sessions were conducted in a semi-structured manner, allowing interviewees to raise their own concerns or choose topics to discuss. The research questions formulated for the study are listed below:

1- What are the uses of artificial intelligence in product design and creating value for customers in online marketing?

2- What are the uses of artificial intelligence in the pricing and design of costs in online marketing?

3- What are the uses of artificial intelligence in advertising and informing customers in online marketing?

4- What are the uses of artificial intelligence in the place of product supply and the way of product presentation in online marketing?

The study utilized the open test method to determine the reliability of the interviews. For each interview, the coded responses were compared twice at short, specific time intervals. The retest validity was determined by coding each interview twice over a 7-day period by the researcher. The retest reliability of the interviews was found to be 81%, exceeding the reliability standard of 60% (Coil, 1996).

The validity of coding was confirmed and for the quantitative part of the research, two individuals who had experience using the best-worst method for prioritization in their thesis or previous research were consulted to determine the appropriate sample size. It was determined that a minimum of eight experts in the field was necessary to ensure a reliable and valid method. To guarantee questionnaire accuracy and completion, twice the required number of questionnaires were distributed, with fifteen questionnaires collected. Therefore, only two had issues with completion.

The best-worst method is a multi-criteria decision-making tool that effectively simplifies the prioritization process. This method determines the importance of each criterion by comparing the best index with other indices and comparing the worst index with other indices, ultimately providing a system of prioritized suggestions. It is important to note that this method requires more steps compared to other ranking methods, such as the Analytical Hierarchy Approach (AHP), which reduces the number of pairwise comparisons needed to determine importance.

However, the best-worst method has two key advantages. The first is that it provides more consistent results (Rezaei, 2015). The second advantage is that it is less restrictive, as it allows for more possible combinations of rankings. The steps for conducting the best-worst method include:

1. Identification of a set of decision indicators that are displayed as$\{c_1, c_2, \ldots, c_n\}$ $\{c_1, c_2, \ldots, c_n\}$.

2. Determination of the best (most important) and worst (least important) indicators, which are displayed with CW and CB, respectively.

3. Determining the relative importance of the best index compared to other indices using experts' opinions and forming the $A_B A_B$ vector as follows, so that $a_{B_j} a_{B_j}$ is the relative importance of the best index of j.

$$A = (a_{B_1}, a_{B_2}, \ldots, a_{B_n}) A = (a_{B_1}, a_{B_2}, \ldots, a_{B_n})$$

4. Determining the relative importance of all indicators compared to the worst indicator using the opinion of experts and forming the vector $A_W A_W$ as follows so that A_{W_j} A_{W_j} is the relative importance of the best indicator compared to the index.

$$A = (a_{W_1}, a_{W_2}, \dots, a_{W_n}) A = (a_{W_1}, a_{W_2}, \dots, a_{W_n})$$

5. Calculation of optimal weights so that the maximum values of $\left|\frac{W_B}{W_j} - a_{Bj}\right| \left|\frac{W_B}{W_j} - a_{Bj}\right|$ and $\left|\frac{W_j}{W_w} - a_{wj}\right| \left|\frac{W_j}{W_w} - a_{wj}\right|$ be minimized for all values of j. In order to solve this equation, the restrictions of weights not being negative and their sum equal to 1 should also be taken into account.

$$\min\max\left\{\left|\frac{W_j}{W_w} - a_{wj}\right|, \left|\frac{W_B}{W_j} - a_{Bj}\right|\right\}$$

s.t.

$$\sum_j W_j = 1$$

$$W_j \geq 0 \; for \; all \; j$$

6. In order to make it easier to solve the above problem, we formulate it as follows.

Min $\lambda\lambda$

s.t.

$$\left|\frac{W_j}{W_w} - a_{wj}\right| \leq \lambda \; for \; all \; j$$

$$\left|\frac{W_B}{W_j} - a_{Bj}\right| \leq \lambda \; for \; all \; j$$

$$\sum_j W_j = 1$$

$$W_j \geq 0 \; for \; all \; j$$

To determine the compatibility rate of the best-worst method, the weight of the best criterion must be derived based on the obtained weights. Next, the mathematical model is solved, resulting in a value known as “landa.” To obtain the incompatibility index, the landa value is divided by the number. It is important to note that inconsistency rates below 0.25 indicate highly consistent results.

Results. To verify the research results, semi-structured interviews were conducted. The meaningful sentences from the interviews were entered into tables and analyzed through a theme analysis approach, resulting in identified factors being grouped together. An example of the interview analysis, along with its verbal evidence, is presented in Table 2.

Table 2

An example of verbal interview evidence

Application of artificial intelligence	Verbal evidence
Analyzing customer sentiments regarding prototype evaluation	In the product design department, using tools such as text mining, it is possible to estimate the products that are in the testing stage by using things such as tweets and comments of social network users.
Identifying customer interest trends in relation to product features	Before designing the product, it is important to know the market trends so that they can be included in the product design, and social network analysis machines are of great help in understanding these trends.
Analysis of product pricing trends in the market	In markets with a lot of players, it is impossible to check each and every player, and analytical machines can check the behavior of others and predict the price trend of the product in the market.
Dynamic pricing	Data helps in accurate marketing on the customer and dynamic and more effective pricing so that the business efficiency increases and the company gets more profit.
Intelligent segmentation of the market based on various factors for greater advertising effectiveness	Clustering techniques have been very prosperous in recent years and the use of these things in intelligent segmentation of the market has helped to increase the effectiveness of advertisements. Many advertising centers today offer this service as an inseparable part of their services.
Identifying the most effective communication channels with customers	Each customer has a specific effectiveness in each marketing channel, and basically one of the communication channels should be considered for each category of customers, which requires a lot of research and detailed study of user behavior with data mining and machine learning tools.
The distribution of distribution forces in distribution branches is proportional to the expected workload of each branch	Using the previous data, we tried to check the amount of sales and crowding of their different branches and provide them with a model for the distribution of people in their branches at different hours of the day. This would not be possible without the use of machine learning models.

In this study, in addition to conducting interviews, a comprehensive background review was also performed, and a summary of the identified applications in the four areas of marketing mix is presented in Table 3.

Table 3

Extracted applications in four areas of marketing mix

Dimensions	applications	References and Interviews:
Product design and value creation	Applying the recommender system to the customer in the development of personalized products	Hernandez, Elena, 2020; Mehra, Ritika, Mohitlire, 2020
	Create and discover a personalized value proposition	Basano, Clara, 2020
	Developing a machine learning model to discover the value proposition of successful products	Zue et al., 2020
	Developing a machine learning model to predict the success of the value proposition in the market	Calcami, Canan, Moy, 2012; Vangvin et al., 2020
	Simulating the prototype of the product and identifying the weak points of the product	Notrambiro, Apara, 2020; Lopez et al., 2020; Kaya et al., 2020
	Analyzing customer sentiments regarding prototype evaluation	Hosain et al., 2009; Calcami, Canan, Moy, 2012; Choi, Louis, Go, 2012
	Identifying value propositions appropriate for each segment of the market	Ahani et al., 2019; Kashvan, vlo, 2013; Huang, Tezing, Ang, 2007; Tasai, Chiu, 2004
	Identifying customer interest trends in relation to product features	Nieto, Rajasari, 2012; Parastasy et al., 2014; Vangvin et al., 2020
	Development of intelligent assistant for product design	
Pricing and design costs	Analysis of product pricing trends in the market	Chiramel et al., 2020; Raju, Narahari, Rivikumar, 2006; Caffart, Hanson, Greenwald, 2000
	Dynamic pricing	Fank et al., 2020; Raju, Narahari, Rivikumar, 2006; Caffart, Hanson, Greenwald, 2000
	Predicting market behavior to calculate product prices	Subhi Kesh, Tota, Sanjita, 2020; Lee, Wu, Wong, 2020
	Intelligent market segmentation based on price sensitivity	
	Pricing based on new product features	Alshaikh et al., 2020
	An intelligent assistant to develop the customer's shopping cart according to the proposed budget	Blicley et al., 2020; Ray et al., 2020
	Collecting and analyzing unstructured customer data related to price	Bavana et al., 2020; Hang, Leo, 2020; Choi, Louis, Go, 2012
	Modeling factors affecting product prices in the market	Demir et al., 2020; Tang et al., 2020; San, Vang, 2020
	Analysis of pricing balance with product features	Feng, Paulson, Zhu, 2018; Kavalikar et al., 2020

Advertising and informing customers	Forecasting the amount of product sales in each segment of the market	Yasin et al., 2014; Calcami, Canan, Moy, 2012
	Development of cause and effect diagram of advertisement quality (online and offline)	
	Predicting the success rate of marketing campaigns	Wafidis et al., 2015, Hematha, Forzana, Nayaki, 2014
	Analyzing customer sentiments regarding advertising	Neo, Rajasri, 2012; shokola et al., 2020; soriano, Avo, Banks, 2013
	Personalization of advertisements according to the previous behavior of customers	Kinzman et al., 2018; Kim et al., 2001
	Suggesting system for marketing campaigns related to products	
	Estimating the effect time of advertisements according to the customer's behavior and converting the audience into a customer	Gerzonka, Suchaka, Buroeik, 2016; Wafidis et al., 2015
	Using a smart assistant to answer and serve the customer online	Ahmad et al., 2020; Pantano, Pease, 2020; Vang, Lu, 2020
	Identifying the best operator to answer various customer questions	Tingano, Chan, Lequier, 2020; Park, 2014; Boosman, Sheir, Arenz, 2000; Tang, Plum, Hakiglo, 2003
	Intelligent segmentation of the market based on different purchases for more effective advertising	Chang, Chu, Tasi, 2020; Kuchran et al., 2020; Chen, 2020
	Identifying the most effective communication channels with customers	Dee et al., 2020; San, Lee, zhu, 2006
	Optimizing customer advertising channels	Park, 2020; Souryano, Aw, Benkes, 2013; kenon, 2001
	Detect and deal with fraud in the generated leads of intermediary marketing	Vang et al., 2020; Caya, Kavdaroglu, Sensoy, 2020; Estaford, Roozpech, 2020; Linder, Titer, 2012
	Recommender system for loyalty programs tailored to each customer's behavior	Wee et al., 2020; Vusoof et al., 2020
	The system offers special offers for stores around the audience according to the profile of the audience	Leen, Batista, 2020; Katwa, Chetvani, Aktar, 2020; Karalis et al., 2020; Lee, Do, 2012
	Predicting the most effective loyalty programs	Abdollah, Salleh, Albalsaghi, 2014

Production Distribution	The system suggests the most suitable sales center according to the customer's profile	Bavana et al., 2020; Black Harest, Apon, 2011; Banus, 2009
	Estimating the time interval between customer service and product delivery	Jonkweez, Krempel, 2019; Batman, 2018; Leo et al., 2008
	Optimizing the product distribution system in order to reduce distribution costs	Lee et al., 2019
	The distribution of distribution forces in distribution branches is proportional to the expected workload of each branch	Tomasen, 2016; Paparizos, Kapyaz Oghlu, geonis, 2011
	Locating the product warehouse in order to minimize the time it takes for the product to reach the customer	Carmiker, Saha, 2015; uzturk, 2012
	Making a cause and effect model of the right place to supply products	Kumar et al., 2020; Alvisus, Bino, 2013; Yang et al., 2015

In the second stage of the study, the best-worst approach was used to prioritize the main categories and applications of artificial intelligence in online marketing. Participants were asked to evaluate the best and worst options through a questionnaire. After scoring, the average was taken for each respondent, and proportional weights were calculated for applications. The results from the best-worst method are presented in Table 4, which shows that the inconsistency rates for each main dimension, calculated to evaluate the correctness of weighting, fall within the acceptable range. All numbers are below 25, indicating high compatibility.

Discussion and Conclusion. Organizations are turning to online marketing as a means to remain competitive in the market, utilizing artificial intelligence to optimize their operations. However, the implementation of artificial intelligence-based systems is often done on a case-by-case basis, without consideration of a comprehensive framework. This highlights the need for further research in the field, which unfortunately remains limited in number and incomplete in addressing the entire process.

A case study conducted by Xieo and Yang (2017) aimed to analyze the evolving nature of sales and marketing and the impact of artificial intelligence, robotics, and machine learning in online marketing. The study began with a thorough literature review of the applications of artificial intelligence in business, specifically in online marketing. Subsequently, through ten semi-structured interviews with experts in marketing, online artificial intelligence, and e-commerce, forty applications of artificial intelligence were identified and categorized using the marketing mix.

The identified applications were then prioritized in four areas of the marketing mix by using a questionnaire survey and the best-worst method. The prioritization was carried out with the participation of industry experts and students from prominent Iranian universities who were familiar with the field of artificial intelligence and online marketing. The results of this research provide useful insights for organizations looking to integrate artificial intelligence into their marketing strategies.

Table 4

Weight allocation and classification of extracted applications in four areas of marketing mix

Dimensions	Dimensions weight	applications	rank	Index weight	Incompatibility index
Product design and value creation	216/0 Second place	Applying the recommender system to the customer in the development of personalized products	6	0.105	0.12 compatibility
		Create and discover a personalized value proposition	8	0.131	
		Developing a machine learning model to discover the value proposition of successful products	1	0.039	
		Developing a machine learning model to predict the success of the value proposition in the market	4	0.093	
		Simulating the prototype of the product and identifying the weak points of the product	3	0.089	
		Analyzing customer sentiments regarding prototype evaluation	7	0.11	
		Identifying value propositions appropriate for each segment of the market	5	0.105	
		Identifying customer interest trends in relation to product features	9	0.261	
		Development of intelligent assistant for product design	2	0.066	
Pricing and Design Costs	198/0 Third place	Analysis of product pricing trends in the market	9	0.143	0.086 compatibility
		Dynamic pricing	8	0.266	
		Predicting market behavior to calculate product prices	7	0.133	
		Intelligent market segmentation based on price sensitivity	6	0.094	
		Pricing based on new product features	5	0.094	
		An intelligent assistant to develop the customer's shopping cart according to the proposed budget	2	0.067	
		Collecting and analyzing unstructured customer data related to price	3	0.077	
		Modeling factors influencing the product price in the market	4	0.092	
		Analysis of pricing balance with product features	1	0.032	

Advertising and informing customers	517/0 First Place	Forecasting the amount of product sales in each segment of the market	8	0.051	0.191 compatibility
		Development of cause and effect diagram of advertising quality (online and offline)	15	0.062	
		Predicting the success rate of marketing campaigns	16	0.055	
		Analyzing customer sentiments regarding advertising	5	0.105	
		Personalization of advertisements according to the previous behavior of customers	11	0.158	
		Suggesting system for marketing campaigns related to products	4	0.046	
		Estimating the effect time of advertisements according to the customer's behavior and converting the audience into a customer	10	0.058	
		Using a smart assistant to answer and serve the customer online	3	0.039	
		Identifying the best operator to answer various customer questions	1	0.019	
		Intelligent segmentation of the market based on different purchase sheets for more effective advertising	7	0.051	
		Identifying the most effective communication channels with customers	14	0.079	
		Optimizing customer advertising channels	9	0.055	
		Detect and deal with fraud in the generated leads of intermediary marketing	2	0.036	
		Recommender system for loyalty programs tailored to each customer's behavior	12	0.063	
		The system offers special offers for stores around the audience according to the profile of the audience	13	0.07	
		Predicting the most effective loyalty programs	6	0.051	

Product distribution	069.0 Fourth	The system suggests the most suitable sales center according to the customer's profile	6	0.344	0.139 compatibility
		Estimating the time interval between service delivery to customers and delivery of goods to customers	4	0.143	
		Optimizing the product distribution system in order to reduce distribution costs	3	0.136	
		The distribution of distribution forces in the distribution branches is proportional to the expected work pressure of each of the branches	1	0.061	
		Locating the product warehouse in order to minimize the time it takes for the product to reach the customer	5	0.19	
		Making a cause and effect model of the right place to supply products	2	0.126	

The study identified and ranked sixteen applications in the realm of product design and value creation, nine applications in pricing and cost design, nine applications in advertising and customer engagement, and six applications in sales location and product supply methodology. The activities were conducted across various fields to identify relevant applications.The results of the research indicate that in the product design and value creation department, identifying customer trends and preferences regarding product features is a priority. Traditionally, businesses achieve this through expensive market studies or by following media trends. Intelligent models of customer interest analysis can address this gap, and further research is needed to develop more effective models.

Wangwin et al. (2020) addressed this issue, illustrating the significant need for this type of research. However, it should be noted that the identification of trends in customer interests is not a novel concept; past studies such as those conducted by Newth and Rajasri (2012) and Parasasti et al. (2014) have addressed it, and researchers have consistently expressed interest in the topic. In today's digital age, personalization has become a necessity, and discovering the right personalized value proposition is crucial. Researchers such as Bassano and Clara (2020) have highlighted its importance in online marketing. Achieving personalization requires complex artificial intelligence that can recognize individual interests and categorize and weigh them effectively.

Most major companies have tested prototypes with sample customers to develop and validate personalized solutions. However, customer reluctance to participate in such programs hinders progress in the field. Therefore, it is important to conduct thorough customer sentiment analysis, particularly regarding prototype evaluation in computer platforms, as emphasized by Ramboukas and Gamma (2013).

Research has shown the significant role of customer suggestion systems in online marketing, as it provides direct access to global audiences that would otherwise be unfeasible or costly. Utilizing the customer suggestion system can also aid in developing personalized products and identifying market-specific value propositions, enabling companies to connect to their target audiences on a deeper level. However, these solutions should also be tailored to each organization's unique marketing challenges and goals.

Regarding pricing and cost design, three specific applications hold greater weight than others. Dynamic pricing is a cutting-edge solution that tops the list, as it enables businesses to make optimal pricing decisions based on predictive models. This can maximize profits and increase customer engagement. It should be noted that such models should be developed internally to ensure controls and responsiveness to crisis scenarios.

The second application is analyzing pricing trends in the market, which can help companies gain a better understanding of competitors and create multivariate regression models based on historical data. Developing deep learning models for more accurate pricing analysis is another option, albeit more expensive. Ultimately, each organization must determine which solutions align best with their budget and needs.

Creating an artificial intelligence tool that predicts market behavior in order to determine product price is a crucial task that can greatly influence the decision to produce a new product. Traditional models based solely on historical data may not be applicable in this case, as predictive artificial intelligence models utilizing artificial general intelligence technology may be required for accuracy.

Personalizing advertisements based on a customer's previous behavior is a top priority in online marketing, as highlighted by Chen (2020) and Shaha and Tripasi (2020). While there are now online advertising platforms that provide personalized services to businesses, it is still important for marketing managers to monitor the quality of these platforms and analyze the results for themselves. If the feedback is low, a new system should be considered in the design of subsequent campaigns. This is further emphasized by researchers such as Kulkarni, Kalro and Sharma (2020) and Fernandez and Yu (2022).

After tailoring advertisements according to the previous behavior of customers and utilizing platforms to enhance personalization, analyzing customer sentiment towards these advertisements becomes a crucial aspect of online marketing. This has been stressed by experts such as Chen (2020) and Shaha and Tripasi (2020).

Another important area of focus is the development of a specialized recommendation system, tailored to suggest special store offers to the target audience. Researchers such as Molitor Spangosse and Richhart (2020) have also highlighted its importance. This AI-based system utilizes classification models mentioned in the literature review and mathematical optimization models to recommend the most suitable stores based on customer preferences. The ranking of stores is in line with expert opinions and should be seriously considered.

An accurate database of stores and their physical locations, along with geo-location based contact classification, is required to ensure the effectiveness of the recommendation system. This concept is also emphasized in the research of Hernandez Gonzalez and Corchado (2020), Jonquiz and Krempel (2019), and Batman (2018). The creation of an appropriate recommendation system based on customer profile is a vital solution to the challenges of online marketing in this sector.

In addition to providing customers with sufficient information about product delivery times and accurately calculating final product prices, researchers have emphasized the importance of optimizing the product distribution system. This can result in reduced distribution costs and more effective marketing of products that require swift delivery.

The proposed framework offers a comprehensive approach to utilizing artificial intelligence in online marketing. This can aid organizations in identifying and prioritizing solutions to various marketing challenges. By implementing the methods outlined in this research, businesses can solve a significant percentage of marketing issues and move closer towards achieving their marketing objectives. Based on the findings of this study, the three main benefits for organizations can be summarized as follows:

According to the prioritization of different components of the marketing mix, this research suggests that businesses should prioritize the use of artificial intelligence in online advertising and customer outreach, followed by product design and value proposition creation. These areas involve understanding the market and interacting with customers. Pricing and cost design are equally important, highlighting the need to balance customer needs with their ability to pay.

It is crucial for businesses to allocate equal attention to both customer needs and the design of costs according to their budget. Neglecting either of these areas can lead to an inadequate response to market demands. In contrast, the weight given to product distribution in this framework is relatively low, indicating that allocating significant budgets for the development of distribution strategies is not as important for a company's competitive power.

This framework can also function as a tool to evaluate the performance of businesses in applying artificial intelligence to their marketing strategies. By implementing a scoring model based on the weights obtained in this research, businesses can evaluate their AI-based marketing strategy and identify areas that require improvement.

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