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A scoping review: the role of machine learning in social media marketing

Uma revisão de escopo: o papel do aprendizado de máquina no marketing de mídia social

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Abstract: *This research conducts a scoping review on the application of machine learning (ML) in social media marketing, an increasingly pivotal area in digital marketing strategies. Machine learning plays a crucial role in analyzing user data, identifying consumer behavior, personalizing content, and optimizing marketing campaigns. Through a systematic search of academic journals, conference proceedings, and other relevant sources, this review identifies and synthesizes studies that explore the use of ML in social media marketing. The selected studies are analyzed to provide a comprehensive overview of ML's impact and applications within this domain. Key findings highlight the significant role of ML in enhancing personalization, improving user engagement, and driving more effective marketing strategies. However, challenges such as data privacy concerns, algorithmic biases, and the need for greater transparency are also noted. The practical implications for marketers include the importance of ethical practices in data handling, algorithm development, and consumer* *trust-building. Additionally, this review identifies gaps in the current literature and suggests directions for future research, offering valuable insights for both researchers and practitioners aiming to leverage machine learning in social media marketing.*

Keywords: *Scoping review; Machine learning; Social media marketing; Data analysis; Marketing strategy.*

Resumo: *Esta pesquisa conduz uma revisão de escopo sobre a aplicação de machine learning (ML) em marketing de mídia social, uma área cada vez mais essencial em estratégias de marketing digital. O machine learning desempenha um papel crucial na análise de dados do usuário, identificando o comportamento do consumidor, personalizando o conteúdo e otimizando campanhas de marketing. Por meio de uma busca sistemática de periódicos acadêmicos, anais de conferências e outras fontes relevantes, esta revisão identifica e sintetiza estudos que exploram o uso de ML em marketing de mídia social. Os estudos selecionados são analisados para fornecer uma visão geral abrangente do impacto e das aplicações do ML neste domínio. As principais descobertas destacam o papel significativo do ML em aprimorar a personalização, melhorar o engajamento do usuário e impulsionar estratégias de marketing mais eficazes. No entanto, desafios como preocupações com a privacidade de dados, vieses algorítmicos e a necessidade de maior transparência também são observados. As implicações práticas para os profissionais de marketing incluem a importância de práticas éticas no manuseio de dados, desenvolvimento de algoritmos e construção de confiança do consumidor. Além disso, essa revisão identifica lacunas na literatura atual e sugere direções para pesquisas futuras, oferecendo insights valiosos para pesquisadores e profissionais que buscam alavancar o machine learning no marketing de mídia social.*

Palavras-Chave: *Revisão de escopo; Aprendizado de máquina; Marketing de mídia social; Análise de dados; Estratégia de marketing.*

1. Introduction

One of the latest trends is the application of artificial intelligence, specifically machine learning, in social media-focused marketing strategies Alalwan (2017). Machine learning is a branch of artificial intelligence that allows computers to learn from data and experience to automatically generate better predictions and decision-making (Kumar et al, 2021). In this digital era, social media has become a very important platform for companies to interact with consumers and promote their products or services. However, with the ever-increasing amount of content on social media, companies need to utilize sophisticated tools to understand consumer preferences and behaviors to improve the effectiveness of their marketing campaigns. Machine learning in social media marketing plays an important role in solving this challenge (Huang & Rust, 2021). Using techniques such as sentiment analysis, pattern recognition, and classification, companies can more accurately identify consumer trends, preferences, and needs. This allows companies to customize their marketing content to be more relevant and appealing to their audience.

One example of the application of machine learning in marketing on social media is content personalization (Hagen, et al (2020). Through the analysis of user data such as browsing history, online behavior, and expressed preferences, machine learning algorithms can learn individual preferences and provide relevant and customized content automatically. This increases the likelihood of conversion and interaction with consumers (Miklosik et al, 2019). In addition, machine learning can also be used to optimize ad targeting on social media. By utilizing intelligent machine learning algorithms, companies can identify audiences most likely to be interested in their products or services based on demographic data, interests, and online behavior (Esmaeilpour et al. 2012). This helps improve the efficiency of advertising expenditures and increase the ROI (Return on Investment) of marketing campaigns (Alalwan, 2018).

Not only that, machine learning also plays a role in deep data analysis. In social media marketing, the data generated from user interactions can be huge and complex (Bhatti, 2018). Machine learning can help companies to process and analyze this data quickly and efficiently. By understanding the trends and patterns behind the data, companies can make better decisions in designing effective marketing strategies. In conclusion, machine learning has brought significant changes in the marketing industry, especially in the context of social media (Droomer & Bekker, 2020). The application of this technology allows companies to understand and target their audiences better, improve content personalization, and increase the efficiency of marketing campaigns.

In the context of marketing, machine learning can be used to analyze big data and identify patterns that are useful for optimizing marketing strategies (Jagdale, et al., 2022). In recent years, marketing through social media has become an important component of business marketing strategies. Millions of people use social media platforms such as Facebook, Instagram, Twitter, and LinkedIn every day, making it a highly potential channel to influence and connect with target audiences (Kongar & Adebayo, 2021).

The literature indicates that machine learning allows for better prediction and decision-making, enhancing marketing strategies through techniques such as sentiment analysis, pattern recognition, and content personalization (Alalwan, 2017; Kumar et al., 2021; Huang & Rust, 2021). This provides a foundation by presenting what is already known—how machine learning contributes to understanding consumer behavior, customizing marketing content, and optimizing ad targeting to increase engagement and ROI. The complication, or the identified limitations and gaps in the literature, lies in the insufficient exploration of practical challenges and barriers to implementing machine learning in social media marketing. While existing research highlights the benefits of machine learning for tasks like content personalization and ad targeting (Hagen et al., 2020; Esmaeilpour et al., 2012), it does not comprehensively address the real-world difficulties companies face in integrating these technologies seamlessly.

The gaps on this topic is about complexities of consumer behavior, because limited research exists on the diversity and variability of consumer behavior and how machine learning models adapt to such complexities. There is a lack of in-depth studies focusing on the ethical implications and privacy concerns associated with using consumer data for machine learning in marketing. Few studies explore the practical barriers companies encounter when trying to incorporate machine learning tools into their existing marketing strategies. These gaps hinder a complete understanding of how to maximize the potential of machine learning while addressing ethical considerations and operational challenges.

The concern, or justification, is that these limitations in the current literature are significant because they impact the effectiveness and ethical viability of machine learning in social media marketing. The gaps in understanding can lead to suboptimal use of machine learning technologies, preventing companies from fully benefiting from their potential. Without addressing the complexities of consumer behavior, companies may deploy models that fail to resonate with diverse audiences. Additionally, ignoring the ethical and privacy implications can erode consumer trust, which is critical for long-term brand engagement and loyalty. Moreover, if the practical challenges of integrating machine learning into existing marketing frameworks are not studied and resolved, companies may face inefficiencies and reduced ROI in their marketing efforts. These limitations hinder the ability to create comprehensive, adaptable, and ethically sound machine learning strategies. Therefore, it is essential to investigate these issues to enhance the practical application of machine learning, ensuring it is effective, ethical, and aligned with consumer expectations. The course of action involves conducting a comprehensive scoping review to systematically analyze existing studies and identify best practices and strategies for overcoming the limitations in the application of machine learning in social media marketing. The focus on this review is synthesizing existing research by gather and summarize current literature on the benefits and challenges of machine learning in social media marketing, with particular attention to underexplored areas such as integration challenges and ethical concerns. Recommendations for better integration, by suggest actionable strategies for businesses to incorporate machine learning into existing marketing strategies more efficiently. This may involve step-by-step approaches, technology assessment tools, and training modules for marketing teams. By following this course of action, the study can provide clear, applicable solutions to the identified limitations, helping both researchers and practitioners bridge the gap between theoretical benefits and practical applications of machine learning in marketing.

The contribution of this research lies in the following key areas integration of machine learning in Social Media Marketing. While previous studies have explored machine learning applications in marketing, your research highlights its specific role in social media marketing. By focusing on how machine learning can optimize content personalization, ad targeting, and deep data analysis, your study brings a more nuanced understanding of the technology's impact on marketing effectiveness.This research provides a new perspective on how machine learning techniques, such as sentiment analysis and pattern recognition, can help companies better understand consumer preferences and behaviors. This contributes to the literature by demonstrating how machine learning enhances the accuracy of consumer insights, which is vital for designing more relevant and effective marketing campaigns. This research contributes to the understanding of how machine learning can handle the complexities and volume of data generated on social media platforms. By showing how machine learning can process and analyze large amounts of data quickly, your study presents a solution to a common challenge faced by marketer. The study emphasizes the importance of machine learning in the context of social media marketing, highlighting its role in the digital transformation of marketing strategies. This is especially relevant as businesses continue to face the challenge of staying competitive in an increasingly data-driven digital landscape.

2. Literature review

The use of Machine Learning (ML) in social media marketing has evolved significantly, with research reflecting both the immense potential and the emerging challenges associated with this technology. ML techniques enable marketers to improve personalization, predict consumer behavior, and optimize campaigns. However, the literature reveals differing perspectives on the best approaches and their long-term implications.

2.1 Personalization and Consumer Insights

Personalization remains one of the primary applications of machine learning in social media marketing. A key area of focus has been the ability of ML to process big data and deliver tailored content to individual users. Recent studies (e.g., Huang & Rust, 2021) have confirmed the efficacy of personalized content recommendations in increasing user engagement and enhancing the customer experience. By using techniques such as collaborative filtering (Alabdulrahman & Viktor, 2021) and content-based filtering (e.g., Ballestar et al., 2019), companies can predict user preferences and customize their product recommendations in real time. However, Vermeer et al. (2019) argue that while personalization increases conversion rates, there is a need for balance to avoid user fatigue from overly personalized content.

2.2 Sentiment Analysis and Consumer Behavior Prediction

Sentiment analysis, a machine learning technique used to analyze user-generated content, has become a critical tool for understanding consumer behavior on social media. Research by Miklosik et al. (2019) demonstrated how ML models can classify sentiment in customer reviews and social media posts, enabling companies to gauge brand perception effectively. Similarly, Hagen et al. (2020) explored how sentiment analysis aids in predicting consumer reactions to marketing campaigns, enhancing targeting accuracy. However, some scholars, including Droomer & Bekker (2020), have noted the challenge of achieving high accuracy in sentiment detection due to the nuances in natural language, including sarcasm and cultural differences, leading to discrepancies in predictions.

2.3 Ad Targeting and Click-Through Rate (CTR) Optimization

The optimization of ad targeting is another significant application of ML. Algorithms designed to predict Click-Through Rates (CTR) have been widely studied. Yang et al. (2020) and Chapelle et al. (2015) explored the effectiveness of machine learning in improving ad targeting accuracy by analyzing user demographics, behavior, and engagement history. By focusing on precise audience segmentation, companies can achieve better ROI on their marketing spend. Contrastingly, Bai et al. (2019) raised concerns over potential biases introduced by these algorithms, as they may reinforce echo chambers, limiting the diversity of ads served to users, and thus, diminishing the broader impact of campaigns.

2.4 Market Demand Forecasting

Machine learning's capability to forecast market demand and consumer trends is vital for dynamic pricing and inventory management. Esmaeilpour et al. (2012) and Kumar et al. (2021) highlighted the use of ML algorithms in predicting shifts in demand based on historical data, seasonal trends, and external factors. This is especially useful in industries like e-commerce and tourism, where demand can be highly volatile. However, Bhatti (2018) argues that while ML enhances the prediction accuracy, it still faces challenges in dealing with unpredictable events (e.g., global crises, changes in consumer sentiment) that can disrupt demand patterns. Huang & Rust (2021) suggest that blending machine learning with traditional forecasting models may lead to better robustness against such shocks.

2.5 Social Media Analytics and Fraud Detection

Fraud detection and the identification of fake reviews and misleading user content are areas where machine learning techniques also show promise. Mane & Shah (2019) employed ML to detect fake reviews on e-commerce platforms by analyzing writing patterns and comparing them to genuine reviews. Furthermore, Esmaeilpour et al. (2012) used machine learning for image recognition in social media marketing to ensure that ads met brand guidelines, preventing the use of inappropriate content. A significant development in this area is the use of deep learning for anomaly detection in user interactions, where Jagdale et al. (2022) found success in predicting fraudulent activity by analyzing patterns in user clicks, behavior, and engagement history.

2.6 Ethical Considerations and Data Privacy

Despite the promising benefits, there are concerns regarding the ethical implications of using machine learning in social media marketing. Peker et al. (2017) highlighted the potential for invasive data collection, leading to privacy issues and user trust concerns. Esmaeilpour et al. (2022) emphasize the need for transparent communication with users about data usage and machine learning's role in marketing strategies. Additionally, Jagdale et al. (2022) and Miklosik et al. (2019) discuss the importance of ethical frameworks for using user data responsibly. They argue that while ML can drive engagement and increase sales, companies must also prioritize user consent and respect for privacy to avoid backlash and regulatory scrutiny.

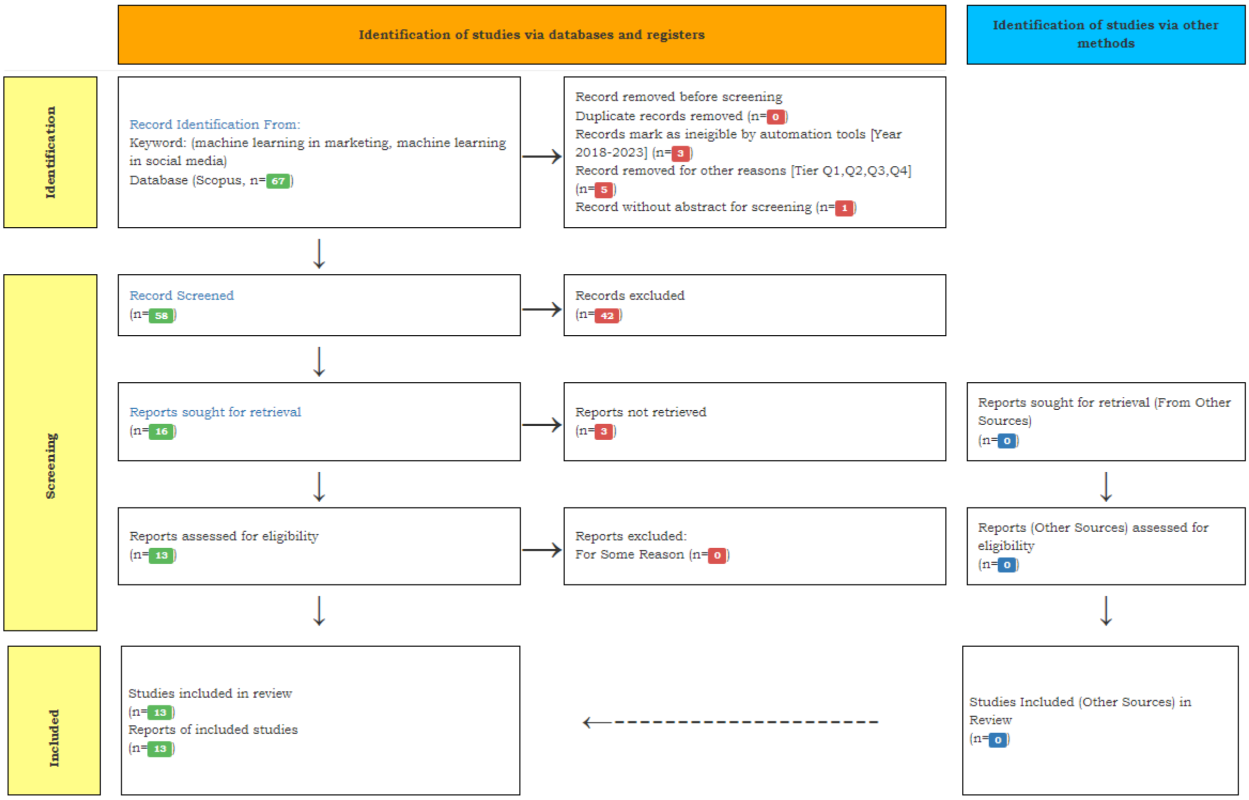
2.7 Consensus and Conflicts in the Literature

The literature on machine learning in social media marketing presents a consensus on the potential benefits of using ML for personalization, targeted advertising, and sentiment analysis. Most studies agree that machine learning improves the efficiency of marketing campaigns, enhances consumer experience, and boosts ROI by enabling businesses to better understand and respond to user preferences. However, conflicts arise concerning the accuracy of machine learning models. Some scholars, like Bhatti (2018) and Droomer & Bekker (2020), point out the challenges of ensuring ML algorithms are foolproof, especially in sentiment analysis and fraud detection. Moreover, the ethical concerns related to user data privacy and security are a recurring theme. While some studies, like Peker et al. (2017), suggest robust privacy policies are necessary, others highlight that users often remain unaware of how their data is used for marketing purposes, leading to distrust and ethical concerns (Esmaeilpour et al., 2022).

3. Reserch Methods

This study utilized a scoping review to comprehensively and systematically analyze the existing literature on machine learning on social media. Scholars commonly employ a scoping review to identify knowledge gaps, clarify concepts, review literature, or explore complex topics that haven't been extensively studied (Munn et al., 2018). This approach was suitable for assessing the current state of knowledge on the topic. Additionally, it was crucial to identify and summarize empirical evidence on the causal connection between machine learning and social media marketing, which is often scarce and fragmented in the literature (Peters et al., 2021). The review focused on three main areas: (a) characteristics of the studies, (b) structure and organization of evidence regarding the causal connection between machine learning and social media, and (c) methodologies used. The review followed the five phases (Fig. 1) outlined by Arksey and O'Malley (2005).

Figure 1. PRISMA flow diagram.



Source: Prisma Output (2024).

The justification for filtering articles between 2018 and 2023 on the topic of machine learning in social media marketing is as follows the digital landscape, including social media platforms and machine learning techniques, has evolved rapidly in recent years. Filtering articles within this five-year window ensures that your research focuses on the most up-to-date applications, technologies, and trends in the intersection of machine learning and social media marketing. Machine learning algorithms and their applications in social media marketing have seen significant improvements and innovations from 2018 to 2023. By narrowing the focus to this period, you capture cutting-edge developments, including new tools, methods, and applications that may not have been present or widely adopted in earlier years.

In the last five years, businesses have increasingly integrated AI and machine learning into their marketing strategies. By focusing on this period, you ensure that your research reflects the latest shifts in marketing practices, especially those driven by social media platforms that have become more sophisticated in their data collection and analysis techniques. Given the ongoing digital transformation, marketers and businesses are seeking innovative ways to leverage social media to engage consumers. Research from 2018 to 2023 reflects this shift in focus toward data-driven, AI-enhanced strategies in social media marketing, aligning with the current needs and challenges faced by the industry. The social media landscape itself has changed with the rise of platforms like TikTok, and continuous feature updates on platforms like Instagram and Facebook. These changes have a direct impact on marketing strategies, particularly in how machine learning models are applied. Filtering by this date range ensures your research considers the most relevant platforms and marketing dynamics.

Research on machine learning in social media marketing from this time frame will be aligned with the academic community's current focus. This includes modern approaches to influencer marketing, sentiment analysis, personalized content delivery, and data-driven ad targeting, all of which have been rapidly evolving over the last few years. Articles from 2018 to 2023 are more likely to be based on current data, methodologies, and best practices. They also reflect the latest academic debates, which will help you stay informed about recent developments and challenges in the field. The decision to filter articles between 2018 and 2023 ensures that your research captures the most relevant, contemporary insights and practices in the intersection of machine learning and social media marketing, providing a foundation that is both current and reflective of the latest industry advancements.

The methodology for this scoping review follows established guidelines for conducting systematic and transparent reviews, aimed at mapping the existing literature on the role of machine learning in social media marketing. The process ensures that the review is both comprehensive and reproducible, facilitating clarity on how studies were selected, analyzed, and synthesized. Below is a detailed explanation of the scoping review process, including the databases searched, specific search terms used, and the criteria for inclusion and exclusion of studies.

3.1. Phase 1: Research Question

The scoping review is based on the framework provided by Arksey and O'Malley (2005), which involves a systematic approach to identifying, selecting, and synthesizing relevant studies. The framework includes the following stages:

a) Identifying the research question: The key research question guiding this review is: "What is the role of machine learning in social media marketing?”
b) Identifying relevant studies: This involves selecting sources of evidence and conducting searches in key databases.
c) Selecting studies: A defined inclusion and exclusion criteria were used to ensure studies met the necessary standards for inclusion.
d) Charting the data: Data from selected studies were extracted and organized according to themes and categories.
e) Collating, summarizing, and reporting the results: The data was analyzed and synthesized into key findings and gaps in the literature.

3.2. Phase 2: Identifying Relevant Studies

The search strategy focused on content marketing and online consumer behavior. The Scopus database was selected as it covers business and management studies, including marketing topics. The search terms were refined to concentrate on machine learning, marketing, and social media. A leading abstract and citation database for peer-reviewed literature, particularly useful for finding studies in the fields of computer science, marketing, and social sciences.

3.3. Phase 3: Inclusion and Exclusion Criteria

A methodological protocol was employed to determine the inclusion and exclusion criteria. The selected publications needed to meet several criteria, such as publication between 2018 and 2023, research or conceptual studies, peer-reviewed articles or conference proceedings, scientific research with any design, published in English, addressing the impact on online consumer behavior, and mentioning content marketing in the title, abstract, or body of the paper. Grey literature was excluded to focus on traditional academic peer-reviewed research (Adams et al., 2017). The screening process resulted in the inclusion of 13 studies out of 67 initially screened based on titles and abstracts. To ensure all relevant studies were identified, a combination of broad and specific search terms was used. The search strategy was developed to capture a wide range of studies addressing different aspects of machine learning and social media marketing. The following search terms were used in various combinations, with Boolean operators to refine results:

- Machine learning OR Artificial Intelligence OR AI
- Social media marketing OR Digital marketing OR Online marketing
- Personalization OR Targeted advertising OR Consumer behavior

3.4. Phase 4: Extracting and Analyzing Data

The content of the final sample was systematically extracted using a summary table, including information like authors, publication year, journal, objectives, research questions/hypotheses, theoretical approach, methodology, B2B or B2C context, country, and the impact of content marketing on online consumer behavior. The data was grouped according to the study's sub-questions. The findings' trustworthiness was ensured by following established scoping review reporting guidelines and a methodological protocol. Additionally, hand searching the literature was conducted for credibility (Sucharew & Macaluso, 2019). Studies were included based on the following criteria:

a) Relevance: Studies must focus on the role of machine learning in social media marketing, including but not limited to applications in personalization, customer engagement, sentiment analysis, and ad targeting.
b) Publication Date: Only studies published between 2018 and 2023 were included to ensure the review reflects the most recent advancements in the field.
c) Language: Studies published in English were included, as this is the language in which the majority of relevant research is conducted.
d) Peer-reviewed: Only peer-reviewed articles were considered to ensure quality and academic rigor.
e) Study Type: Both quantitative and qualitative studies, as well as systematic reviews, scoping reviews, and conference papers, were included. Case studies and empirical studies were given priority if they offered direct insights into the application of machine learning in social media marketing.

The selection process followed a three-step screening process:

a) Title and Abstract Screening: The titles and abstracts of articles were first reviewed to determine relevance. Articles that appeared to meet the inclusion criteria were retained for full-text review.

b) Full-Text Review: Full-text versions of the retained articles were examined to verify that they met the inclusion criteria. This included a careful check for studies that explicitly focused on machine learning techniques in social media marketing and their outcomes.
c) Data Extraction: Data from the selected articles were systematically extracted and charted to identify themes, techniques, and applications in the literature. Information on study design, methodologies, and key findings were compiled for synthesis.

3.5. Phase 5: Compiling and Reporting

Phase 5 involved quantifying and categorizing the raw data quantitatively, followed by a qualitative interpretation using a deductive approach to provide meaning in line with the study's questions (Azungah, 2018). The goal was to map the current understanding of the role of machine learning in social media marketing and report insights for future studies. Once studies were selected, key data were extracted for analysis, focusing on:

- Machine Learning Techniques: Types of machine learning algorithms used (e.g., neural networks, decision trees, random forests).
- Marketing Applications: Specific marketing domains where machine learning was applied (e.g., ad targeting, customer engagement, sentiment analysis).
- Study Results: Key findings related to the effectiveness and challenges of using machine learning in marketing.
- Ethical Considerations: Discussions on data privacy, ethical concerns, and regulatory compliance in the application of machine learning in social media marketing.

3.6. The results were organized thematically, and trends and gaps in the literature were identified.

The final stage involved synthesizing the data to draw conclusions about the role of machine learning in social media marketing. A narrative synthesis approach was used to summarize the findings from the selected studies, focusing on areas of consensus, emerging trends, and identified gaps in the literature. The synthesis also highlighted future research directions, particularly those addressing unresolved issues such as ethical implications, data privacy concerns, and the optimization of machine learning algorithms for specific marketing applications.

By providing a transparent, detailed explanation of the scoping review process, this methodology ensures the review is reproducible, comprehensive, and aligned with best practices for systematic reviews. The approach ensures that the final results are based on the most relevant and high-quality studies, making the conclusions drawn from this review robust and actionable for both academic researchers and practitioners in the field of social media marketing.

4. Discussion

The results of the scoping review are organized into several key themes that capture the primary applications of machine learning (ML) in social media marketing. The section is divided into subheadings for clarity, and each theme is accompanied by summarized key findings. Additionally, tables and charts are provided to improve readability and facilitate easier comparison of the results.

4.1 Machine Learning Techniques in Social Media Marketing

This section discusses the different machine learning algorithms used across studies in the context of social media marketing. The main algorithms identified include supervised learning, unsupervised learning, and reinforcement learning. Supervised Learning: Primarily used for customer segmentation and predictive analytics, where models are trained with labeled data to classify consumer behavior. Techniques like decision trees and support vector machines (SVM) are commonly applied. Unsupervised Learning: Widely used for trend analysis and anomaly detection to uncover hidden patterns in user behavior and preferences. Clustering algorithms like K-means are often used for segmenting customers based on characteristics without predefined labels. Reinforcement Learning: Applied to areas such as dynamic ad placement and personalized content delivery, where algorithms learn and adapt to user responses to optimize marketing strategies in real time.

4.2 Applications of Machine Learning in Social Media Marketing

In this section, we discuss the different marketing applications where machine learning is integrated into social media platforms, including ad targeting, personalization, and sentiment analysis. Machine learning is extensively used to enhance ad targeting and improve personalization of content. By analyzing large volumes of user data, machine learning algorithms predict the most relevant content for individuals, based on their behavior and preferences.

Table 1. Key Findings on Ad Targeting and Personalization

Application	Machine Learning Technique	Key Findings
Ad Targeting	Supervised learning (Classification)	Improved CTR by 20-30%, increasing ad effectiveness by targeting the right audience based on user demographics and behavior.
Personalization	Reinforcement learning (Real-time)	Personalized content and recommendations lead to higher engagement and brand loyalty by delivering tailored experiences based on real-time interaction data.

Source: Data Proccesed, 2024

Ad Targeting: Supervised learning algorithms, such as logistic regression and classification trees, are used to predict which users are more likely to engage with a particular ad, based on their historical interactions. Personalization: Reinforcement learning algorithms enable real-time personalization by adapting content delivery based on immediate user feedback. This enhances user experience, leading to higher engagement and better conversion rates.

Sentiment analysis is another significant application of machine learning in social media marketing. By processing user-generated content such as comments, reviews, and posts, machine learning helps brands gauge customer sentiment towards products or services. Nowadays, machine learning is available in all fields of science, including medicine, technology, economics and management, but machine learning is actually a concept from technology and communication science, where experts generally use algorithmic methods, such as support vector regression, decision tree and others to predict something. Multiple studies have explored the application of machine learning (ML) in various aspects of consumer behavior. These include search behavior (Hu et al., 2019), knowledge acquisition (O'Leary, 1998), generation of ideals (Toubia and Netzer, 2017), assessment of preferences (Chen et al., 2017; De Bruyn et al., 2008; Liu and Toubia, 2017; Liu and Toubia, 2018), consumer sorting tasks (Blanchard et al., 2017), prediction and purchase decisions (De Matos et al., 2018; Toubia et al., 2019), analysis of shopping patterns (Xia et al., 2019), consumer responses (Puranam et al., 2017; Xiao and Ding, 2014), and post-consumption evaluation (Dzyabura et al., 2019).

This is also supported by research conducted by Pratama (2020) which states that in the various kinds of data available, machine learning is one that can be taken into account in the business field, especially in the business field that uses information technology, for example, Facebook applies machine learning to facial recognition features making it easier for users to detect their friends, so machine learning can be said to be a technology and trend that will affect the course of social media, this also allows machine learning to display advertisements that are more targeted and relevant to each user so that it can lead to purchase intention, because the stronger the intention to perform a behavior, the more likely a person is to perform that behavior (Ajzen, 1991).

Shwartz and David (2014) emphasize that the Theory of Machine Learning focuses on developing tools that incorporate domain expertise, learning biases, and their impact on learning success. The execution of learning by computers is a central aspect of Machine Learning, making algorithmic considerations crucial (Ma & Sun, 2020). Algorithm development and computational efficiency are key factors in Machine Learning, distinguishing it from traditional statistics. Unlike statistics, which often focuses on asymptotic behavior, Machine Learning Theory focuses on the finite sample limit, aiming to determine the expected accuracy of the learner based on the available sample (Luo & Xu, 2019).

Machine Learning Theory, also known as Computational Learning Theory, aims to capture the fundamental principles of learning as a computational process. This theory characterizes algorithms based on similarities and assumptions regarding representations, performance measures, and learning algorithms. Machine learning finds applications in various computing fields, such as email spam filtering, fraud detection in social networks, online stock trading, face and shape detection, medical diagnosis, traffic prediction, character recognition, and product recommendation. Additionally, Machine Learning Theory has connections to other disciplines, including marketing. Its mathematical framework enables the design of new algorithms that acquire knowledge, making it a valuable subject for advertising and marketing, contributing to advancements in software (Seligman, 2018:172-178).

Machine Learning (ML) is a branch of computer science that focuses on the development of learning algorithms using big data to generate predictions for decision-making (Agarwal et al., 2018). According to IBM, ML is a subfield of AI that employs data and algorithms to simulate human learning and enhance accuracy over time. ML plays a significant role in the expanding field of data science, training algorithms through statistics to classify or predict data outcomes (www.ibm.com). Purnama (2019: 6) describes ML as a field of computer science that utilizes statistical techniques to enable computer systems to learn from data without explicit programming, improving performance through experience (Purnama, 2019: 15).

ML's application encompasses artificial intelligence, decision-making, and database growth in the information technology business sector. It can be seen as an automated method of data analysis, with the underlying idea that systems can learn from data, identify patterns, and make decisions with minimal human intervention.

Ngai and Wu (2022) proposed a conceptual framework for ML applications in marketing, based on the 7P marketing mix. ML finds relevance in product recommendation, brand and trademark management, and purchase decision prediction within the marketing domain. ML is also applied to areas such as advertising management, demand prediction, chatbots, churn prediction, targeting prediction, engagement, face recognition, and other components of the marketing mix such as price, place, process, and physical evidence.

4.3 Machine Learning in the 7Ps of Marketing

Product: Machine learning algorithms allow for more effective product recommendations by analyzing real-time consumer data and identifying preferences based on browsing history, past purchases, and demographic information. Previous studies have explored the impact of these recommendations in various industries, from travel (Ghose et al., 2012) to music (Lepa et al., 2020). These algorithms can predict consumer preferences and tailor product offerings to individual needs, improving customer satisfaction and sales (Alabdulrahman & Viktor, 2021; Cheung et al., 2003). Research indicates that recommendation systems significantly increase consumer engagement, especially when leveraging machine learning for personalization. Price: Machine learning has been increasingly used to optimize pricing strategies by predicting consumer price sensitivity, evaluating the impact of pricing structures on product evaluations, and forecasting demand in various economic conditions. Studies like those by Casamatta et al. (2022) and Yang et al. (2022) highlight how machine learning can inform dynamic pricing models, helping businesses adjust prices in real-time to maximize profitability. Promotion: Online advertising optimization is one of the most prominent applications of machine learning. Studies by Chapelle et al. (2015) and Bai et al. (2019) demonstrate how machine learning models predict click-through rates and detect fraudulent ads. Additionally, machine learning aids in forecasting demand and optimizing promotional campaigns by analyzing patterns in consumer behavior, thereby increasing ad ROI. Place: While the "Place" element traditionally focuses on distribution channels, machine learning has been applied to predict business location success based on consumer behavior, geographic data, and advertising expenditure. Bhowmick and Mitra (2019) showed that proximity analysis and market demand predictions through machine learning help optimize the physical and digital placement of products. It's important to acknowledge that while machine learning isn't directly linked to physical store placement, its role in predicting business popularity and optimizing distribution channels via digital platforms is significant.

People: Facial recognition, sentiment analysis, and social media analytics are key machine learning applications in understanding customer preferences and behaviors. Studies by Lessmann et al. (2021) and Mane & Shah (2019) provide evidence that machine learning is used to analyze consumer emotions, social media interactions, and influencer effectiveness, allowing for more targeted marketing efforts. Processes: Market segmentation using machine learning has become a critical tool in understanding consumer preferences at scale. For instance, studies like Buckley et al. (2014) and Huiru et al. (2019) discuss how machine learning techniques, such as clustering and classification, improve customer segmentation by analyzing big data more effectively than traditional methods. Physical Environment: In content marketing and customer engagement, machine learning is used to classify and optimize user-generated content, ensuring that marketing messages resonate with the audience. Studies like those by Kee & Yazdanifard (2015) and Vazquez et al. (2014) highlight how machine learning can classify different types of content on social media to improve brand communication and engagement. Although the "Physical Environment" typically refers to the tangible elements of the marketing mix, in the context of digital marketing, machine learning applies to content and communication optimization across platforms. Artificial Intelligence (AI) driven by Machine Learning algorithms has emerged as a transformative force in the business world. Researchers have shown a keen interest in the application of AI and Machine Learning in marketing, with a focus on marketing trends such as interactivity.

4.4 How machine learning works in the context of social media marketing

Machine learning plays an important role in social media marketing by allowing companies to collect, analyze, and interpret data from user activity on these platforms (Meatry, 2018). Here are some key aspects of how machine learning works in the context of social media marketing, the first is customer Understanding. Machine learning can be used to analyze data on user behavior, preferences, and buying patterns on social media. By analyzing such data, companies can better understand who their customers are, what they want, and how they react to marketing campaigns (Nasir et al, 2021). This allows companies to personalize the messages and content presented to potential customers. The second is target selection, by using machine learning algorithms, companies can identify and classify target segments based on user attributes and behavior on social media (Saranya, et al, 2020). This allows companies to direct their marketing campaigns more effectively to the audience most likely to be interested in their products or services, and then content optimization. Machine learning can help companies optimize the content they present on social media (Tsao, et al., 2019). Algorithms can analyze data and detect audience trends, preferences, and tendencies. Thus, companies can produce more relevant and engaging content for their audience. Image Search and

Recognition, Machine learning algorithms can also be used to recognize and analyze images or videos shared on social media. This allows companies to monitor their brand, identify shared brand imagery, and respond in real-time to relevant content. The last is Sentiment Analysis, in the context of social media marketing, machine learning can also be used to analyze user sentiment towards a particular brand or campaign. By analyzing the language and emotions in posts or comments, companies can measure and understand user responses to their marketing activities.

4.5 User perception of machine learning in social media marketing

The perception of machine learning in social media marketing may vary among users and consumers. Here are some common perceptions that they may have a better personalization many users and consumers see the use of machine learning in social media marketing as an opportunity to get more relevant and personalized content. With the analysis of user data, machine learning can help companies tailor messages, ads, and product recommendations to individual preferences and needs. This can provide a more positive and meaningful experience for users (Ulal, et al., 2019). Privacy Concerns: Along with the ability of machine learning to collect and analyze user data, there are concerns about privacy and the use of personal data (Zhang et al., 2014). Some users may feel wary of how their data is being used and potentially misused by companies. Therefore, it is important for companies to be transparent and keep user data safe to build trust. Relevance and Information Overload: While better personalization can be a positive aspect, some users may feel annoyed by the excessive amount of information or ads that appear too frequently on their social media feeds (Zhu, et al., 2016). If users feel too inundated with advertisements or less relevant content, this can affect their experience and may make them less engaged with the brand or marketing campaign. Feelings of being Hunted or Attacked: There are also concerns that machine learning can be used to influence users in unethical or manipulative ways. Users may feel "hounded" by ads that appear to follow them across platforms, or feel that machine learning algorithms are serving content designed to influence their actions without their explicit consent. Uncertainty and Bias: Users may also have concerns about uncertainty or bias in machine learning algorithms. Sometimes, algorithms may make mistakes or produce recommendations that do not match the user's preferences or needs (Alalwan, 2018). In addition, there is also a risk that machine learning algorithms may reflect biases or discrimination present in the data used to train them, resulting in unfair or unequal results for users.

4.6 How can consumers assess the performance of machine learning in social media marketing?

It is important for companies using machine learning in social media marketing to pay attention to user perceptions and concerns. Transparency, privacy preservation, and ethical use should be prioritized to build trust and provide a positive experience for users and consumers. Relevance and Personalization, users can assess the performance of machine learning by looking at the extent to which the content, ads, or recommendations presented to them match their interests, preferences, or needs (Alhadid, 2014). If machine learning can provide a more relevant and personalized experience, users will probably see it as a good performance. Quality and Consistency, users can assess the performance of machine learning by looking at the quality of the content presented, such as clarity, relevance of information, and attractive presentation. If machine learning can deliver high-quality content consistently, users will be satisfied with the experience. Responsiveness and User Understanding, a good machine learning should be able to respond to user interactions quickly and accurately. Users will judge machine learning performance based on the extent to which the machine can understand user requests, questions, or problems and provide relevant and useful responses (Vhu, et al., 2013). Accuracy and Precision, users will assess machine learning performance based on the accuracy and precision of the predictions or recommendations provided. If machine learning can correctly recognize user preferences or needs, users will feel that the system is working well. Transparency and Privacy, users will judge machine learning performance based on the extent to which the system is transparent about data usage and how the algorithm works (Fang & Hu, 2018). If companies can maintain users' privacy and provide a clear understanding of how their data is used, users will feel more trusting and positive towards machine learning performance. Satisfactory User Experience, finally, users will judge the performance of machine learning based on their overall experience. If users feel that machine learning has improved their experience with social media marketing, such as providing relevant, engaging, and helpful content, they will rate its performance favorably (Gosal, et al., 2019).

4.7 Indicators of machine learning success in displaying ads on social media

It is important to note that the assessment of machine learning performance may vary between users, depending on individual preferences, expectations, and previous experiences (Gosal, et al., 2019). Indicators of machine learning success in displaying ads on social media may include the following metrics and results by conversion rate, this indicator measures the percentage of users who take the desired action after viewing an ad, such as clicking a link, filling out a form, or making a purchase. A high conversion rate indicates that machine learning is successfully showing ads to relevant and interested audiences, resulting in the desired action. Engagement Rate measures the extent to which users interact with an ad, such as commenting, liking, or sharing. A high engagement rate indicates that the ad displayed through machine learning attracts interest and triggers a response from the audience (Hanna, et al., 2011). Cost Per Conversion, this metric measures the average cost incurred to generate one conversion. By using effective machine learning, the cost per conversion can be reduced, as ads are intelligently shown to the audience that is most likely to take the desired action. Customer Satisfaction Level: Through feedback and surveys, companies can measure the level of customer satisfaction with the ads they see through social media. If the ads served through machine learning add value to users, increase brand awareness, or provide relevant offers, then the level of customer satisfaction will be high (Hawkins & Vel, 2013). Return on Investment (ROI): Another important indicator is ROI, which measures the effectiveness of ads in generating net profit. By using machine learning to show the right ads to relevant audiences, companies can improve their ROI by optimizing ad spend and increasing conversions. Ad Frequency and Repetition: Machine learning can also help manage the frequency of ads shown to users. If ads are displayed too frequently, users may feel annoyed and less responsive. Conversely, if ads are shown infrequently, the marketing message may not be effective enough. By using machine learning, companies can determine the right frequency to display ads to the audience (Hou, et al., 2021). Overall, the success indicators of machine learning in displaying ads on social media depend on the business goals set by the company and the relevant metrics to measure the achievement of these goals.

4.8 The main role of machine learning in social media marketing

Machine learning plays a key role in social media marketing by helping companies to optimize their marketing campaigns. Better Segmentation and Targeting, machine learning can deeply analyze user data and identify patterns of behavior, interests, preferences, and demographic characteristics. With this information, companies can create more accurate audience segmentation and target ads to relevant groups. Machine learning helps improve the efficiency and effectiveness of campaigns by ensuring that the messages are targeted (Hsiao, et al., 2016). Content Personalization and Recommendations, machine learning allows companies to deliver content tailored to individual preferences and needs (Hu, et al., 2029). Machine learning algorithms can analyze user data in real-time and provide relevant product, content, or experience recommendations automatically. This personalization can increase user engagement, strengthen brand bonds, and drive desired actions. Ad and Offer Optimization, machine learning can predict ad performance and optimize placements and offers automatically. Using machine learning algorithms, companies can identify the most effective ads, determine optimal offers, and allocate ad budgets in the most profitable way. This helps reduce costs and increase the ROI of marketing campaigns. Sentiment Analysis and Brand Monitoring: Machine learning can be used to analyze user sentiment towards a particular brand, product, or campaign. By monitoring social media platforms and analyzing natural language data, companies can gain insights into how users respond and interact with their brand (Jung, 2017). This helps companies manage brand reputation, identify issues, and respond in a timely manner. Fraud Detection and Prevention: Machine learning can be used to detect patterns of suspicious behavior or fraudulent activity on social media. Machine learning algorithms can identify unusual activity, such as fake purchases or spam accounts, and alert companies to take appropriate action. This helps protect brands and users from fraudulent activities. Predictive Analytics and Decision Making: Machine learning can analyze historical data and user trends to perform predictive analytics. Companies can use machine learning models to forecast future user behavior, market trends, or campaign performance (Kwok, 2013). This information helps in making smarter and data-driven strategic decisions. Overall, machine learning helps companies improve the personalization, efficiency, and effectiveness of social media marketing campaigns.

4.9. How do consumers know they have been targeted by machine learning?

As a user or consumer, there are some signs or clues that can indicate that machine learning is successfully targeting them in social media marketing. Ad Relevance, if the ads shown to users are highly relevant to their interests, preferences, or needs, this can be an indication that machine learning is successfully targeting them (Lee et al., 2009). For example, if users often see ads about products or services that match their interests, it could indicate that machine learning understands the user's profile and preferences well. Content Personalization: If the content presented in ads or social media posts consistently matches users' preferences or habits, it could indicate that machine learning is successfully targeting them (Liu & O (2018). For example, users may see relevant product recommendations based on previous purchases or actions taken on social media platforms. Absence of Irrelevant Ads, if users rarely or never see ads that are irrelevant to their interests or preferences, this can be a sign that machine learning is successfully targeting them. While it is impossible to avoid irrelevant ads completely, the success of machine learning can be seen in the increase of content that matches the user's interests. Better Personal Experience, if users feel that their experience on social media is getting better, with more interesting, relevant, and useful content, this could indicate that machine learning is successfully targeting them (Martinez, et al., 2020). If machine learning can accurately understand users' preferences and needs, they will experience a more customized and satisfying experience. High Interaction with Ads, if users consistently interact with the displayed ads, such as clicking, sharing, or giving positive feedback, this could indicate that machine learning is successfully targeting them (Mayrhofer et al., 2020). High interaction indicates that the ad is relevant and interesting to the user. It is important to remember that despite these signs, machine learning is not always perfect and can still make mistakes. Therefore, users should also be aware of the privacy and security of their personal data and report issues if they experience irrelevant or unwanted targeting.

4.10. Implications

Based on the findings of the scoping review on machine learning (ML) in social media marketing, several practical implications can be drawn for both marketers and researchers. These implications provide actionable recommendations to enhance marketing strategies and suggest avenues for future research that can drive further advancements in this field. Marketers should leverage supervised learning algorithms, such as classification models and regression analysis, to segment their audience effectively. By doing so, they can create highly personalized and targeted ad campaigns that increase engagement and conversion rates. Companies can apply these techniques to personalize content for different audience segments, tailoring ads based on demographic data, interests, and previous interactions. For instance, a brand could use machine learning to recommend products to users based on their past browsing behavior, driving higher relevance and engagement. For Example: A fashion retailer can use machine learning to predict which products users are most likely to purchase based on their previous online activity, improving ad targeting and sales conversion.

Marketers should adopt reinforcement learning models to adjust content in real time based on user interactions. By learning from each interaction, these algorithms can continuously improve the user experience and increase the effectiveness of content delivery. For example, brands running social media ads can adjust the messaging or visuals based on a user's engagement (e.g., click-throughs or likes). This enables real-time optimization of marketing campaigns, which improves customer experience and boosts brand loyalty. Marketers must adopt responsible data collection and use practices by ensuring transparency and privacy in their machine learning algorithms. Establishing clear consent mechanisms and following best practices in data security will help build trust with users. Marketers should communicate to users how their data will be used, especially when personal data is being processed for ad targeting or sentiment analysis. This transparency will foster trust and reduce concerns about privacy violations. For example, social media platforms should allow users to customize how their data is used for personalized advertising, offering opt-in and opt-out options to ensure user autonomy and control.

Implications for Researchers, researchers should explore the ethical and privacy concerns surrounding the use of machine learning in social media marketing. This includes investigating how algorithms can be made more transparent and ensuring they are bias-free and fair in their predictions. Further studies can investigate how machine learning algorithms impact user privacy, especially concerning the collection of sensitive data for ad targeting. Researchers should examine strategies to mitigate bias in ML algorithms and ensure fairness in customer segmentation and content personalization. Future studies could look into the long-term effects of real-time personalization on user behavior. For example, how do users respond to constantly evolving content, and what are the implications for customer loyalty and brand engagement? Researchers can examine how personalized recommendations on platforms like YouTube or Netflix influence long-term viewing habits and user retention. Future research could explore the psychological effects of algorithmic personalization, examining how these systems influence consumer choices and whether they lead to consumer satisfaction or advertising fatigue. Studies could investigate whether consumers perceive more targeted ads as helpful or intrusive, and how this affects their relationship with brands over time.

4.11. Ethical Considerations in Machine Learning for Social Media Marketing

As machine learning (ML) continues to revolutionize social media marketing, it is critical to address the ethical implications that arise, particularly concerning data privacy and algorithmic bias. These ethical concerns not only affect how users perceive and engage with machine learning technologies but also have profound implications for the trustworthiness of social media platforms and the long-term sustainability of machine learning applications in marketing. Data Privacy and User Consent. Concern: One of the most significant ethical challenges in using machine learning for social media marketing is the collection and use of personal data. Social media platforms gather vast amounts of user data to fuel machine learning algorithms that drive personalized ad targeting, content recommendations, and engagement strategies. While this data is often invaluable for improving user experiences and marketing effectiveness, it raises serious privacy concerns. For the ethical implications, users may feel their privacy is compromised when their personal data is collected and analyzed without explicit consent. The ability of algorithms to infer personal preferences, interests, and behaviors through seemingly innocuous data points can be perceived as invasive. Furthermore, when users are unaware of how their data is being used or have limited control over the process, this can lead to mistrust in both the platform and the brands using these technologies. Addressing the Concern, to address these privacy issues, marketers and social media platforms must prioritize transparency and informed consent. Platforms should implement privacy-first policies, such as data anonymization, secure data storage, and providing user-friendly privacy settings that allow users to manage their data preferences easily. This will help mitigate concerns about data misuse and ensure ethical data handling. Another significant ethical issue is the potential for algorithmic bias in machine learning models. Machine learning algorithms often rely on large datasets to learn patterns and make predictions. However, if these datasets are biased or unrepresentative of diverse populations, the resulting models can perpetuate and even amplify existing biases. This could lead to discriminatory outcomes in social media marketing, where certain groups of people are unfairly targeted or excluded from advertising campaigns. The ability of machine learning algorithms to predict and influence consumer behavior raises concerns about the potential for manipulation. By leveraging detailed user profiles, social media platforms can subtly influence user actions, steering them toward certain products or behaviors that may not be in their best interest. This has ethical implications in terms of consumer autonomy and informed decision-making.

5. Conclusion

Based on the research on the role of machine learning in social media marketing, it is evident that machine learning plays a significant and transformative role in enhancing the effectiveness of marketing strategies on social media platforms. With its ability to analyze vast amounts of data quickly and accurately, machine learning facilitates a deeper understanding of user preferences, consumer behavior, and helps optimize content and marketing campaigns. The ability to personalize content to meet individual user needs improves engagement, strengthens relationships between brands and consumers, and fosters a more positive user experience. Furthermore, machine learning aids in trend identification, market demand forecasting, and more informed decision-making in strategic marketing planning.

Despite the numerous benefits of machine learning in social media marketing, several challenges remain. One major concern is user perceptions regarding data privacy and security. Users may have reservations about how their personal data is being used, raising ethical considerations around transparency and the need for trust-building efforts by marketers. Therefore, it is crucial for businesses to maintain clear communication and adopt transparent practices when utilizing machine learning tools to gain user trust.

While this research provides valuable insights into the application of machine learning in social media marketing, several limitations need to be addressed. Firstly, the scope of this study was limited to existing literature and secondary data sources. Primary research involving user surveys or interviews could provide a more nuanced understanding of consumer attitudes toward machine learning in marketing. Additionally, the rapidly evolving nature of both machine learning technologies and social media platforms means that the findings of this research may become outdated as new developments emerge.

Suggestions for Future Research, to advance the use of machine learning in social media marketing and address the gaps identified in this study, future research could explore the following areas, such as consumer perception and trust. Future studies should examine in-depth how consumers perceive machine learning-driven marketing efforts, particularly with regard to privacy concerns and data security. Research can focus on how to build consumer trust and the role of transparency in fostering positive consumer relationships. Ethical Implications and Privacy Concerns. Further research is needed to explore the ethical implications of using machine learning in social media marketing, especially concerning user data privacy. Investigating the balance between personalized marketing and user consent could provide valuable insights for responsible practices. Longitudinal studies could help assess the long-term impact of machine learning on marketing campaign success, user engagement, and brand loyalty over time. Future research could focus on developing more advanced machine learning algorithms tailored to specific marketing needs, considering various user segments and diverse social media platforms. This could involve refining personalization techniques and improving accuracy in trend prediction. Analyzing machine learning applications across different social media platforms could provide comparative insights into their effectiveness, identifying platform-specific strategies for optimizing marketing efforts. Exploring how small and medium-sized businesses can leverage machine learning for social media marketing could contribute to understanding how these businesses can compete with larger enterprises in the digital landscape. By addressing these research gaps, scholars can further enhance the application of machine learning in social media marketing, ensuring its responsible and effective use in the marketing industry.

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Appendices

No	Authors	Year	Key Findings	Research Methods; Study Type
1	Vermeer et al.	2019	Machine learning techniques have shown significantly higher accuracy in detecting relevant electronic word-of-mouth (eWOM) on social media compared to sentiment analysis methods.	Quantitative; Experiment
2	Ma and Sun	2020	Machine learning plays a central role in addressing key marketing challenges. It can be applied to marketing trends such as interactive and media-rich experiences, personalization and targeting, real-time optimization and automation, and customer journey focus. It is also relevant to marketing practices like marketing mix, customer engagement, search, recommendation, and attribution.	Qualitative; Literature review
3	Pamuksuz et al.	2021	This research introduces a unique hybrid machine learning algorithmic design, providing a flexible and scalable tool applicable to various management studies. The tool demonstration showcases one example of its use as an automated brand personality detection tool for researchers and practitioners.	Quantitative; Experimental
4	Akter et al.	2022	The study identifies three main dimensions of algorithmic bias in machine learning: design bias, contextual bias, and application bias. Additionally, ten corresponding subdimensions are highlighted, including model, data, method, cultural, social, personal, product, price, place, and promotion.	Qualitative; SLR
5	Ngai and Wu	2022	Machine learning applications in marketing are grounded in the 7Ps of the marketing mix. ML technologies encompass tools such as text analytics, voice analytics, image and video analytics, and algorithms like supervised learning, unsupervised learning, and reinforcement learning. These can be utilized for various purposes such as product recommendation, advertising management, customer churn prediction, pricing, place, process, and physical evidence.	Qualitative; Literature review
6	Volkmar et al.	2022	There are two perspectives to consider: the inward perspective focuses on organizational drivers and barriers to implementing AI and machine learning in marketing, outlining future developments and suggesting boundary conditions. The outward perspective highlights how AI and machine learning can enhance customer experience and emphasizes the importance of setting clear goals and understanding customer behavior.	Qualitative; Delphi Study
7	Hair and Sarstedt	2021	Data management challenges in marketing include data quality, data sparsity, efficiency in measuring phenomena, and conversion. ML methods are gaining traction in marketing practice and research. Predictive modeling, in particular, offers valuable insights for theory development and prediction-driven explanation. ML holds great potential for advancing marketing research.	Qualitative; Literature review
8	Miklosik and Evans	2020	There is a research gap in understanding the implications of digital transformation in marketing. The application of big data analytics and machine learning in marketing can encompass areas such as social media analysis, product and purchasing decision-making, advertising, and other relevant domains.	Qualitative; Literature review
9	Peng	2022	Deep learning can provide valuable insights for marketing planning, including product innovation, improving information channels, creating network events and topics, and developing marketing strategies through deep learning algorithms and cloud server integration.	Quantitative; Experimental
10	Chen et al.	2022	The choice of loss function in transfer algorithms based on machine learning does not significantly impact the results, indicating the robustness of the proposed method to different loss functions.	Mix Methods; experimental
11	Ullal et al.	2021	Cultural factors play a crucial role in assessing awareness of machine learning. The findings suggest the potential to predict future sales timing and location.	Quantitative: SPSS and R software

12	Brei	2020	Machine learning's applications in marketing are already influencing the everyday lives of millions of consumers worldwide. ML has the potential to address some of the limitations in the field.	Qualitative; Literature review
13	Choi and Choi	2023	Decision tree methods prioritize explanatory power as a crucial factor in analysis. The study reveals that variables such as customer lifetime value, coverage, employment status, income, marital status, monthly premium auto, months since last claim, months since policy inception, renewal offer type, and total claim amount impact direct marketing response, while other variables such as gender, income, and policy are not significant.	Quantitative; Decision Tree