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Artificial Intelligence for Big Data in Modern Marketing: A Review about Trends, Applications, and Challenges.

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Abstract: The rapid digital transformation has triggered an explosion in data generation, with its core impact on the marketing landscape. Big data, with huge volumes, speed, and variety, is thus a significant field of opportunities and challenges for marketers seeking to unravel actionable insights. Traditional approaches to data processing are only inefficient and unable to manage such scale and complexity of data. However, with the advent of AI, quite a few advanced tools can handle big data with greater efficiency, thus enabling better consumer understanding, personalization of marketing strategies, and quick decision-making. It has revolutionized marketing, where systems can now analyze big datasets, recognize patterns, and predict customer behaviors. From descriptive analytics, the shift toward predictive and prescriptive has empowered businesses to optimize campaigns toward enhanced customer experiences. This integration of AI means it can be done instantly, enabling real-time response and fostering more relevant consumer engagement. This review delivers a critical outlook on the current trends in AI, their application to marketing, and the challenges businesses face in implementing these new technologies. Ethical issues around data privacy, transparency, and bias in AI models are discussed. The paper highlights future research directions, including federated learning, quantum computing, and multimodal AI, which hold great promise for even further transformation of the marketing domain.

Keywords: Artificial Intelligence, Machine Learning, Big Data, Marketing, Predictive Analytics

I. Introduction

The digital revolution has ushered in an era of unprecedented data generation, profoundly transforming the marketing landscape [1]. The concept of big data, which encompasses vast volumes of diverse information generated from various sources such as social media interactions, e-commerce transactions, web browsing behaviors, and IoT devices, has become central to modern marketing strategies [2,3]. This explosion of data presents both opportunities and challenges for marketers seeking to gain deep insights into consumer behavior, preferences, and trends [4]. Effectively processing and analyzing these data to derive actionable insights has become a critical competitive advantage.

Traditional data processing methods are increasingly inadequate in handling big data due to its scale, speed, and unstructured nature [5]. Therefore, the emergence of Artificial Intelligence (AI) have offered advanced tools and techniques that enhance the ability to analyze big data more efficiently due to their intelligent systems capable of performing human-like tasks, such as data cleaning, data analysis, recognizing patterns, and making predictions (Figure 1) [6–8]. These technologies enable marketers to personalize strategies, optimize campaigns, and enhance customer experiences at an unprecedented scale. For instance, AI-driven predictive models can accurately forecast customer behavior, while continuously learn from new data, adapting to changing market conditions [9]. Integrating AI into marketing represents a paradigm shift from descriptive to predictive and prescriptive analytics. This shift has opened up new possibilities for improving customer segmentation, personalization, and campaign optimization [6]. Real-time processing capabilities allow marketers to respond to consumer interactions as they happen, enhancing the relevance and effectiveness of marketing efforts [10].

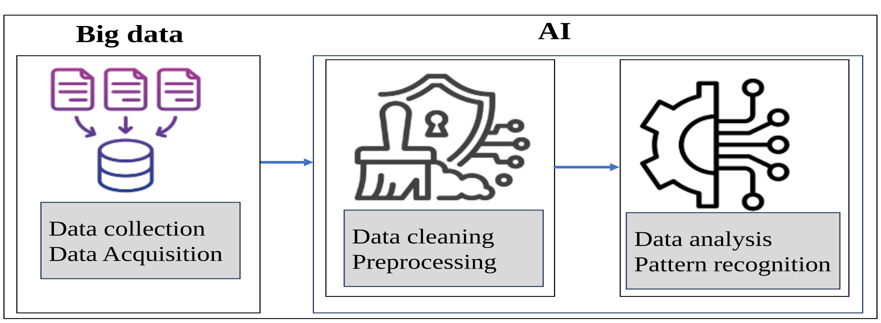

Figure 1: Application of AI and big data for marketing.

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Given the rapid evolution and increasing importance of AI in marketing and big data analysis, this review aims to provide a comprehensive overview of the current state of this field. It synthesizes recent advancements in AI applications, evaluates its impact on deriving actionable marketing insights, and explores real-world applications across various industries. Additionally, the review addresses the challenges and ethical considerations associated with using AI in marketing. Finally, the review outlines future research directions. This contribution seeks to bridge the gap between academic research and practical application, offering valuable insights for marketers and researchers navigating the complexities of big data in the digital age.

Theoretical Framework

In the current digital milieu, big data and AI confluence has become a cornerstone of modern marketing strategies. These technologies, each with unique characteristics and capabilities, collectively enable marketers to process vast amounts of data and make data-driven decisions with unprecedented accuracy and efficiency. This section explores the fundamental concepts underpinning these technologies and their synergistic role in transforming marketing practices.

Big data

Big data refers to the massive and continually growing datasets generated from various sources, including social media platforms, e-commerce transactions, IoT devices, and more. Initially described by its volume, velocity, and variety (3Vs), big data has since expanded to include additional dimensions such as Veracity, Variability, Visualization, and Value, forming the "7Vs" framework as shown in Figure 2 [11,12]. Volume reflects the enormous scale of data generated daily, mainly from digital interactions such as social media activity and online transactions. Managing and analyzing these large datasets requires advanced data storage solutions and processing techniques [13]. Velocity denotes the rapid speed at which data is produced and must be processed. In marketing, this entails the ability to analyze consumer interactions in real-time, allowing businesses to respond swiftly to emerging trends and behaviors effectively [5]. Variety refers to the diverse data types, ranging from structured data like customer purchase records to unstructured data such as social media posts and multimedia content. The ability to integrate and analyze this diverse data is crucial for gaining a comprehensive understanding of consumer behavior [14].

Veracity addresses the accuracy and reliability of data, which is essential for making informed marketing decisions. Ensuring data quality involves dealing with uncertainties and inconsistencies through techniques like data cleansing and validation [13]. Variability highlights the changing nature of data and its varying significance depending on how the data was generated. Marketers must be equipped to handle these fluctuations to maintain the relevance of their insights [12]. Visualization involves representing data in a graphical format to make complex data more accessible and actionable. Practical visualization tools are essential for communicating insights and facilitating decision-making [11]. While value emphasizes the importance of deriving actionable insights from raw data to drive business decisions and marketing strategies. Extracting meaningful Value from Big Data is a central challenge for marketers [12].

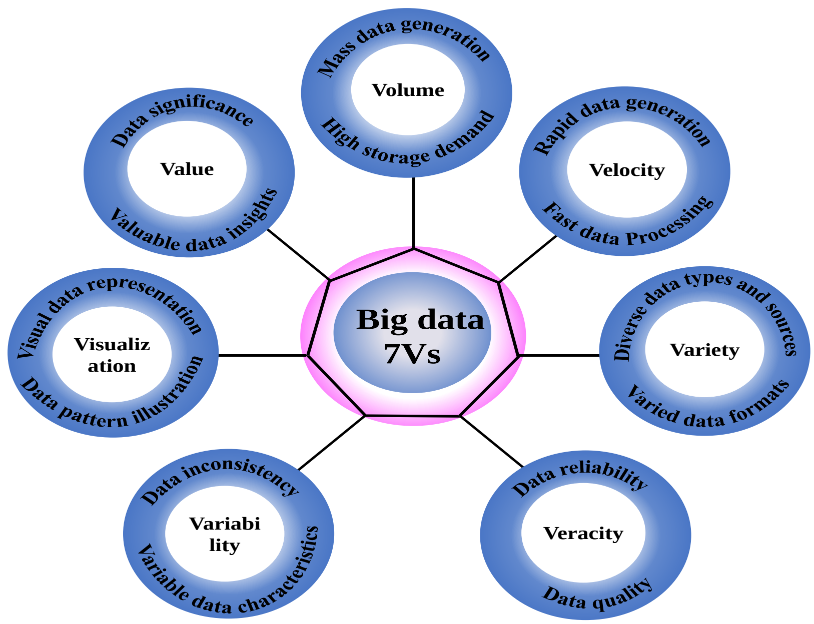

Figure 2 7Vs framework of big data.

AI

AI encompasses developing systems that can perform tasks typically requiring human intelligence, such as recognizing patterns, making decisions, and understanding natural language [15]. As shown In Figure 3, AI technologies, including natural language processing (NLP), computer vision, deep learning, and other techniques, enable machines to simulate human cognitive functions and continuously learn and improve from data [9,16]. AI's capabilities extend to automating complex tasks, enhancing

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personalization, and providing real-time analytics in marketing. For example, AI-powered sentiment analysis can process vast amounts of unstructured text data from social media to gauge consumer opinions, while AI-driven recommendation systems can personalize marketing content based on individual user preferences [17,18]. Another example is bots, which improve customer engagement by providing continuous support, lowering error rates, and freeing up human agents for difficult situations [16,19].

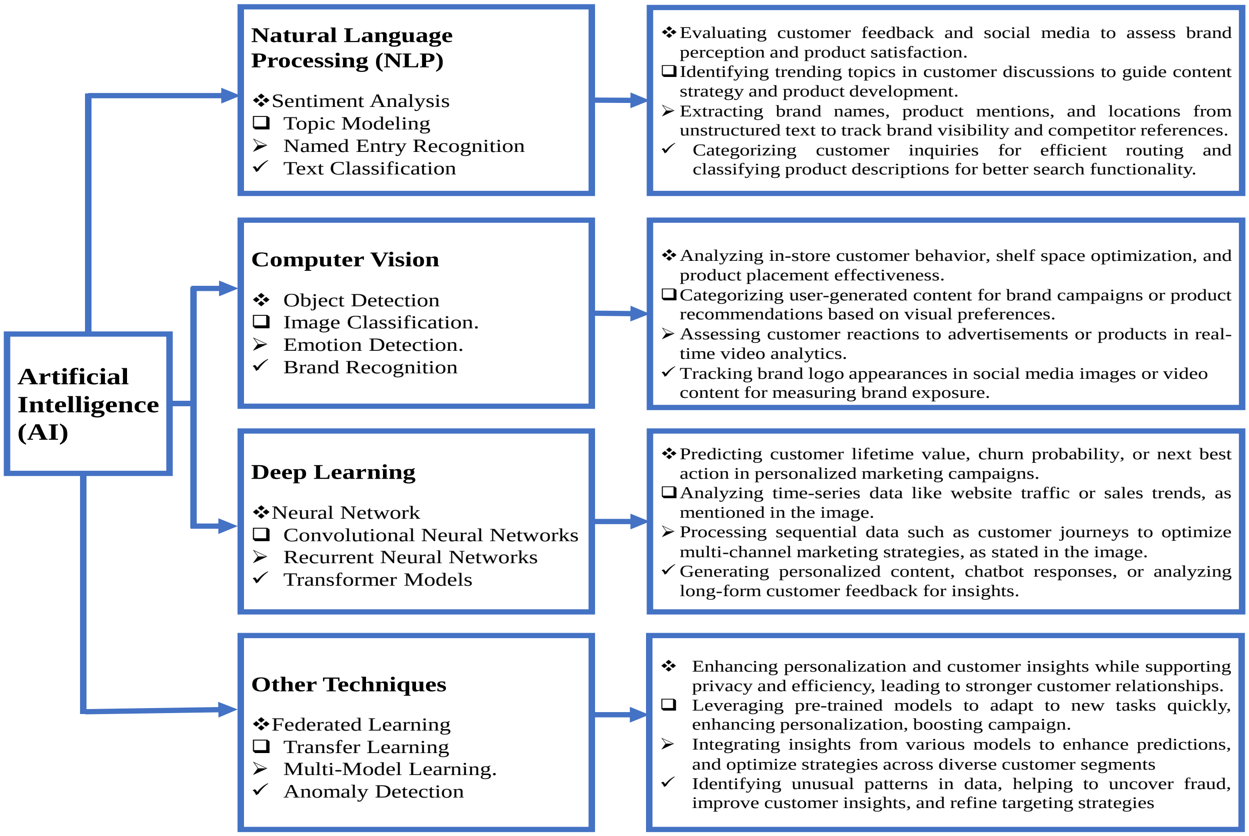

Figure 3 Summary of the application of AI technologies for marketing

Machine learning (ML), a subset of AI, focuses on developing algorithms that enable computers to learn from and make predictions based on data [16,17]. ML techniques are broadly categorized into different types, including supervised learning, unsupervised learning, semi-supervised, and reinforcement learning, as shown in Figure 4. Supervised learning utilizes labeled datasets to train algorithms for tasks such as regression and classification. Examples of Supervised learning algorithms include Linear Regression (LR), Decision Trees (DT), Random Forests (RT), Gradient Boosting Machine (GBM), Neural Networks (NN), and support vector machines (SVM), which are valuable in marketing for tasks such as the prediction of customer behavior, customer segmentation, and sales forecasting [14,20].

Unsupervised learning is a technique that identifies hidden patterns or intrinsic structures in unlabeled data. This approach employs various algorithms, including Self-Organizing Maps (SOM), to uncover patterns and relationships within the dataset. Clustering algorithms, such as K-Means, Fuzzy K-Means, and Hierarchical Clustering, are utilized for tasks like customer segmentation and market basket analysis, aiming to reveal groupings or associations in the data. Furthermore, dimensionality reduction techniques, such as Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE), serve to reduce the dimensionality of the data while preserving its essential characteristics [6,21]. Semi-supervised and reinforcement learning combines a small amount of labeled data with a large amount of unlabeled data or learns from the environment through trial and error. These techniques are particularly effective in dynamic environments such as real-time bidding in digital advertising [22–24].

Semi-supervised classification can improve customer behavior targeting and reduce labeling costs, while semi-supervised regression predicts continuous metrics like customer lifetime value. Self-training iteratively labels and retrains on unlabeled data, refining customer segmentation, while co-training utilizes diverse features to improve classification by training two models simultaneously [25]. In Reinforcement Learning (RL), proximal policy optimization and policy gradient methods optimize long-term pricing and ad allocation strategies. Multi-armed bandits test multiple strategies at once, balancing exploration and exploitation, while Deep Q-networks (DQN) and Q-learning personalize marketing by learning optimal actions based on customer interactions [26]. Therefore, unlike traditional statistical methods, ML algorithms can process structured and unstructured data, such as customer interactions, purchase history, and social media activity, making them indispensable for real-time marketing insights and automation.

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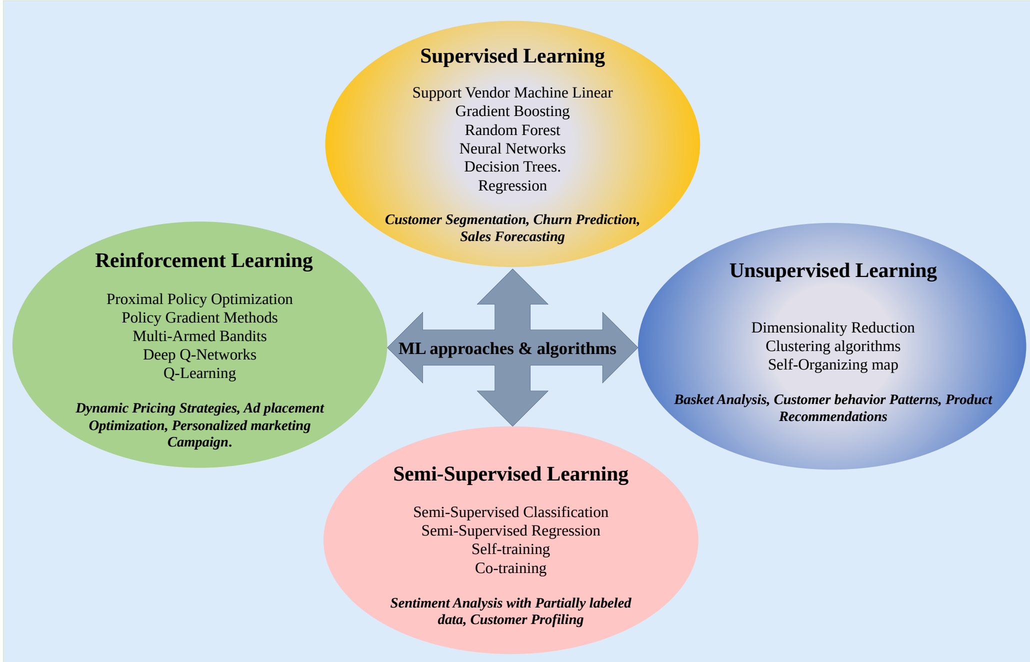

Figure 4 Overview of ML approaches and algorithms for marketing

AI for Big Data processing

The vast amount of digital platform data offers opportunities and challenges for optimizing customer engagement and decision-making. This section covers big data sources, data collection and integration methods, and the importance of data cleaning. Advanced ML algorithms help analyze data, uncover insights, identify trends, and personalize marketing strategies, fostering innovation in a competitive market.

Data source, data collection and integration

Big data in marketing originates from various sources (Figure 5), each providing unique insights into consumer behavior, market trends, and business performance. Understanding these sources is vital for marketers seeking to extract actionable intelligence. Efficient data collection and integration are fundamental to successful big data marketing initiatives. With the increasing volume and variety of data sources, AI tools have become essential for gathering, organizing, and consolidating marketing data into a unified system. This enables marketers to efficiently process large datasets, uncover patterns, and make data-driven decisions.

Figure 5 Source of big data for marketing

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Social Media Platforms

Social media platforms, such as Facebook, Instagram, Twitter, TikTok, Weibo, and LinkedIn, are among the richest marketing data sources, generating vast amounts of user-generated content like posts, comments, likes, shares, and interaction patterns [2]. This data provides real-time insights into consumer sentiment, brand perception, and emerging trends [27,28]. Marketers can access this data through APIs, such as the X API and Facebook Graph API, which allow direct interaction with user-generated content and behaviors [29]. Advanced social listening tools, like Brandwatch and Sprout Social, further enhance data collection by employing natural language processing (NLP) to interpret the context, sentiment, and trends in social media conversations. These tools track brand mentions and help categorize content and predict viral trends, offering marketers a more comprehensive understanding of consumer behavior and enabling dynamic, data-driven marketing strategies [30].

Internet of Things (IoT) Devices

IoT devices, such as smart speakers, wearable technology, and connected vehicles, provide marketers with valuable data on consumer preferences and behaviors [31,32]. For example, smart home devices can track media consumption patterns, while wearable fitness trackers offer insights into user health and lifestyle choices [33]. This data enables highly personalized marketing strategies, aligning messages and product offerings with individual consumer habits [34]. The proliferation of IoT devices has expanded marketing data collection, with platforms like AWS IoT Core and Google Cloud IoT facilitating real-time data gathering from connected devices. These platforms use edge computing and AI to process data at the source, reducing latency and enabling instant decision-making. Retailers can leverage IoT data to track product interactions, analyze foot traffic, and monitor real-time customer responses, enhancing customer engagement and optimizing operations [35].

Customer Relationship Management (CRM) Systems

CRM systems collect and store extensive data about customer interactions, including purchase history, service interactions, and communication preferences [36,37]. This data helps marketers build detailed customer profiles and map complex customer journeys, enabling more effective targeting and personalized marketing efforts. AI-enhanced CRM systems can predict customer behaviors, such as churn risks, and suggest customized engagement strategies [38–40].

Websites

Websites provide marketers with a wealth of data through web analytics and scraping. Web analytics deliver comprehensive insights into website traffic, user behavior, and e-commerce transactions by tracking page views, click patterns, conversion rates, and user flow [41,42]. Advanced tools like heat maps and session recordings further enhance understanding of user interactions, enabling businesses to optimize the customer journey and refine digital marketing strategies [43]. Integrating web analytics with other data sources, such as CRM systems, offers a more complete picture of the customer experience [44].

In addition to analytics, web scraping is a powerful technique for extracting data from websites [45,46]. While traditional tools like BeautifulSoup and Scrapy are effective for parsing HTML and XML files, modern AI-driven solutions such as Octoparse and Import.io have improved the efficiency and scalability of data collection. These tools use machine learning to navigate dynamic content, understand complex webpage structures, and bypass anti-scraping measures. For example, Octoparse's computer vision techniques allow for the recognition and extraction of visually similar elements across different sites, making it particularly useful for tracking competitor prices and aggregating product data. Web analytics and web scraping offer marketers valuable tools to gather and integrate data for more effective decision-making and strategy development [47].

Mobile Applications

Mobile applications generate vast amounts of real-time and context-rich data, including location information, usage patterns, and purchase behaviors [48]. This data allows marketers to develop time-sensitive and personalized marketing strategies, such as location-based offers or push notifications tailored to individual user preferences. Integrating mobile app data with social media and IoT data creates a complete picture of consumer behavior, enhancing personalization efforts [6].

Point of Sale (POS) Systems

POS systems are crucial for capturing detailed transactional data during the purchasing process. They provide valuable insights into consumer purchasing patterns, peak shopping times, and product popularity [49]. When integrated with customer loyalty programs, POS data supports the development of personalized marketing approaches, helping businesses foster customer retention and tailor their marketing strategies based on historical purchasing behavior [50]

Surveys and Market Research

Surveys remain a valuable source of direct consumer insights, offering data on consumer preferences, opinions, and attitudes. Advanced survey techniques, like mobile ethnography and real-time experience tracking, expand the scope and depth of data collected [43,51]. AI-driven survey analysis enhances the ability to process unstructured data from open-ended responses, revealing patterns that human analysts might miss [52]. Each source contributes distinct yet complementary insights into consumer behavior, making them integral to any data-driven marketing strategy. The effective integration of data from these

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sources allows businesses to develop a comprehensive and dynamic view of their customer base, enhancing the personalization and precision of marketing efforts.

Customer Data Platforms (CDPs)

CDPs like Segment and Tealium have revolutionized data integration by creating a coherent view of each customer [53]. CDPs unify data from multiple touchpoints, including websites, mobile apps, social media, and offline interactions, using ML to resolve identity conflicts and accurately link different data points to the same individual across various platforms. These platforms also employ predictive analytics to forecast customer behaviors, enabling marketers to deliver highly personalized and dynamic marketing campaigns [54].

Data Lake Solutions

As the volume of marketing data continues to grow, data lakes have emerged as more flexible and scalable alternatives to traditional data warehouses. Solutions like Apache Hadoop and Amazon SageMaker provide the infrastructure for storing massive amounts of structured and unstructured data [13,55]. These data lakes are often integrated with AI tools for advanced analytics. For example, Amazon SageMaker can build, train, and deploy ML models directly on stored data, facilitating the analysis of historical data and enabling long-term trend identification [13]. Effective data collection and integration are essential for building a solid foundation for big data analysis in marketing. With AI tools, businesses can gather and unify data from disparate sources, enabling a comprehensive view of customer behavior and preferences.

Data Cleaning and Preprocessing

Data cleaning and preprocessing are crucial in preparing marketing big data for analysis. Given the diverse and often messy nature of the data collected from various sources, refining and standardizing the information is essential to ensure accuracy and reliability. AI techniques are vital in automating and enhancing these processes and preparing the data for advanced analytics.

Data Deduplication

Data duplication is common, especially when integrating information from multiple sources. Duplicate entries can skew analysis, leading to misleading insights. Traditional rule-based deduplication methods are replaced by more advanced techniques, such as Locality-Sensitive Hashing (LSH), which quickly identifies similar items in large datasets [56]. Moreover, deep learning models can recognize semantic similarities between records, even if the data does not match exactly, ensuring higher precision in deduplication efforts [23].

Missing Value Imputation

Handling missing data is critical to prevent biased analysis, which can lead to flawed marketing strategies. Simple techniques like mean or median replacement are often inadequate for complex datasets [23]. Advanced imputation methods, such as Multiple Imputation by Chained Equations (MICE), leverage the relationships between variables to estimate missing values more accurately [57]. Additionally, deep learning models like Denoising Autoencoders have shown promise in imputing missing values in high-dimensional datasets, capturing complex non-linear relationships, and improving overall data quality [58].

Outlier Detection

Outliers can distort data analysis, but distinguishing between meaningful outliers and errors is essential [58]. ML techniques, such as Isolation Forests and One-Class SVMs, effectively detect anomalies in high-dimensional data, making them particularly useful in marketing for identifying fraudulent transactions or pinpointing high-value customers. More recent approaches use Autoencoders to learn standard patterns within data and flag deviations, providing an automated way to manage anomalies in large datasets [59].

Data Normalization and Standardization

Normalization and standardization ensure that different data points contribute equally to analysis, especially with diverse data types like purchase history, demographic information, and browsing behavior. Techniques like Principal Component Analysis (PCA) and Canonical Correlation Analysis (CCA) help reduce the dimensionality of datasets while preserving important features. Adaptive normalization methods, which adjust based on the statistical properties of the data, are becoming more common in optimizing data preparation for ML models [21,60]. Effective data cleaning and preprocessing are essential for maintaining the integrity and accuracy of marketing data. By applying advanced ML techniques, businesses can significantly enhance the quality of their data, ensuring that it is clean, complete, and ready for analysis. This process is crucial for deriving actionable insights that drive data-driven marketing strategies and improve decision-making.

Data Analysis and Pattern Recognition

Data analysis and pattern recognition are the core processes that transform raw marketing data into actionable insights. With the vast amounts of structured and unstructured data collected from various sources, ML algorithms are essential for uncovering patterns, predicting consumer behavior, and enabling data-driven decision-making.

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Clustering Algorithms for Customer Segmentation

Clustering algorithms are widely used to segment customers based on behavior, preferences, or demographics, allowing marketers to target specific groups more effectively [21]. The K-Means algorithm remains popular due to its simplicity, but more advanced techniques like DBSCAN (Density-Based Spatial Clustering of Applications with Noise) can identify clusters of arbitrary shapes and handle noise in the data [61]. Hierarchical clustering methods offer deeper insights by revealing nested relationships between customer segments [61]. In recent years, Spectral Clustering has shown promise for segmenting customers based on social network interactions, further enhancing precision in customer segmentation [21].

Association Rule Mining for Understanding Consumer Behavior

Association Rule Mining (ARM) identifies correlations between physical or virtual items that frequently appear together in consumers' shopping baskets. This method, often applied to e-commerce platforms, helps marketers discover patterns in customer buying behavior [62]. The Apriori and FP-Growth algorithms are commonly used for mining association rules [63]. At the same time, newer approaches like Fuzzy Association Rule Mining are more effective at handling numerical data, allowing for a more nuanced understanding of customer preferences and product relationships [62].

RF for Predictive Modeling

RF have become a go-to algorithm for predictive tasks in marketing, particularly for customer churn prediction, lifetime value estimation, and identifying key factors influencing purchasing decisions [9]. This ensemble method combines multiple decision trees to improve accuracy and robustness while reducing overfitting [64]. Oblique Random Forests have recently been used to capture complex decision boundaries, improving predictive accuracy in marketing contexts.

GBM for High-Accuracy Predictions

GBM such as XGBoost and LightGBM, are widely used for tasks like click-through rate prediction and customer response modeling. As ensemble models, these algorithms offer high predictive accuracy and are particularly effective with large datasets. XGBoost, in particular, is known for its computational speed and regularization capabilities, which prevent overfitting. LightGBM excels in handling categorical data and is optimized for large-scale marketing applications involving vast customer data [65]. Both algorithms have been enhanced with better parameter tuning, incorporating swarm intelligence techniques like the Artificial Bee Colony (ABC) algorithm to optimize performance [66].

AI-Driven Pattern Recognition and Anomaly Detection

AI techniques have revolutionized pattern recognition, particularly in analyzing complex and unstructured data such as images, text, and video [67]. Deep Learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), excel at identifying patterns in high-dimensional marketing data, such as customer interactions or sales trends [68,69]. For instance, CNNs are used to analyze time-series data like website traffic, while RNNs are particularly effective for processing sequential data, such as customer journeys [20]. Autoencoders are increasingly employed for anomaly detection, compressing high-dimensional data, and identifying deviations from normal behavior, making them valuable for fraud detection and unusual market trends [70]. ML techniques for data analysis and pattern recognition empower marketers to process vast datasets, uncover hidden insights, and make real-time, data-driven decisions. By leveraging these tools, businesses can optimize customer segmentation, predict behavior, and enhance marketing strategies, ultimately driving growth and improving customer engagement.

Specific techniques

Several specific AI techniques are vital in processing and analyzing big data for marketing. These methods are essential for uncovering insights from complex, high-volume datasets, enabling marketers to enhance decision-making, personalize campaigns, and optimize marketing strategies. The following techniques are integral to achieving these outcomes.

NLP for Text Analysis

NLP enables systems to process and analyze large volumes of unstructured text data, such as social media posts, customer reviews, and online interactions [71]. Advanced NLP models like BERT and GPT are widely used for sentiment analysis, topic modeling, and text classification [58,71]. These models help marketers gauge consumer sentiment in real time, classify customer inquiries, and identify trending topics in customer feedback. Sentiment analysis, in particular, is valuable for understanding brand perception and customer satisfaction. NLP-driven Named Entity Recognition (NER) systems can rapidly extract structured information about brands, products, and competitors from vast datasets, allowing marketers to track brand mentions and monitor market dynamics [52].

Computer Vision for Image and Video Analysis

Computer vision techniques enable visual data analysis, such as images and videos, which are increasingly important in marketing due to the rise of social media and user-generated content [72]. CNNs such as YOLO are commonly used for image classification and object detection, allowing marketers to track brand visibility, analyze user-generated content, and even assess customer emotions based on facial expressions [73,74]. For example, YOLO can process millions of social media images to

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identify products, logos, and other visual elements associated with a brand, helping businesses measure brand exposure. Emotion detection algorithms, which analyze video frames to interpret emotional responses to products or advertisements, provide deeper insights into consumer reactions at scale [75].

RL for Adaptive Marketing Strategies

RL is a cutting-edge AI technique that enables systems to learn from dynamic environments and make real-time decisions [76]. In marketing, RL is particularly effective for optimizing pricing strategies and real-time bidding in programmatic advertising. Multi-armed bandit algorithms, such as Contextual Bandits, continuously process user interaction data to optimize content delivery and allocation of resources across marketing channels [77]. More advanced methods, such as Deep Q-Networks (DQNs) and Policy Gradient Methods, are used to make decisions in complex scenarios, such as adjusting bids in real time based on changing user behaviors and market conditions [76].

Federated Learning and Privacy-Preserving Techniques

As privacy concerns grow, Federated Learning (FL) has emerged as a solution that allows ML models to be trained on decentralized data without sharing raw data between organizations. This technique helps businesses leverage insights from distributed datasets while adhering to privacy regulations [78]. FL enables collaborative learning without compromising consumer privacy, making it an increasingly attractive option for industries handling sensitive data.

Transfer Learning for Efficient Model Adaptation

Transfer learning (TL) is a technique where a pre-trained model is adapted to a new task with limited data. In marketing, this allows for the efficient use of pre-trained models, such as those built for image recognition or language understanding, to perform tasks like brand recognition or customer sentiment analysis with minimal additional training. This technique significantly reduces the computational and data resources needed to train models from scratch, enabling faster deployment of AI solutions in marketing applications [52,79]. These AI and ML techniques offer powerful tools for handling the complexities of big data in marketing. By applying these advanced methods, businesses can derive actionable insights, create more personalized customer experiences, and optimize real-time marketing strategies, driving engagement and profitability. A summary of Data Analysis and Pattern Recognition models for marketing is provided in Table 1.

Table 1 A summary of Data Analysis and Pattern Recognition models for marketing

Model Types	Models	Application
Clustering	K-Means, DBSCAN, Hierarchical, and Spectral	Segment customers by behavior, preferences, or demographics for effective targeting. K-Means is simple, DBSCAN handles noise and irregular clusters, Hierarchical reveals nested relationships, and Spectral enhances precision using social network interactions.
Association rule mining	Apriori, FP-Growth	Uncovers correlations between items in shopping baskets, aiding marketers in identifying buying patterns.
	Fuzzy association rule mining	Offers deeper insights by effectively handling numerical data.
Ensemble	RF	Predicting marketing tasks like customer churn and lifetime value estimation, improving accuracy, and reducing overfitting
	GBM	Famous for click-through rate prediction, it offers high accuracy and efficiency.
NN	CNNs,	Identifying patterns in complex data, image, video, and time-series analysis
	RNNs	Processing sequential data like customer journeys, enabling better decision-making and strategy optimization.
NLP	BERT, GPT	BERT and GPT analyze unstructured text data, like social media posts and customer reviews, for sentiment analysis, topic modeling, and text classification, helping marketers gauge consumer sentiment and identify trends.
	NER	Extracts structured information about brands and products, aiding in tracking mentions and market dynamics.
Other	RL	Enables real-time decision-making in dynamic environments by optimizing pricing and bidding through Contextual Bandits and advanced methods like Deep Q-Networks to adjust bids based on

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		user behavior.
	FL,	Allows ML models to train on decentralized data without sharing raw data, enabling insights while maintaining privacy and compliance, making it suitable for sensitive data industries.
	TL	Adapts pre-trained models for new tasks with limited data, enhancing brand recognition and sentiment analysis. This method reduces training resources, enabling faster AI deployment to improve engagement and profitability.

Applications of AI in Marketing

Due to its ability to process vast amounts of data and derive actionable insights. AI enhance customer segmentation, personalize interactions, optimize campaigns, and predict consumer behavior, ultimately leading to more effective and data-driven marketing strategies, as shown in Figure 6.

Customer Segmentation and Profiling

AI significantly improve customer segmentation and profiling by moving beyond traditional demographic-based methods. Instead, ML models can identify complex behavioral patterns, preferences, and needs across diverse data sources; techniques like deep learning enable multidimensional customer profiling, allowing for dynamic segmentation that adapts in real time to changes in consumer behavior [80]. This results in highly personalized marketing strategies, which enhance customer satisfaction and loyalty by tailoring messages, offers, and products to specific groups [80,81].

Personalization and Customer Experience

Personalization has become a key component of modern marketing, driven by AI technologies that analyze individual customer data to deliver tailored experiences. Recommendation systems powered by ML algorithms have evolved to incorporate contextual understanding, such as browsing history, past purchases, and external factors like location and time of day [18]. These systems recommend products or services with increasing accuracy, particularly in cold-start scenarios with limited historical data [82]. Additionally, sentiment analysis using multimodal data (text, voice, and facial expressions) enables marketers to gauge customer emotions during interactions, helping to personalize responses and improve overall customer engagement [79,83].

Predictive Analytics for Consumer Behavior

Predictive analytics is critical in forecasting customer behavior and informing marketing strategies. Predictive models such as RF can estimate the likelihood of future actions, such as purchases, churn, and product preferences, by analyzing historical data, such as transaction histories and browsing patterns [84]. These models enable businesses to implement next-best offer strategies, anticipate customer needs, and allocate resources more effectively. The integration of behavior informatics allows for a deeper understanding of customer actions, further enhancing the accuracy of predictions and improving decision-making processes in marketing [9].

Campaign Optimization

AI-driven technologies allow for the real-time optimization of marketing campaigns across multiple channels [85]. Multi-armed bandit algorithms dynamically allocate resources by learning from real-time performance data, ensuring optimal campaign effectiveness. These algorithms can automatically adjust budget allocation, content personalization, and bidding strategies based on campaign performance metrics [86]. In programmatic advertising, RL techniques are essential for real-time bidding (RTB), where AI models analyze user data in milliseconds to determine the best bids for targeted ads [87]. Predictive analytics and historical campaign data further enhance campaign performance by enabling marketers to forecast outcomes and make adjustments proactively [85,88].

Dynamic Pricing and Demand Forecasting

AI have transformed pricing strategies by enabling dynamic pricing based on real-time data analysis. Algorithms consider market demand, competitor pricing, and customer behavior to set optimal prices that maximize revenue and maintain customer satisfaction. ML models continuously learn from new data, refining pricing strategies to respond to shifting market conditions. Similarly, demand forecasting models leverage historical sales data, seasonal trends, and external variables like weather or local events to predict future demand [89]. These insights allow businesses to optimize inventory management, reducing waste and ensuring product availability when needed [90].

Chatbots and Conversational AI for Customer Service

Chatbots and conversational AI have revolutionized customer service, offering 24/7 support and enhancing customer engagement [91]. Powered by NLP and ML, chatbots provide personalized responses based on customer queries, ensuring faster and more efficient interactions [92,93]. Recent advancements in emotional intelligence integration have enabled chatbots to recognize customer emotions, improving the overall quality of service [94]. By analyzing past interactions, chatbots can continuously improve, learning to offer more relevant and personalized solutions to customers over time. These AI-driven tools also reduce human labor costs while maintaining high service levels, making them integral to modern omnichannel marketing strategies [39].

AI applications in marketing allow businesses to process data more efficiently, enhance customer engagement through personalization, optimize campaigns in real-time, and predict consumer behavior with greater accuracy. These technologies provide a competitive advantage by enabling data-driven decisions that drive customer loyalty, improve ROI, and increase marketing effectiveness across industries.

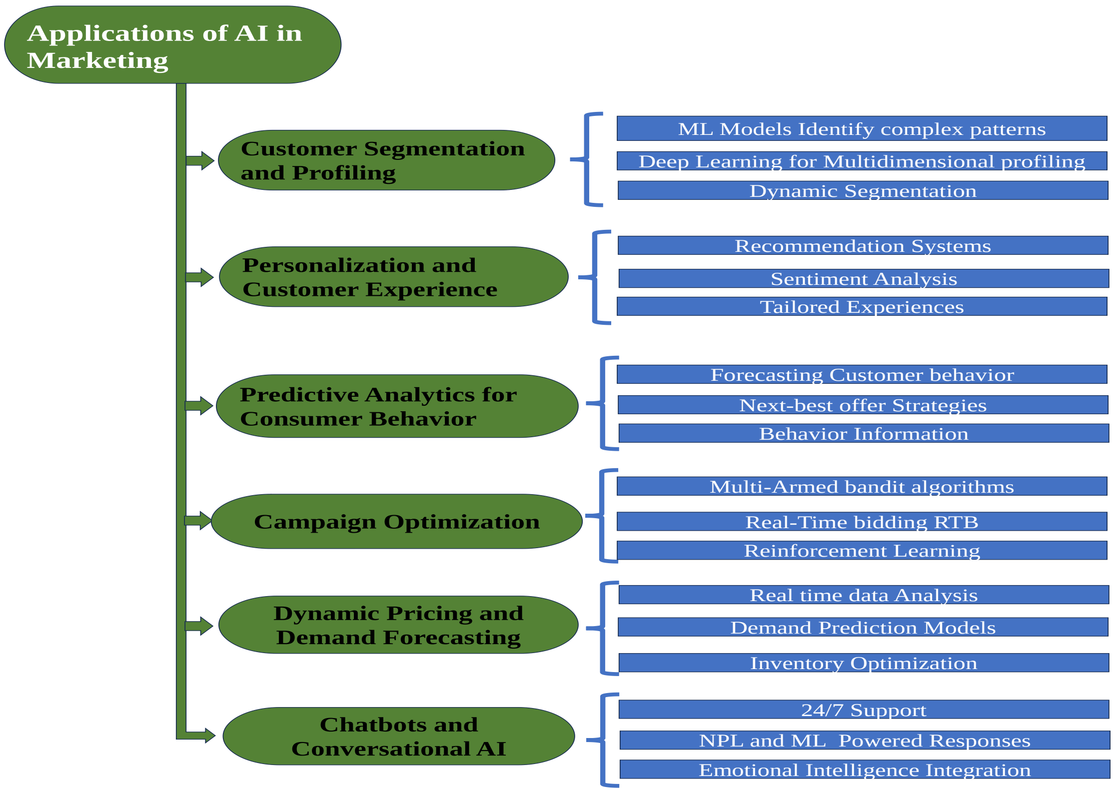

Figure 6: Applications of AI in Marketing

Benefits and Impact on Marketing Insights

By automating data processing and enabling real-time analysis, AI transform marketers' understanding of consumer behavior, optimize campaigns, and make data-driven decisions.

Efficiency and Speed in Data Processing

AI's ability to process vast amounts of structured and unstructured data at unprecedented speeds is one of its most significant advantages. Unlike traditional methods requiring extensive manual effort, AI-driven systems can analyze multiple data streams simultaneously [22]. This capability enables marketers to identify emerging trends and customer preferences in real time, allowing them to react swiftly to market changes [7,95]. For instance, AI systems can process millions of social media posts, customer interactions, and transaction records in hours, tasks that would have taken human analysts weeks to complete. The speed of AI-driven analysis provides a competitive advantage, enabling businesses to capitalize on insights while they are still relevant and timely [30].

Enhanced Decision-Making Capabilities

AI improve decision-making by offering a more comprehensive view of marketing data [96]. These technologies enable marketers to integrate data from diverse sources, such as sales figures, weather patterns, and social media sentiment, creating a multifaceted consumer behavior analysis. AI enhances the speed of analysis and the accuracy of insights, leading to more informed decisions. AI testing thousands of hypotheses simultaneously helps marketers identify the most promising strategies, allowing them to focus on high-impact areas. AI augments human decision-making by giving marketers more profound insights into consumer preferences and market trends, which helps refine marketing strategies and improve overall business performance [97,98].

Improved Accuracy and Precision in Targeting

AI-driven targeting significantly increases the precision of marketing efforts [97]. In addition, by analyzing vast datasets, ML algorithms can create highly accurate customer segments based on behavioral patterns, preferences, and purchasing habits. This

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level of precision allows marketers to deliver personalized content and offers that resonate with specific audiences, leading to higher engagement and conversion rates [20]. AI systems also continuously refine targeting strategies using real-time data, enabling marketers to adapt to changing consumer behaviors and market conditions, further improving the effectiveness of their campaigns [99].

Cost-Effectiveness and Improved ROI

Implementing AI in marketing leads to significant cost savings and improved return on investment (ROI). While the initial setup and integration of AI technologies can be expensive, the long-term benefits often outweigh the costs. AI optimizes ad spending by targeting high-value customers more effectively and reducing wasted resources on less promising prospects. Automation also reduces the need for manual labor in tasks like data analysis, campaign optimization, and customer service. This combination of higher efficiency, better targeting, and reduced labor costs translates to an overall improvement in ROI [100]. Companies that leverage AI in their marketing efforts experience improved performance and financial outcomes due to more precise resource allocation and higher conversion rates [101].

Real-Time Insights and Agile Marketing

AI enables marketers to gain real-time insights, allowing for more agile marketing practices. With real-time data processing, businesses can adjust their strategies based on immediate feedback from consumers. This dynamic approach, often called agile marketing, allows companies to respond rapidly to changing market conditions, consumer sentiment, and emerging trends [102]. By continuously analyzing data, AI-powered systems can optimize real-time content delivery, campaign performance, and customer engagement, keeping marketing strategies relevant and effective [103].

Uncovering Hidden Patterns and Trends

AI excels at uncovering hidden patterns in large, complex datasets that traditional analysis methods may miss. By identifying subtle correlations and trends, ML algorithms provide marketers with new insights into consumer behavior and market dynamics. For instance, AI can analyze transactional data, customer interactions, and external factors like competitor actions to discover unique trends that inform pricing strategies or product recommendations. This ability to reveal deep, previously unnoticed insights helps businesses stay ahead of the competition and tailor their strategies to meet evolving customer needs [104,105]. AI and ML offer transformative benefits to marketing, from improving the speed and accuracy of data processing to enhancing decision-making and delivering precise, personalized marketing strategies. These technologies help businesses uncover hidden insights, optimize resources, and drive growth by empowering marketers to make smarter, data-driven decisions in real-time. The result is greater efficiency and a deeper understanding of consumer behavior, leading to improved customer engagement and overall business performance.

Case Studies and Real-world Examples

AI and ML have been widely adopted by leading companies across various industries, significantly enhancing their marketing strategies. The following case studies illustrate how AI and ML technologies are used in real-world scenarios to drive personalization, optimize campaigns, and improve customer experiences.

Nike's Data-Driven Product Design

Nike has been at the forefront of utilizing big data and AI to inform product design and marketing. Customers can customize shoes through its Nike by You platform, generating valuable data on consumer preferences. Nike employs ML to analyze this data, identifying emerging trends that inform future product designs. Additionally, Nike's acquisition of Celect, an AI-powered analytics platform, has enhanced its ability to predict local demand for specific products, optimizing inventory distribution and reducing waste [106]. Nike also uses AI-powered tools in its Nike Fit app, which scans customers' feet to recommend the perfect shoe size, improving customer satisfaction and gaining insights into foot dimensions across demographics.

Coca-Cola's AI-Driven Marketing Campaigns

Coca-Cola has implemented AI in its marketing strategy, mainly focusing on personalization and real-time optimization. One example is Coca-Cola's use of AI in vending machines, where dynamic pricing is adjusted based on real-time factors like demand, weather, and local events, leading to increased sales and improved customer satisfaction [18]. Coca-Cola also uses AI for content creation, such as developing advertising scripts, which, while requiring human oversight, bring fresh, data-driven perspectives to creative processes. Additionally, by analyzing consumer data across different channels, Coca-Cola personalizes its marketing messages to match individual preferences, significantly enhancing engagement and conversion rates [5,18,85].

Target corporation

Target has been a leader in using predictive analytics to optimize its marketing strategies. Target's AI-driven system forecasts product demand by analyzing vast historical sales data, allowing the company to optimize inventory management [107]. During the COVID-19 pandemic, Target's predictive models quickly adapted to shifts in consumer behavior, such as increased demand for home office supplies and fitness equipment. Additionally, Target uses a proprietary algorithm called Guest ID, which tracks individual customer interactions, enabling the company to personalize offers and recommendations [108]. This personalized

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approach has increased engagement and average transaction values [109,110]. Target also integrates AI-powered visual search into its mobile app, allowing customers to upload images of products they like and receive recommendations for similar items available at Target stores [108].

Starbucks' AI-Enhanced Location Intelligence and Personalization

Starbucks leverages AI to optimize store locations and customer experiences through its mobile app. The company's Deep Brew AI system analyzes data points like foot traffic, demographics, and weather to select new store locations strategically. This data-driven approach minimizes the risk of cannibalization between stores and ensures optimal customer reach [85,111]. Starbucks also uses ML algorithms to personalize its mobile app, providing tailored product recommendations based on each customer's purchase history, preferences, and time of day. This personalization has significantly increased customer loyalty and engagement. Furthermore, Starbucks applies predictive analytics to optimize inventory management, ensuring popular products are in stock based on forecasted demand [112]. These case studies showcase how companies across different industries leverage AI to improve their marketing strategies. From optimizing inventory and personalizing customer experiences to dynamic pricing and predictive analytics, AI-driven insights are helping businesses make more informed decisions, reduce operational inefficiencies, and deliver more targeted, effective marketing campaigns.

Challenges, Future perspectives and Ethical considaration

Integrating AI, ML, and big data into marketing offers substantial benefits, but also presents several challenges and limitations that businesses must overcome to unlock their full potential. As AI technologies continue to evolve, emerging trends and areas of research are reshaping the future of marketing, promising to not only enhance the capabilities of AI-driven strategies but also address existing challenges.

Challenges and limitations

Data Integration and Quality

A major challenge in marketing big data lies in integrating diverse data sources, such as social media, IoT devices, web analytics, and CRM systems, often using different formats and structures. Without proper integration, companies face data silos that prevent comprehensive analysis, reducing the ability to make informed marketing decisions [103,113]. Additionally, ensuring the quality of this data is essential; inaccuracies, inconsistencies, and missing values can lead to poor predictions and ineffective marketing strategies. Rigorous data cleansing and quality control are necessary to maintain reliable insights [103,114].

Data Storage and Management

The sheer volume of marketing data requires advanced storage solutions, as traditional methods are insufficient for scale and complexity. Data lakes and cloud-based systems are crucial to storing and managing this data while ensuring accessibility and security. Compliance with regulations like the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) also adds complexity to data management, as companies must implement stringent data protection measures [113,115].

Data Privacy, Security, and Ethical Concerns

Data privacy and security remain significant challenges, particularly with the increasing amounts of personal data collected. Regulations such as GDPR and CCPA enforce strict guidelines on data usage, and non-compliance can lead to penalties and a loss of consumer trust [115,116]. AI models are also susceptible to ethical issues like algorithmic bias, where biased training data can lead to unfair targeting of specific demographic groups. Moreover, the "black box" nature of many advanced AI models raises concerns over accountability and transparency, making it difficult for marketers to explain decision-making processes [117]. Organizations are responding by adopting privacy-enhancing technologies like FL and differential privacy and establishing AI ethics frameworks tailored to marketing applications [118,119].

Data Analysis

Another critical hurdle is extracting actionable insights from vast amounts of unstructured and semi-structured data (e.g., text, images, videos). Marketers must utilize advanced AI analytical tools that require specialized knowledge and computational resources. Implementing these tools effectively demands substantial investments in both infrastructure and talent, presenting further difficulties for businesses, especially those with limited budgets [103,114].

Interpretability of ML Models

Many ML models, particularly deep learning algorithms, function as "black boxes," making it difficult to interpret how decisions are made. This lack of transparency can generate skepticism, especially when AI-driven decisions impact customer experiences [120]. The growing field of Explainable AI (XAI) seeks to address these issues by offering insights into how models arrive at their conclusions. Techniques like LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (Shapley Additive exPlanations) help make AI decisions more interpretable, although applying these methods in real-world marketing contexts remains challenging [120,121].

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Skill Gaps and Organizational Adaptation

Implementing AI technologies in marketing requires a blend of technical and marketing expertise. However, there is a noticeable skills gap, with professionals with this hybrid knowledge being in short supply. This creates a highly competitive job market, making it difficult for companies to find and retain talent [17,122]. Furthermore, many organizations struggle with cross-functional collaboration between marketing, IT, and data science teams due to siloed organizational structures. A culture encouraging data-driven decision-making and continuous learning is essential for successful AI integration, but many businesses find this difficult to cultivate [85].

Integration and System Upgrades.

Integrating AI tools with legacy systems poses significant technical challenges, leading to inefficiencies and fragmented data [123]. Furthermore, rapid AI advancements require frequent system upgrades, adding additional costs and resource demand. The lack of standardization across AI technologies complicates implementation, making it harder for businesses to benchmark their progress or share best practices [124]. Addressing these challenges through improved data privacy practices, better system integration, and enhanced model transparency will be critical for businesses to harness the power of AI in marketing fully. By overcoming these limitations, companies can drive more effective marketing strategies, improve customer engagement, and maintain a competitive edge in an increasingly data-driven market.

Future perspectives

Advancements in AI/ML Technologies for Marketing

Explainable AI (XAI): As AI becomes increasingly integral to marketing, the need for transparency and interpretability grows. XAI aims to demystify how complex AI models arrive at decisions, helping marketers and consumers trust AI-driven insights. XAI tools such as LIME and SHAP are expected to become more refined and user-friendly, allowing businesses to build AI models that are both powerful and interpretable. This development is critical for ensuring accountability, especially in areas like customer segmentation and personalization, where fairness and transparency are paramount [120,121,125].

FL is gaining traction as a privacy-preserving approach to ML. It allows AI models to be trained across multiple decentralized devices or servers without exchanging raw data, thus ensuring data privacy. FL is particularly beneficial for industries dealing with sensitive consumer information, such as healthcare and finance, while enabling collaborative learning and large-scale data analysis [126]. In marketing, FL can help companies personalize customer experiences without compromising privacy, aligning with increasing regulatory demands such as GDPR [127].

Quantum Machine Learning: Although still in its infancy, Quantum Machine Learning (QML) holds significant promise for marketing. As quantum computing progresses, it may revolutionize data processing by solving complex problems exponentially faster than classical computers. QML could enable marketers to analyze massive datasets in real time, optimize advertising strategies, and improve predictive models. Early research suggests potential applications in customer segmentation, recommendation systems, and real-time bidding, which will be closely watched in the coming years [128,129].

Adaptive AI for Real-Time Marketing: As consumer behavior and market conditions change rapidly, adaptive AI systems are emerging to provide real-time adjustments to marketing strategies. Using reinforcement learning and online learning algorithms, these systems can continuously learn from new data and adapt to shifting patterns in customer preferences, pricing trends, and campaign performance [17,130]. This real-time adaptability will become increasingly important as marketers strive to stay ahead in dynamic environments.

Multimodal AI: Future AI systems will increasingly integrate multiple data types such as text, images, videos, and audio to create a more holistic understanding of consumer behavior. Multimodal AI can enable marketers to analyze complex, cross-channel customer interactions more effectively. For instance, by combining data from social media text posts, product images, and video content, multimodal AI can generate more accurate sentiment analysis, better brand perception insights, and more targeted recommendations.

Integration with Emerging Technologies

IoT-Enhanced Marketing: The convergence of AI with the IoT creates new frontiers in data collection and real-time decision-making. IoT devices generate continuous streams of real-time consumer data, allowing AI models to process this information and offer hyper-personalized experiences [43]. For example, predictive maintenance models powered by AI can anticipate consumer needs based on IoT data, enabling proactive marketing strategies. This integration allows businesses to create seamless omnichannel marketing experiences that bridge online and offline consumer behaviors [43].

Augmented Reality (AR) and Virtual Reality (VR): AI is transforming AR and VR experiences in marketing by making them more interactive and personalized. In retail, AR allows customers to visualize products in real-world settings before purchasing, while VR provides immersive shopping experiences [85]. AI-driven insights enhance these experiences by analyzing user behavior and preferences within AR/VR environments, delivering personalized recommendations, and increasing engagement. The combination of AI with AR/VR technologies is expected to expand further, offering innovative ways for brands to interact with consumers [131,132].

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Blockchain for Data Privacy and Security: As concerns about data privacy and security grow, blockchain technology is emerging as a solution to ensure secure and transparent data transactions. Blockchain can enhance trust between businesses and consumers by providing a decentralized and tamper-proof system for storing and sharing data [133]. In marketing, blockchain could be used to verify the authenticity of consumer data, ensuring that AI models are trained on clean and reliable information while giving consumers more control over how their data is used [134].

Ethical AI and Bias Mitigation

The ethical use of AI in marketing is becoming increasingly important as the technology becomes more pervasive. Addressing algorithmic bias and ensuring fairness in AI-driven marketing strategies are key research areas. Techniques for detecting and mitigating bias in AI models will continue to evolve, focusing on ensuring that AI systems treat all demographic groups fairly and without discrimination. In parallel, developing ethical frameworks for AI applications in marketing, which prioritize transparency, accountability, and consumer trust, will be critical for responsible AI deployment in the industry. As AI and ML continue to advance, these emerging trends and research directions will shape the future of marketing. Businesses that invest in explainable, adaptive, and privacy-conscious AI technologies will be well-positioned to offer more personalized, efficient, and ethical marketing experiences. Marketers can stay ahead in an increasingly competitive and data-driven landscape by embracing innovations like federated learning, quantum computing, and multimodal AI.

II. Conclusion

Integrating AI and ML into marketing has revolutionized how businesses analyze data, personalize customer experiences, and optimize marketing strategies. AI provide the tools to process vast amounts of big data from diverse sources such as social media, IoT devices, and e-commerce platforms. These technologies allow for more precise customer segmentation, enhanced personalization, real-time campaign optimization, and predictive analytics that drive smarter decision-making and improved ROI. Case studies from leading companies like Nike, Coca-Cola, Target, and Starbucks illustrate how AI have been successfully applied to create data-driven marketing solutions, enabling businesses to stay competitive in an increasingly dynamic market.

However, challenges such as data privacy concerns, integration difficulties, algorithmic transparency, and skill gaps within organizations must be addressed for AI to achieve its full potential in marketing. Ethical considerations, including the need for explainable AI and fairness in automated decision-making, are critical to building consumer trust and ensuring the responsible use of AI technologies. Emerging trends such as federated learning, quantum computing, multimodal AI, and the convergence of AI with IoT and AR/VR hold the promise of even more transformative marketing applications. Sustainable AI development, emphasizing energy efficiency, transparency, and social responsibility, will be critical to aligning the continued growth of AI technologies with global sustainability goals. As the field evolves, businesses that embrace these advancements while addressing the associated challenges will be better positioned to harness the full power of AI, driving innovation and success in the future of marketing.

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Conflict of Interest

The authors declare no conflict of interest.

References

1. the Impact of Machine Learning on Prescriptive Analytics for Optimized Business Decision-Making, Glob. Mainstream J. 1 (2024) 7–18. https://doi.org/10.62304/ijmisds.v1i1.112.
2. A. Hemmati, H.M. Arzanagh, A.M. Rahmani, A taxonomy and survey of big data in social media, Concurr. Comput. Pract. Exp. 36 (2024). https://doi.org/10.1002/cpe.7875.
3. M. Bilal, Y. Zhang, S. Cai, U. Akram, A. Halibas, Artificial intelligence is the magic wand making customer-centric a reality! An investigation into the relationship between consumer purchase intention and consumer engagement through affective attachment, J. Retail. Consum. Serv. 77 (2024) 103674. https://doi.org/10.1016/j.jretconser.2023.103674.
4. M. Taylor, D. Reilly, C. Wren, Internet of things support for marketing activities, J. Strateg. Mark. 28 (2020) 149–160. https://doi.org/10.1080/0965254X.2018.1493523.
5. S. Tyagi, Machine Learning for Societal Improvement , Modernization , and Progress, (2023). https://doi.org/10.4018/978-1-6684-4045-2.ch011.
6. L. Ma, B. Sun, Machine learning and AI in marketing – Connecting computing power to human insights, Int. J. Res. Mark. 37 (2020) 481–504. https://doi.org/10.1016/j.ijresmar.2020.04.005.
7. S. Verma, R. Sharma, S. Deb, D. Maitra, Artificial intelligence in marketing : Systematic review and future research direction, Int. J. Inf. Manag. Data Insights. (2021) 100002. https://doi.org/10.1016/j.jjimei.2020.100002.
8. A.A.R. R., P. R., Deep Learning for Social Media Data Analytics, Springer International Publishing, Cham, 2022. https://doi.org/10.1007/978-3-031-10869-3.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue II, February 2025

9. David Iyanuoluwa Ajiga, Ndubuisi Leonard Ndubuisi, Onyeka Franca Asuzu, Oluwaseyi Rita Owolabi, Tula Sunday Tubokirifuruar, Rhoda Adura Adeleye, Ai-Driven Predictive Analytics in Retail: a Review of Emerging Trends and Customer Engagement Strategies, Int. J. Manag. Entrep. Res. 6 (2024) 307–321. https://doi.org/10.51594/ijmer.v6i2.772.
10. A. Jabbar, P. Akhtar, S. Dani, Real-time big data processing for instantaneous marketing decisions : A problematization approach, Ind. Mark. Manag. 90 (2020) 558–569. https://doi.org/10.1016/j.indmarman.2019.09.001.
11. U. Sivarajah, M.M. Kamal, Z. Irani, V. Weerakkody, Critical analysis of Big Data challenges and analytical methods, J. Bus. Res. 70 (2017) 263–286. https://doi.org/10.1016/j.jbusres.2016.08.001.
12. C. González García, E. Álvarez-Fernández, What Is (Not) Big Data Based on Its 7Vs Challenges: A Survey, Big Data Cogn. Comput. 6 (2022) 1–29. https://doi.org/10.3390/bdcc6040158.
13. T.R. Rao, P. Mitra, R. Bhatt, A. Goswami, The big data system, components, tools, and technologies: a survey, Springer London, 2019. https://doi.org/10.1007/s10115-018-1248-0.
14. A.K. Tyagi, R. G, Machine Learning with Big Data, SSRN Electron. J. (2019) 1011–1020. https://doi.org/10.2139/ssrn.3356269.
15. G. Volkmar, P.M. Fischer, S. Reinecke, Artificial Intelligence and Machine Learning: Exploring drivers, barriers, and future developments in marketing management, J. Bus. Res. 149 (2022) 599–614. https://doi.org/10.1016/j.jbusres.2022.04.007.
16. N. Anute, M. Paliwal, M. Patel, N. Kandale, Impact of artificial intelligence and machine learning on business operations, J. Manag. Res. Anal. 8 (2021) 69–74. https://doi.org/10.18231/j.jmra.2021.015.
17. A. Haleem, M. Javaid, M. Asim Qadri, R. Pratap Singh, R. Suman, Artificial intelligence (AI) applications for marketing: A literature-based study, Int. J. Intell. Networks. 3 (2022) 119–132. https://doi.org/10.1016/j.ijin.2022.08.005.
18. V. Kumar, A.R. Ashraf, W. Nadeem, AI-powered marketing: What, where, and how?, Int. J. Inf. Manage. 77 (2024) 102783. https://doi.org/10.1016/j.ijinfomgt.2024.102783.
19. V. Kumar, D. Ramachandran, B. Kumar, Influence of new-age technologies on marketing: A research agenda, J. Bus. Res. 125 (2021) 864–877. https://doi.org/10.1016/j.jbusres.2020.01.007.
20. M. Rajyalaxmi, C. Vijai, K. Srivastava, N.B. Kalyan, B. Pravallika, A. Dutt, Application of Machine Learning Algorithms for Customer Segmentation in E-commerce Management, Proc. 2024 Int. Conf. Sci. Technol. Eng. Manag. ICSTEM 2024. (2024) 1–5. https://doi.org/10.1109/ICSTEM61137.2024.10560944.
21. V. Duarte, S. Zuniga-Jara, S. Contreras, Machine Learning and Marketing: A Literature Review., SSRN Electron. J. (2022) 1–19. https://doi.org/10.2139/ssrn.4006436.
22. A. Ravisankar, M. Ponniah, V. Tripathi, K. Kulshreshtha, A.P. Srivastava, V. Singh, Analysis Role of ML and Big Data Play in Driving Digital Marketing’s Paradigm Shift, Proc. - 2023 IEEE World Conf. Appl. Intell. Comput. AIC 2023. 10 (2023) 388–394. https://doi.org/10.1109/AIC57670.2023.10263813.
23. C. Fan, M. Chen, X. Wang, J. Wang, B. Huang, A Review on Data Preprocessing Techniques Toward Efficient and Reliable Knowledge Discovery From Building Operational Data, Front. Energy Res. 9 (2021) 1–17. https://doi.org/10.3389/fenrg.2021.652801.
24. P.J. Lou, M. Johnson, Improving disfluency detection by self-training a self-attentive model, Proc. Annu. Meet. Assoc. Comput. Linguist. (2020) 3754–3763. https://doi.org/10.18653/v1/2020.acl-main.346.
25. M. TAKEUCHI, T. IMAFUKU, Y. SAKAI, M. GOTO, A Semi-Supervised Learning Model for Predicting User Attributes Based on Ladder Network, Total Qual. Sci. 9 (2023) 109–120. https://doi.org/10.17929/tqs.9.109.
26. L. Murphy, F. Perales, A. Gopal, Y. Gyurdieva, V. Gueorguiev, P. Shandilya, Time for marketing to embrace reinforcement learning, J. Digit. Soc. Media Mark. 10 (2022) 135. https://doi.org/10.69554/MOYX6262.
27. N. Cavlak, The Role of Big Data in Digital Marketing, (2021). https://doi.org/10.4018/978-1-7998-8003-5.ch002.
28. V.U. Gongane, M. V. Munot, A.D. Anuse, Detection and moderation of detrimental content on social media platforms: current status and future directions, Springer Vienna, 2022. https://doi.org/10.1007/s13278-022-00951-3.
29. A. Acker, A. Kreisberg, Social media data archives in an API-driven world, Arch. Sci. 20 (2020) 105–123. https://doi.org/10.1007/s10502-019-09325-9.
30. J.L. Hayes, B.C. Britt, W. Evans, S.W. Rush, N.A. Towery, A.C. Adamson, Can Social Media Listening Platforms’ Artificial Intelligence Be Trusted? Examining the Accuracy of Crimson Hexagon’s (Now Brandwatch Consumer Research’s) AI-Driven Analyses, J. Advert. 50 (2021) 81–91. https://doi.org/10.1080/00913367.2020.1809576.
31. B. Baykal, Connected Consumers: Unleashing the Power of IoT for Personalized Marketing, Sos. Bilim. Akad. Araştırma ve Değerlendirmeler - IV. (2023). https://doi.org/10.58830/ozgur.pub261.c1432.
32. G.G. de Oliveira, F.L. Lizarelli, J.G. Teixeira, G.H. de S. Mendes, Curb your enthusiasm: Examining the customer experience with Alexa and its marketing outcomes, J. Retail. Consum. Serv. 71 (2023) 103220. https://doi.org/10.1016/j.jretconser.2022.103220.
33. J. Bzai, F. Alam, A. Dhafer, M. Bojović, S.M. Altowaijri, I.K. Niazi, R. Mehmood, Machine Learning-Enabled Internet of Things (IoT): Data, Applications, and Industry Perspective, Electron. 11 (2022) 1–33. https://doi.org/10.3390/electronics11172676.
34. Y. Sun, Y. Bai, Z. Zhou, Collaboration of AI, big data, and blockchain in Internet of Things (IoT): Emerging trends and perspectives, Internet of Things (Netherlands). (2024) 10–13. https://doi.org/10.1016/j.iot.2024.101234.

35. H. Kumar, T. Chinmaya, K. Dehury, P. Kumar, S. Bharadwaj, Predictive Analytics in Cloud, Fog, and Edge Computing, 2023. https://doi.org/10.1007/978-3-031-18034-7.
36. M.K. Kamila, S.S. Jasrotia, Ethics and marketing responsibility: A bibliometric analysis and literature review, Asia Pacific Manag. Rev. 28 (2023) 567–583. https://doi.org/10.1016/j.apmrv.2023.04.002.
37. B. Vlačić, L. Corbo, S. Costa e Silva, M. Dabić, The evolving role of artificial intelligence in marketing: A review and research agenda, J. Bus. Res. 128 (2021) 187–203. https://doi.org/10.1016/j.jbusres.2021.01.055.
38. A.R.E. Alshawawreh, F. Liébana-Cabanillas, F.J. Blanco-Encomienda, Impact of big data analytics on telecom companies' competitive advantage, Technol. Soc. 76 (2024). https://doi.org/10.1016/j.techsoc.2024.102459.
39. C. Ledro, A. Nosella, A. Vinelli, Artificial intelligence in customer relationship management: literature review and future research directions, J. Bus. Ind. Mark. 37 (2022) 48–63. https://doi.org/10.1108/JBIM-07-2021-0332.
40. P. Gaczek, G. Leszczyński, A. Mouakher, Collaboration with machines in B2B marketing: Overcoming managers' aversion to AI-CRM with explainability, Ind. Mark. Manag. 115 (2023) 127–142. https://doi.org/10.1016/j.indmarman.2023.09.007.
41. M.A. Camilleri, The use of data-driven technologies for customer-centric marketing, Int. J. Big Data Manag. 1 (2020) 50. https://doi.org/10.1504/ijbdm.2020.106876.
42. D. Zumstein, A. Drobnjak, A. Meier, Data privacy in web analytics: An empirical study and declaration model of data collection on websites, WEBIST 2011 - Proc. 7th Int. Conf. Web Inf. Syst. Technol. (2011) 466–472. https://doi.org/10.5220/0003301404660472.
43. N. Rane, Enhancing Customer Loyalty through Artificial Intelligence (AI), Internet of Things (IoT), and Big Data Technologies: Improving Customer Satisfaction, Engagement, Relationship, and Experience, SSRN Electron. J. (2023). https://doi.org/10.2139/ssrn.4616051.
44. M. Singh, Cross-Channel Marketing Analytics: Integrating Offline and Online Data for Holistic Campaign Analysis, Int. J. Enhanc. Res. …. (2024). https://doi.org/10.55948/IJERMCA.2024.0305.
45. M.A. Khder, Web scraping or web crawling: State of art, techniques, approaches and application, Int. J. Adv. Soft Comput. Its Appl. 13 (2021) 144–168. https://doi.org/10.15849/ijasca.211128.11.
46. F. Villarroel Ordenes, R. Silipo, Machine learning for marketing on the KNIME Hub: The development of a live repository for marketing applications, J. Bus. Res. 137 (2021) 393–410. https://doi.org/10.1016/j.jbusres.2021.08.036.
47. P. Matta, S. Sharma, N. Uniyal, Comparative Study Of Various Scraping Tools: Pros And Cons, 2022 IEEE Delhi Sect. Conf. DELCON 2022. (2022) 1–5. https://doi.org/10.1109/DELCON54057.2022.9753358.
48. V. Truong, Optimizing mobile in-app advertising effectiveness using app publishers-controlled factors, J. Mark. Anal. (2023). https://doi.org/10.1057/s41270-023-00230-w.
49. I. Hidayati, S. Sudarmiatin, A. Hermawan, Analysis of Point of Sale System Implementation in Coffee Shop, J. Pendidik. Dan Kewirausahaan. 11 (2023) 932–947. https://doi.org/10.47668/pkwu.v11i3.881.
50. C.P. Marques, A.S. Guedes, R. Bento, Tracking changes in tourism demand with point-of-sale data: The case of Portugal, Tour. Hosp. Res. 23 (2023) 101–107. https://doi.org/10.1177/14673584221075175.
51. Gold Nmesoma Okorie, Zainab Efe Egieya, Uneku Ikwue, Chioma Ann Udeh, Ejuma Martha Adaga, Obinna Donald DaraOjimba, Osato Itohan Oriekhoe, Leveraging Big Data for Personalized Marketing Campaigns: a Review, Int. J. Manag. Entrep. Res. 6 (2024) 216–242. https://doi.org/10.51594/ijmer.v6i1.778.
52. Y. Roh, G. Heo, S.E. Whang, A Survey on Data Collection for Machine Learning: A Big Data - AI Integration Perspective, IEEE Trans. Knowl. Data Eng. 33 (2021) 1328–1347. https://doi.org/10.1109/TKDE.2019.2946162.
53. R. Wolniak, W. Grebski, The application of business analytics in cost reduction, Sci. Pap. Silesian Univ. Technol. Organ. Manag. Ser. 2023 (2023). https://doi.org/10.29119/1641-3466.2023.184.36.
54. R. Chaban, O. Taran, J. Tutt, T. Holotyak, S. Bonev, S. Voloshynovskiy, Machine learning attack on copy detection patterns: Are 1× 1 patterns cloneable?, 2021 IEEE Int. Work. Inf. Forensics Secur. WIFS 2021. (2021) 1–6. https://doi.org/10.1109/WIFS53200.2021.9648387.
55. A. Nambiar, D. Mundra, An Overview of Data Warehouse and Data Lake in Modern Enterprise Data Management, Big Data Cogn. Comput. 6 (2022). https://doi.org/10.3390/bdcc6040132.
56. D. Li, W. Zhang, S. Shen, Y. Zhang, SES-LSH: Shuffle-Efficient Locality Sensitive Hashing for Distributed Similarity Search, Proc. - 2017 IEEE 24th Int. Conf. Web Serv. ICWS 2017. (2017) 822–827. https://doi.org/10.1109/ICWS.2017.99.
57. G. Chhabra, V. Vashisht, J. Ranjan, A Comparison of Multiple Imputation Methods for Data with Missing Values, Indian J. Sci. Technol. 10 (2017) 1–7. https://doi.org/10.17485/ijst/2017/v10i19/110646.
58. A. Mumuni, F. Mumuni, Automated data processing and feature engineering for deep learning and big data applications: A survey, J. Inf. Intell. (2024). https://doi.org/10.1016/j.jiixd.2024.01.002.
59. S. Thudumu, P. Branch, J. Jin, J. (Jack) Singh, A comprehensive survey of anomaly detection techniques for high dimensional big data, J. Big Data. 7 (2020). https://doi.org/10.1186/s40537-020-00320-x.
60. G. KARATAŞ BAYDOĞMUŞ, The Effects of Normalization and Standardization an Internet of Things Attack Detection, Eur. J. Sci. Technol. (2021) 187–192. https://doi.org/10.31590/ejosat.1017427.
61. J.M. John, O. Shobayo, B. Ogunleye, An Exploration of Clustering Algorithms for Customer Segmentation in the UK Retail Market, Analytics. 2 (2023) 809–823. https://doi.org/10.3390/analytics2040042.

62. L.H. Bin Ahmad Sabri, A.H.L. Lim, H.N. Goh, Click Analysis: How E-ommerce Companies Benefit from Exploratory and Association Rule Mining, J. Syst. Manag. Sci. 12 (2022) 511–531. https://doi.org/10.33168/JSMS.2022.0630.
63. M.H. Santoso, Application of Association Rule Method Using Apriori Algorithm to Find Sales Patterns Case Study of Indomaret Tanjung Anom, Brill. Res. Artif. Intell. 1 (2021) 54–66. https://doi.org/10.47709/brilliance.v1i2.1228.
64. A.M. Zaki, N. Khodadadi, W.H. Lim, S.K. Towfek, Predictive Analytics and Machine Learning in Direct Marketing for Anticipating Bank Term Deposit Subscriptions, Am. J. Bus. Oper. Res. 11 (2024) 79–88. https://doi.org/10.54216/ajbor.110110.
65. M.C. Iban, S.S. Bilgilioglu, Snow avalanche susceptibility mapping using novel tree-based machine learning algorithms (XGBoost, NGBoost, and LightGBM) with eXplainable Artificial Intelligence (XAI) approach, Stoch. Environ. Res. Risk Assess. 37 (2023) 2243–2270. https://doi.org/10.1007/s00477-023-02392-6.
66. X. Hao, C. Cheng, Telecom Big Data based Precision Marketing Algorithms for Financial Industry, Proc. - 2021 20th Int. Conf. Ubiquitous Comput. Commun. 2021 20th Int. Conf. Comput. Inf. Technol. 2021 4th Int. Conf. Data Sci. Comput. Intell. 20. (2021) 579–585. https://doi.org/10.1109/IUCC-CIT-DSCI-SmartCNS55181.2021.00095.
67. V. Nunavath, M. Goodwin, The Role of Artificial Intelligence in Social Media Big data Analytics for Disaster Management -Initial Results of a Systematic Literature Review, 2018 5th Int. Conf. Inf. Commun. Technol. Disaster Manag. ICT-DM 2018. (2018) 1–4. https://doi.org/10.1109/ICT-DM.2018.8636388.
68. A. Aldoseri, K.N. Al-Khalifa, A.M. Hamouda, Re-Thinking Data Strategy and Integration for Artificial Intelligence: Concepts, Opportunities, and Challenges, Appl. Sci. 13 (2023). https://doi.org/10.3390/app13127082.
69. M. Rithani, R.P. Kumar, S. Doss, A review on big data based on deep neural network approaches, Springer Netherlands, 2023. https://doi.org/10.1007/s10462-023-10512-5.
70. T. Lin, J. Jiang, Anomaly Detection with Autoencoder and Random Forest, (2020) 96–99. https://doi.org/10.1109/ICS51289.2020.00028.
71. J. Hartmann, O. Netzer, Natural Language Processing in Marketing, 20 (2023) 191–215. https://doi.org/10.1108/s1548-643520230000020011.
72. A. Jaiswal, S. Tarar, Real-Time Biometric System for Security and Surveillance Using Face Recognition, 2020. https://doi.org/10.1007/978-981-15-6634-9_27.
73. F. Nkinahamira, A. Feng, L. Zhang, H. Rong, P. Ndagijimana, D. Guo, B. Cui, H. Zhang, Machine learning approaches for monitoring environmental metal pollutants: Recent advances in source apportionment, detection, quantification, and risk assessment, TrAC Trends Anal. Chem. 180 (2024) 117980. https://doi.org/10.1016/j.trac.2024.117980.
74. U. Sirisha, S.P. Praveen, P.N. Srinivasu, P. Barsocchi, A.K. Bhoi, Statistical Analysis of Design Aspects of Various YOLO-Based Deep Learning Models for Object Detection, Int. J. Comput. Intell. Syst. 16 (2023) 126. https://doi.org/10.1007/s44196-023-00302-w.
75. A.F. Del Carpio, Analyzing computer vision models for detecting customers: practical experience in a mexican retail, Int. J. Adv. Intell. Informatics. 10 (2024) 131–147. https://doi.org/10.26555/ijain.v10i1.1112.
76. V. Singh, B. Nanavati, A.K. Kar, A. Gupta, How to Maximize Clicks for Display Advertisement in Digital Marketing? A Reinforcement Learning Approach, Inf. Syst. Front. 25 (2023) 1621–1638. https://doi.org/10.1007/s10796-022-10314-0.
77. F. Lu, Adaptive Recommendation System Strategies : An Exploration of Online Machine Learning Algorithms, (2024) 447–451. https://doi.org/10.5220/0012949200004508.
78. J. Li, T. Chen, S. Teng, A comprehensive survey on client selection strategies in federated learning, Comput. Networks. 251 (2024). https://doi.org/10.1016/j.comnet.2024.110663.
79. R. Das, T.D. Singh, Multimodal Sentiment Analysis: A Survey of Methods, Trends, and Challenges, ACM Comput. Surv. 55 (2023). https://doi.org/10.1145/3586075.
80. M.S.E. Kasem, M. Hamada, I. Taj-Eddin, Customer profiling, segmentation, and sales prediction using AI in direct marketing, Neural Comput. Appl. 36 (2024) 4995–5005. https://doi.org/10.1007/s00521-023-09339-6.
81. M. Mandapuram, S.S. Gutlapalli, M. Reddy, A. Bodepudi, Application of Artificial Intelligence (AI) Technologies to Accelerate Market Segmentation, Glob. Discl. Econ. Bus. 9 (2020) 141–150. https://doi.org/10.18034/gdeb.v9i2.662.
82. J. Chen, Z. Liu, X. Huang, C. Wu, Q. Liu, G. Jiang, Y. Pu, Y. Lei, X. Chen, X. Wang, K. Zheng, D. Lian, E. Chen, When large language models meet personalization: perspectives of challenges and opportunities, World Wide Web. 27 (2024) 1–24. https://doi.org/10.1007/s11280-024-01276-1.
83. L. Wu, X. He, X. Wang, K. Zhang, M. Wang, A Survey on Accuracy-Oriented Neural Recommendation: From Collaborative Filtering to Information-Rich Recommendation, IEEE Trans. Knowl. Data Eng. 35 (2023) 4425–4445. https://doi.org/10.1109/TKDE.2022.3145690.
84. H. Ghorbantanhaei, P. Boozary, S. Sheykhan, M. Rabiee, F. Rahmani, I. Hosseini, Results in Control and Optimization Predictive analytics in customer behavior : Anticipating trends and preferences, Results Control Optim. 17 (2024) 100462. https://doi.org/10.1016/j.rico.2024.100462.
85. Y.Y. Raghav, R.K. Tipu, R. Bhakhar, T. Gupta, K. Sharma, The future of digital marketing: Leveraging artificial intelligence for competitive strategies and tactics, Use Artif. Intell. Digit. Mark. Compet. Strateg. Tactics. (2023) 249–274. https://doi.org/10.4018/978-1-6684-9324-3.ch011.
86. M. Gigli, F. Stella, Multi-armed bandits for performance marketing, Int. J. Data Sci. Anal. (2024). https://doi.org/10.1007/s41060-023-00493-7.

87. M. Liu, L.I. Jiaxing, Z. Hu, J. Liu, X. Nie, on Model-Free Reinforcement Learning in Display Advertising, (2020) 213587–213601. https://doi.org/10.1109/ACCESS.2020.3037940.
88. K.R.P. Vittala, K.M. Kiran, R. Seranmadevi, A.K. Tyagi, Artificial intelligence-internet of things integration for smart marketing: Challenges and opportunities, Adv. Softw. Eng. Through AI, Fed. Learn. Large Lang. Model. (2024) 295–307. https://doi.org/10.4018/979-8-3693-3502-4.ch019.
89. Md Sumon Gazi, Md Rokibul Hasan, Nisha Gurung, Anik Mitra, Ethical Considerations in AI-driven Dynamic Pricing in the USA: Balancing Profit Maximization with Consumer Fairness and Transparency, J. Econ. Financ. Account. Stud. 6 (2024) 100–111. https://doi.org/10.32996/jefas.2024.6.2.8.
90. Y. Kayikci, S. Demir, S.K. Mangla, N. Subramanian, B. Koc, Data-driven optimal dynamic pricing strategy for reducing perishable food waste at retailers, J. Clean. Prod. 344 (2022) 131068. https://doi.org/10.1016/j.jclepro.2022.131068.
91. A. Rese, L. Ganster, D. Baier, Chatbots in retailers' customer communication: How to measure their acceptance?, J. Retail. Consum. Serv. 56 (2020) 102176. https://doi.org/10.1016/j.jretconser.2020.102176.
92. S.Z. Kamoonpuri, A. Sengar, Hi, May AI help you? An analysis of the barriers impeding the implementation and use of artificial intelligence-enabled virtual assistants in retail, J. Retail. Consum. Serv. 72 (2023) 103258. https://doi.org/10.1016/j.jretconser.2023.103258.
93. A. Miklosik, N. Evans, A.M.A. Qureshi, The Use of Chatbots in Digital Business Transformation: A Systematic Literature Review, IEEE Access. 9 (2021) 106530–106539. https://doi.org/10.1109/ACCESS.2021.3100885.
94. A.P. Chaves, M.A. Gerosa, How should my chatbot interact? A survey on social characteristics in human-chatbot interaction design (preprint), (2020).
95. H.N. DURMUŞ ŞENYAPAR, The Future of Marketing: The Transformative Power of Artificial Intelligence, Int. J. Manag. Adm. 8 (2024) 1–19. https://doi.org/10.29064/ijma.1412272.
96. S. Gupta, T. Justy, S. Kamboj, A. Kumar, E. Kristoffersen, Big data and firm marketing performance: Findings from knowledge-based view, Technol. Forecast. Soc. Change. 171 (2021). https://doi.org/10.1016/j.techfore.2021.120986.
97. K. Abrokwah-Larbi, Y. Awuku-Larbi, The impact of artificial intelligence in marketing on the performance of business organizations: evidence from SMEs in an emerging economy, J. Entrep. Emerg. Econ. 16 (2024) 1090–1117. https://doi.org/10.1108/JEEE-07-2022-0207.
98. D.M. Dave, S. Mandvikar, Augmented Intelligence: Human-Ai Collaboration in the Era of Digital Transformation, Int. J. Eng. Appl. Sci. Technol. 8 (2023) 24–33. https://doi.org/10.33564/ijeast.2023.v08i06.003.
99. M. Wedel, P.K. Kannan, Marketing analytics for data-rich environments, J. Mark. 80 (2016) 97–121. https://doi.org/10.1509/jm.15.0413.
100. S. Mukhopadhyay, R.K. Singh, T. Jain, Developing artificial intelligence enabled Marketing 4.0 framework: an Industry 4.0 perspective, Qual. Mark. Res. (2024). https://doi.org/10.1108/QMR-06-2023-0086.
101. P.K. Kannan, H.A. Li, US CR, Int. J. Res. Mark. (2016). https://doi.org/10.1016/j.ijresmar.2016.11.006.
102. P. Akhtar, A.M. Ghouri, A. Ashraf, J.J. Lim, N.R. Khan, M.A. Shuang, Smart product platforming powered by AI and generative AI: Personalization for the circular economy, Int. J. Prod. Econ. 273 (2024) 109283. https://doi.org/10.1016/j.ijpe.2024.109283.
103. A.T. Rosário, J.C. Dias, How has data-driven marketing evolved: Challenges and opportunities with emerging technologies, Int. J. Inf. Manag. Data Insights. 3 (2023). https://doi.org/10.1016/j.jjimei.2023.100203.
104. G. Stalidis, D. Karapistolis, A. Vafeiadis, Marketing Decision Support Using Artificial Intelligence and Knowledge Modeling: Application to Tourist Destination Management, Procedia - Soc. Behav. Sci. 175 (2015) 106–113. https://doi.org/10.1016/j.sbspro.2015.01.1180.
105. M. Paolanti, E. Frontoni, Multidisciplinary Pattern Recognition applications: A review, Comput. Sci. Rev. 37 (2020) 100276. https://doi.org/10.1016/j.cosrev.2020.100276.
106. D.U. Puterisari, Strategic Management in Industry 4.0: Digital Transformation in NIKE Inc. Using the Dynamic Capability Approach, Int. J. Business, Humanit. Educ. Soc. Sci. 4 (2022) 103–108. https://doi.org/10.46923/ijbhes.v4i2.204.
107. A. Mathews, How Target Used AI To Become A Retail Giant, AIM Media House LLC. (2024). https://aimresearch.co/market-industry/how-target-used-ai-to-become-a-retail-giant.
108. GarimaKaneria, Artificial Intelligence in Banking Industry, Impact Artif. Intell. Organ. Transform. (2022) 327–348. https://doi.org/10.1002/9781119710301.ch19.
109. S. Punia, S. Shankar, Predictive analytics for demand forecasting: A deep learning-based decision support system, Knowledge-Based Syst. 258 (2022) 109956. https://doi.org/10.1016/j.knosys.2022.109956.
110. A. Islam, M. Islam, M.U. Hossain Uzir, S. Abd Wahab, A.S. Abdul Latiff, The panorama between COVID-19 pandemic and Artificial Intelligence (AI): Can it be the catalyst for Society 5.0?, Int. J. Sci. Res. Manag. 8 (2020) 2011–2025. https://doi.org/10.18535/ijsrm/v8i12.em02.
111. M. Rodgers, S. Mukherjee, B. Melamed, A. Baveja, A. Kapoor, Solving business problems: the business-driven data-supported process, Ann. Oper. Res. 332 (2024) 705–741. https://doi.org/10.1007/s10479-023-05770-z.
112. S.-Y. Lee, Study on Digital Transformation Strategies: Starbucks Case Study, J. Digit. Contents Soc. 21 (2020) 1809–1816. https://doi.org/10.9728/dcs.2020.21.10.1809.
113. A. Kumari, A. Golyan, R. Shah, N. Raval, Introduction to Data Analytics, Recent Trends Futur. Dir. Data Anal. (2024) 1–14. https://doi.org/10.4018/9798369336090.ch001.

114. Md. Aminul Islam, Impact of Big Data Analytics on Digital Marketing: Academic Review, J. Electr. Syst. 20 (2024) 786–820. https://doi.org/10.52783/jes.2327.
115. P. Bauch, Data Privacy and Regulation, SSRN Electron. J. (2024). https://doi.org/10.2139/ssrn.4723359.
116. R.Y. Wong, A. Chong, R. Cooper Aspegren, Privacy Legislation as Business Risks: How GDPR and CCPA are Represented in Technology Companies' Investment Risk Disclosures, Proc. ACM Human-Computer Interact. 7 (2023) 1–26. https://doi.org/10.1145/3579515.
117. M.S. De Carvalho, G.L. Da Silva, Inside the black box: Using Explainable AI to improve Evidence-Based Policies, Proc. - 2021 IEEE 23rd Conf. Bus. Informatics, CBI 2021 - Main Pap. 2 (2021) 57–64. https://doi.org/10.1109/CBI52690.2021.10055.
118. J. Liu, J. Lou, J. Liu, L. Xiong, J. Pei, J. Sun, Dealer: An end-to-end model marketplace with differential privacy, Proc. VLDB Endow. 14 (2021) 957–969. https://doi.org/10.14778/3447689.3447700.
119. T.D. Cao, H.L. Truong, T. Truong-Huu, M.T. Nguyen, Enabling Awareness of Quality of Training and Costs in Federated Machine Learning Marketplaces, Proc. - 2022 IEEE/ACM 15th Int. Conf. Util. Cloud Comput. UCC 2022. (2022) 41–50. https://doi.org/10.1109/UCC56403.2022.00015.
120. V. Hassija, V. Chamola, A. Mahapatra, A. Singal, D. Goel, K. Huang, S. Scardapane, I. Spinelli, M. Mahmud, A. Hussain, Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence, Cognit. Comput. 16 (2024) 45–74. https://doi.org/10.1007/s12559-023-10179-8.
121. T. Speith, A Review of Taxonomies of Explainable Artificial Intelligence (XAI) Methods, ACM Int. Conf. Proceeding Ser. (2022) 2239–2250. https://doi.org/10.1145/3531146.3534639.
122. M. Obschonka, D.B. Audretsch, Artificial intelligence and big data in entrepreneurship: a new era has begun, Small Bus. Econ. 55 (2020) 529–539. https://doi.org/10.1007/s11187-019-00202-4.
123. S. Akter, S. Sultana, M. Mariani, S.F. Wamba, K. Spanaki, Y.K. Dwivedi, Advancing algorithmic bias management capabilities in AI-driven marketing analytics research, Ind. Mark. Manag. 114 (2023) 243–261. https://doi.org/10.1016/j.indmarman.2023.08.013.
124. Y.K. Dwivedi, L. Hughes, E. Ismagilova, G. Aarts, C. Coombs, T. Crick, Y. Duan, R. Dwivedi, J. Edwards, A. Eirug, V. Galanos, P.V. Ilavarasan, M. Janssen, P. Jones, A.K. Kar, H. Kizgin, B. Kronemann, B. Lal, B. Lucini, R. Medaglia, K. Le Meunier-FitzHugh, L.C. Le Meunier-FitzHugh, S. Misra, E. Mogaji, S.K. Sharma, J.B. Singh, V. Raghavan, R. Raman, N.P. Rana, S. Samothrakis, J. Spencer, K. Tamilmani, A. Tubadji, P. Walton, M.D. Williams, Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy, Int. J. Inf. Manage. 57 (2021). https://doi.org/10.1016/j.ijinfomgt.2019.08.002.
125. P.P. Angelov, E.A. Soares, R. Jiang, N.I. Arnold, P.M. Atkinson, Explainable artificial intelligence: an analytical review, Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 11 (2021) 1–13. https://doi.org/10.1002/widm.1424.
126. M. Aledhari, R. Razzak, R.M. Parizi, S. Member, Federated Learning : A Survey on Enabling Technologies , Protocols , and Applications, 8 (2020) 140699–140725. https://doi.org/10.1109/ACCESS.2020.3013541.
127. U. Ahmed, G. Srivastava, J.C. Lin, Reliable customer analysis using federated learning and exploring deep-attention edge intelligence, Futur. Gener. Comput. Syst. 127 (2022) 70–79. https://doi.org/10.1016/j.future.2021.08.028.
128. T.M. Khan, A. Robles-Kelly, Machine Learning: Quantum vs Classical, IEEE Access. 8 (2020) 219275–219294. https://doi.org/10.1109/ACCESS.2020.3041719.
129. K. Mullangi, N. Dhameliya, S. Kumar, R. Anumandla, V. Krishna, AI-Augmented Decision-Making in Management Using Quantum Networks AI-Augmented Decision-Making in Management Using Quantum Networks, (2023). https://doi.org/10.18034/abr.v13i2.718.
130. Y. Gao, H. Liu, Artificial intelligence-enabled personalization in interactive marketing: a customer journey perspective, J. Res. Interact. Mark. 17 (2023) 663–680. https://doi.org/10.1108/JRIM-01-2022-0023.
131. P.K. Kopalle, M. Gangwar, A. Kaplan, D. Ramachandran, W. Reinartz, A. Rindfleisch, Examining artificial intelligence (AI) technologies in marketing via a global lens: Current trends and future research opportunities, Int. J. Res. Mark. 39 (2022) 522–540. https://doi.org/10.1016/j.ijresmar.2021.11.002.
132. M. Wedel, E. Bigné, J. Zhang, Virtual and augmented reality : Advancing research in consumer marketing, Int. J. Res. Mark. 37 (2020) 443–465. https://doi.org/10.1016/j.ijresmar.2020.04.004.
133. R. Gs, M.S. Lingam, Blockchain Technology In Digital Advertising : Transparency , Fraud Prevention And Trust, 30 (2024) 3041–3049. https://doi.org/10.53555/kuey.v30i4.1477.
134. A. Khandekar, S. Fahad, Secured IoT architecture for personalized marketing using blockchain framework with deep learning technology, Cluster Comput. 27 (2024) 11069–11084. https://doi.org/10.1007/s10586-024-04372-z.