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Review

Enhancing Social Media Platforms with Machine Learning Algorithms and Neural Networks

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Abstract: Network analysis aids management in reducing overall expenditures and maintenance workload. Social media platforms frequently use neural networks to suggest material that corresponds with user preferences. Machine learning is one of many methods for social network analysis. Machine learning algorithms operate on a collection of observable features that are taken from user data. Machine learning and neural network-based systems represent a topic of study that spans several fields. Computers can now recognize the emotions behind particular content uploaded by users to social media networks thanks to machine learning. This study examines research on machine learning and neural networks, with an emphasis on social analysis in the context of the current literature.

Keywords: social media; artificial neural networks; machine learning; social networks

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Citation: Taherdoost, H. Enhancing Social Media Platforms with Machine Learning Algorithms and Neural Networks. *Algorithms* **2023**, *16*, 271. https://doi.org/10.3390/a16060271

Academic Editors: Mukesh Prasad, Faezeh Karimi, Dinesh Vishwakarma and Zahid Akhtar

Received: 14 May 2023
Revised: 24 May 2023
Accepted: 25 May 2023
Published: 29 May 2023

1. Introduction

Machine learning is a process of autonomous learning that occurs through the processing of typically very large data sets according to a statement by L'heureux et al. [1]. The techniques of the past, referred to as "symbolic artificial intelligence (AI)," were based on algorithms consisting of logical sets of instructions for encoding a given output (typically referred to as the target) for all potential inputs. In contrast, the new machine learning algorithms "learn" directly from data and estimate mathematical functions that discover representations of an input or learn to link one or more inputs to one or more outputs to make predictions using new data [2].

In recent years, the application of machine learning has gained traction across various disciplines in the social sciences. For instance, in the field of economics, researchers such as Varian [3], Blumenstock et al. [4], Athey and Imbens [5], and Mullainathan and Spiess [6] have incorporated machine learning methods into their studies. Similarly, in political science, Bonikowski and DiMaggio [7] have explored the use of machine learning techniques. In sociology, scholars such as Baldassarri and Abascal [8] and Evans and Aceves [9] have applied machine learning in their research. Communication science has also embraced machine learning with studies conducted by Bail [10]. Furthermore, machine learning has found practical applications in the public administration sector (Athey [5] and Berk et al. [11]), as well as in the operations of private companies.

Kleinberg et al. [12] state that machine learning encompasses a wide variety of approaches and instruments. The function of user-generated content, which is also subject to feedback from other users [13,14], is expanding as a result of the proliferation of social media. Given that social networking sites (SNSs) offer abundant opportunities for social comparison [15], researchers have begun to investigate their implications for psychological health [16]. By spending a great deal of time observing the posts of others, users are inevitably drawn into the process of social comparison, particularly when using SNSs devoted to visual content, such as Instagram [17]. Social comparison research investigates how people respond when comparing themselves to others. It distinguishes between upward and descending comparisons. When comparing themselves to others negatively, people make an upward comparison. By comparing themselves to those they perceive to be superior, individuals may experience unpleasant and agonizing emotions, or they may be motivated to better themselves. A downward comparison occurs when individuals compare themselves favorably to those they perceive to be less fortunate. It can aid in restoring not only damaged self-esteem, but also joy and pride [18]. Thus, neither comparison is always uncomplicated, and they can have both positive and negative effects on the formation of self-evaluation and identity [18,19].

It is an undeniable fact that digitalization is altering the conventional procedures and balances of the current social and economic organizational model [20]. Approximately 15 percent of the city's annual budget is allocated to the implementation of these measures. Therefore, it is necessary to conduct an exhaustive analysis of the information on the crimes that have occurred so that the lines of preventative action can be focused on the most affected areas [21].

The advent of social networks has greatly enhanced global communication among Internet users. The analysis of social networks plays a vital role in summarizing the interests and opinions of users (referred to as nodes), uncovering interaction patterns (referred to as links) between users, and extracting valuable insights from the events occurring on online platforms. The information gleaned from social network analysis holds immense potential for various applications. Some notable examples include targeted online advertising [22], personalized recommendations [23], viral marketing [24], social healthcare [25], analysis of social influence [26], and studying academic networks [27].

Machine learning and neural networks have exhibited remarkable capabilities in processing vast amounts of data, identifying patterns, and making predictions with remarkable accuracy [28]. However, as their influence permeates society, it becomes crucial to examine the social considerations associated with their deployment, particularly in the context of media and networks. This critical review will explore the social implications of machine learning and neural networks in the domains of media and networks, investigating the challenges, risks, and opportunities that arise. Through an analysis of the existing literature, this paper aims to provide a comprehensive understanding of the complex interplay between technology and society in these contexts. Additionally, it will examine the measures and interventions proposed to address the identified challenges, fostering a nuanced discussion about the responsible use of these powerful tools. In light of these objectives, the central research question guiding this study is:

What are the social implications of machine learning and neural networks in the domains of media and networks, and what measures and interventions have been proposed to address the associated challenges?

2. Theoretical Background

2.1. Machine Learning and Neural Networks

2.1.1. Overview of Machine Learning

AI is a subfield of computer science that incorporates a wide range of computational operations, from algorithmic production to machine learning and deep learning methods [29]. Traditional AI problem-solving methods are based on if–then rules, whereas machine learning and deep learning seek to iteratively evolve comprehension of a data set without explicitly coding any rules [30,31]. This permits the computing system on which they are implemented to automatically acquire knowledge and develop predictions beginning with a set of input data, adjusting the parameters by optimizing the performance standard defined on the data and decreasing the error rate at every phase of the learning process [32].

In other words, the objective of machine learning is to create software that adapts and learns on its own, i.e., without a pre-programmed system dictating its behavior. Due to the fact that training data are used as examples, algorithms can learn from their errors.

Consequently, the amount a model learns is contingent on the quality and quantity of the example information to which it has been exposed [33].

Machine learning provides a variety of mathematical tools for solving a broad range of problems. Artificial neural networks, which are trained to solve a specific task, are currently the most ubiquitous and essential tool. Neurons are organized into layers and precisely connected to form a network. As previously stated, a neural network is considered “deep” when the number of layers is considerable. The approach of deep learning attempts to mathematically model how the human brain processes data from vision and hearing: the stimuli of the ears and eyes, passing through the human brain, are broken down into simple concepts and gradually reconstructed into increasingly complex and abstract visualizations [32,34].

Similarly, in a deep neural network, a visage is represented as an array of pixel values. The initial layer can readily identify edges with varying orientations. Subsequent layers combine these elements to create rounded corners and extended contours. By locating specific groups of contours and corners, subsequent layers can detect entire portions of specific objects. These are then combined with additional processing layers to enable us to represent the faces we wish to learn [32,35,36].

Machine learning is an approach to developing data-driven AI. It is a subset of AI with many assets, and employs predictive statistical techniques [37]. It was created in the 1940s, but it has only recently been possible to incorporate it into daily routines. In general, machine learning algorithms employ both unsupervised and supervised learning techniques. Unsupervised learning does not require human feedback, whereas supervised learning does [38]. The most significant strengths of machine learning are its methodology and reinforcement learning. The machine learning methodology entails training an algorithm to recognize patterns in new data sets [39]. Reinforcement learning is a subfield of machine learning in which an intelligent system acquires knowledge through trial and error by receiving incentives or penalties for its actions.

2.1.2. Overview of Neural Networks

A neural network is a model that simulates the function of the human brain nervous system by simulating and connecting neurons [40], the fundamental units of the human brain, and creating an artificial system with intelligent information processing functions such as pattern recognition, memory, association, and learning [41]. An essential characteristic of a neural network is its ability to learn from its surroundings and store the results of its learning in its synaptic connections. A neural network’s learning is a process. Under the influence of its environment, a sequence of sample patterns is fed into the network, and the weight matrix of each network layer is adjusted according to a set of rules. The learning process concludes when the weight of each stratum of the network converges to a certain value. A neural network is an acyclic graph comprising interconnected neurons. The output of the previous layer of neurons functions as the input for the next layer of neurons, which are typically arranged regularly and constructed with multiple neurons in layers of connections. A typical neural network structure is referred to as a full connection layer [42]. Neurons in the same stratum are not connected.

Social media networks have become increasingly dependent on neural networks. They enable personalized content recommendations based on user preferences, sentiment analysis, image and video recognition, natural language processing (NLP), fraud detection and security, and NLP of images and videos. Social media platforms can utilize neural networks to improve user engagement [43], content curation [44], and platform security [45]. However, there are repercussions associated with the use of neural networks in social media networks. Algorithmic bias can contribute to discriminatory content recommendations and practices. As social media platforms need to manage and safeguard sensitive user information, privacy and data security are concerns. Personalization can result in filter bubbles and polarization, and misinformation and false news can undermine the credibility of the information shared on these platforms.

To address and mitigate algorithmic bias, social media platforms need to implement robust data acquisition processes, diverse training sets, and regular audits. To address privacy and data security concerns, appropriate data anonymization, encryption, and consent mechanisms are required. Platforms need to establish a balance between personalization and exposure to diverse viewpoints. Continuous monitoring, fact-checking mechanisms, and user-reporting systems are required in order to reduce the dissemination of misinformation. In this manner, social media platforms can maximize the benefits of neural networks while minimizing their potential consequences. Figure 1 illustrates the significance of neural networks in social media by spotlighting their diverse applications and repercussions.

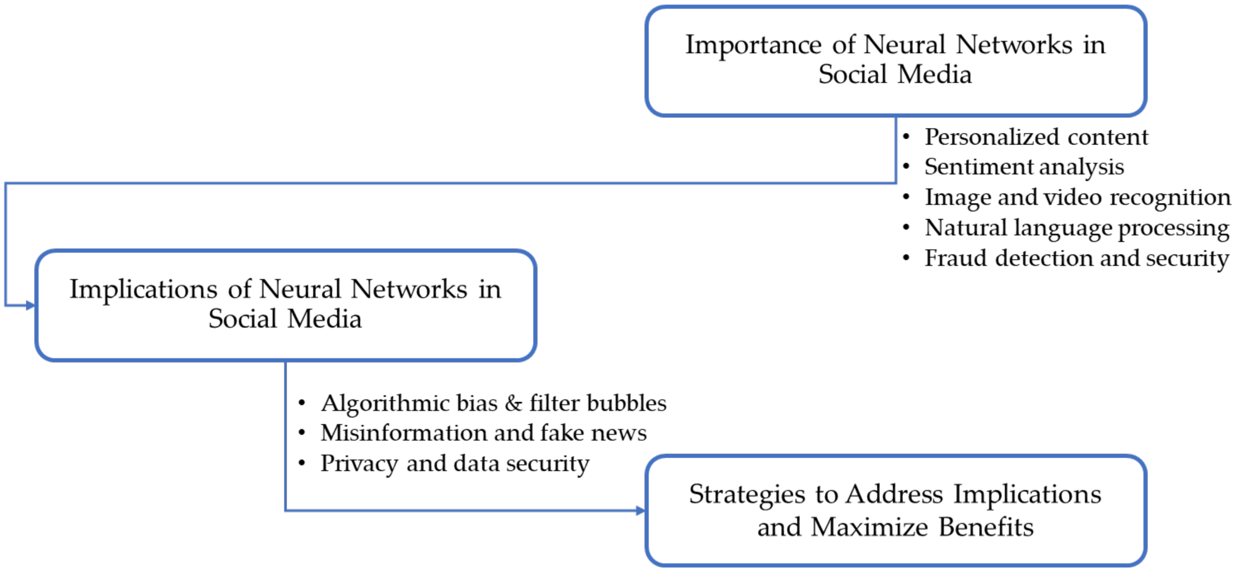

Figure 1. Unleashing the power of neural networks in social media.

2.1.3. Applications of Machine Learning and Neural Networks in Social Fields

Several disciplines, including social domains, have been revolutionized by machine learning and neural networks. In the field of social media analysis, machine learning techniques facilitate the extraction of valuable insights from vast amounts of data, such as sentiment analysis [46], trend identification, and the detection of fake news. In addition, neural network-powered recommendation systems provide personalized content suggestions based on user behavior, thereby enhancing the user experience.

Understanding and analyzing social media posts, remarks, and reviews is impossible without NLP. Using neural networks such as recurrent neural networks or transformers, machine learning algorithms enable tasks such as sentiment analysis, topic modeling, and text classification. By deciphering the meaning of textual data, NLP enables a more in-depth comprehension of user sentiments and preferences.

Similarly, machine learning and neural networks are indispensable for social network analysis. These techniques can analyze the intricate structures of social networks, identify influential users, detect communities, and predict individual relationships. Graph neural networks (GNNs) are especially efficient at modeling and comprehending social network data, thereby revealing valuable insights and connections.

The applications of machine learning extend beyond social media to social welfare and humanitarian efforts. Using predictive models and neural networks, machine learning supports disaster responses, public health initiatives, and humanitarian aid resource allocation. These technologies can predict disease outbreaks, identify vulnerable areas during natural disasters, and optimize relief efforts, ultimately sparing lives and reducing suffering. The applications of machine learning and neural networks in various social disciplines are summarized in Table 1.

Table 1. Applications of machine learning and neural networks in social fields.

Field	Applications
Social Media Analysis	Sentiment analysis Trend identification Fake news detection
Recommendation Systems	Personalized content suggestions based on user behavior
NLP	Sentiment analysis Topic modeling Text classification
Social Network Analysis	Influential user identification Community detection Relationship prediction
Social Good and Humanitarianism	Disaster response Public health initiatives Resource allocation for humanitarian aid
Online Advertising	Targeted advertising based on user preferences and behavior
Personalized Education	Adaptive educational content based on individual learning styles
Fraud Detection	Detection of fraudulent activities such as credit card fraud and online scams
Cybersecurity	Network traffic analysis for detecting anomalies and identifying cyber threats
Mental Health Analysis	Identification of individuals at risk of mental health issues through social media analysis

Various machine learning algorithms and neural network architectures have been utilized for social network analysis and content recommendation systems, each with its own strengths and limitations. Traditional algorithms, such as logistic regression and decision trees, offer interpretability and simplicity, making them suitable for comprehending relationships and making explicit feature-based predictions. However, their efficacy may be limited when presented with complex data or feature spaces with high dimensions. Alternatively, deep learning architectures such as convolutional neural networks and recurrent neural networks excel at capturing intricate patterns and temporal dependencies, making them useful for tasks such as sentiment analysis and sequence modeling. To achieve optimal performance, however, these architectures frequently require substantial computational resources and vast quantities of labeled data. In addition, their black-box nature hinders interpretability, which is vital for certain applications such as elucidating recommendations or identifying biased patterns. Hybrid approaches that combine the strengths of various algorithms and architectures, such as ensemble methods and hybrid deep learning models, have emerged as promising solutions, enabling improved accuracy, interpretability, and scalability in social network analysis and content recommendation systems. The optimal strategy is determined by the specific mission, available data, interpretability needs, and computational resources.

2.2. Social Considerations

Various facets of our lives have been revolutionized by neural networks and machine learning algorithms, which offer tremendous potential and opportunities. However, the widespread adoption of these technologies raises essential social concerns that need to be addressed to ensure their responsible development and deployment.

2.2.1. Bias, Equality, and Discrimination

The potential for biased decision making is a primary concern with neural networks and machine learning models [47]. When these algorithms learn from biased or prejudiced training data, they can perpetuate and amplify existing biases, resulting in discrimination or unjust treatment of certain individuals or groups. This is especially concerning in areas such as employment, lending, and criminal justice.

To reduce bias, it is essential to collect diverse and representative training data that accurately reflects the heterogeneity of the population. Regular model audits, interpretability techniques, and fairness metrics can assist in identifying and addressing bias in algorithmic decision making. Moreover, involving multidisciplinary teams, including ethicists, social scientists, and domain experts, in the development process can provide valuable insights to reduce bias and promote fairness.

2.2.2. Privacy, Data Protection, and Security

Neural networks and machine learning algorithms rely on vast quantities of data for performance enhancement and training. However, this dependence raises privacy and security concerns. Personal information collected during data collection and processing may be susceptible to unauthorized access, misuse, or intrusions, which could result in privacy violations or identity theft.

To safeguard privacy, developers need to adhere to stringent data protection practices, such as anonymization and encryption, and conform with applicable privacy regulations. Transparent data usage policies, user consent mechanisms, and data minimization strategies can enable individuals to make educated decisions regarding their data. Moreover, ensuring a secure infrastructure, conducting regular vulnerability assessments, and instituting robust access controls are essential for protecting sensitive data.

2.2.3. Accountability, Openness, and the Ability to Explain

It can be difficult to comprehend the interior workings of neural networks and machine learning algorithms due to their complexity, raising concerns regarding algorithmic accountability and transparency [48]. In fields with significant repercussions, such as autonomous vehicles or healthcare, it is essential to comprehend how and why a decision is made.

Promoting transparency requires the development of interpretable machine-learning techniques, the provision of justifications for decisions, and the establishment of clear lines of responsibility between developers, users, and regulatory authorities. To ensure the reliability of algorithms, they should endure rigorous testing and validation, and mechanisms for auditing and challenging algorithmic decisions should be implemented.

2.2.4. Workforce Redundancy and Skill Gap

As automation technologies driven by neural networks and machine learning advance, fears of job displacement and a widening skill divide emerge [49]. While these technologies can streamline processes and increase efficiency, they also have the potential to replace certain tasks presently performed by humans, leading to unemployment and socioeconomic challenges, especially for those in low-skilled or routine jobs.

To address these challenges, the workforce needs to be retrained and reskilled to meet the altering demands of the labor market. Governments, educational institutions, and businesses should collaborate to provide training programs and resources that equip individuals with the skills needed for emerging fields. Additionally, investigating new forms of work arrangements, such as job-sharing or reduced working hours, can assist in the distribution of available work and mitigate the effects of automation. The relationship between social sciences, machine learning, and neural networks is depicted in Figure 2. The social sciences, which include sociology and psychology, influence the development of machine learning and neural networks through the identification of research questions and the collection of pertinent data. Neural networks, a type of machine learning model, understand complex patterns from the data. Machine learning utilizes social science data to train and optimize models. The social sciences are influenced by the outputs and insights generated by machine learning and neural networks, which shape theories, policies, and future research. This iterative procedure propels progress in the social sciences, machine learning, and neural networks.

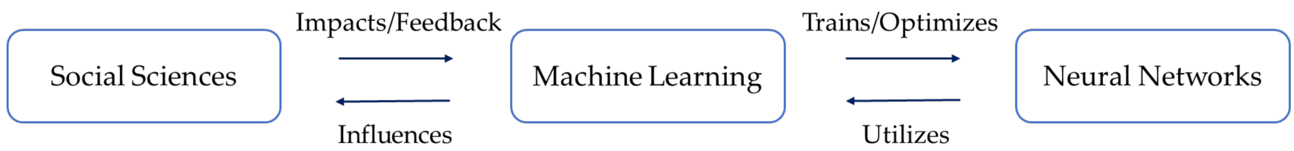

Figure 2. An iterative relationship of the insights and advancements in machine learning and neural networks in social sciences.

3. Research Design

The objective of this review is to investigate the social implications of machine learning and neural networks. An exhaustive search strategy was employed to identify scholarly articles from which to collect pertinent data. The sections that follow detail the key steps performed during the literature search.

3.1. Research Question Formulation

The research query was formulated to direct the literature search and guarantee the retrieval of pertinent material. The question examined the social implications of machine learning and neural networks, concentrating on the impact of these technologies on various aspects of society.

3.2. Search Strategy

A variety of databases were chosen to ensure comprehensive coverage of the pertinent literature. The most important databases included IEEE Xplore, Google Scholar, ScienceDirect, and Scopus. A list of keywords was generated to represent the research question's essential concepts. These terms included "machine learning" and "neural networks" in the title, as well as "social" in the title/abstract/keywords.

3.3. Database Search

The search string was executed in each chosen database, and the initial search results were obtained (8 May 2023). Relevance and date were used to filter the results, and duplicates were eliminated. Inclusion and exclusion criteria were applied to the search results (Table 2). By covering five years, a wide range of research studies, experiments, and practical applications that emerged during this time period could be captured.

Table 2. Inclusion and exclusion criteria.

Including	**Articles written between 2017 and 2022** The source type should be just a journal.	**The document type should be just an article** Focused on social sciences
Excluding	All subject areas except social sciences Articles in press papers	Articles written in any language except English Articles that do not propose a method

3.4. Screening and Selection

To choose the most relevant articles, a two-stage screening approach was used. Titles and abstracts were reviewed in the first round based on predetermined inclusion and exclusion criteria. Full-text publications were retrieved and assessed for final inclusion in the second step. Additional sources were found by screening relevant references within the selected articles. Finally, 26 articles were chosen from a total of 955 (Figure 3).

3.5. Data Extraction

To acquire important information from the selected articles, data extraction was performed. Author(s), publication year, research methodology, important findings, and implications relating to social issues of machine learning and neural networks were all covered.

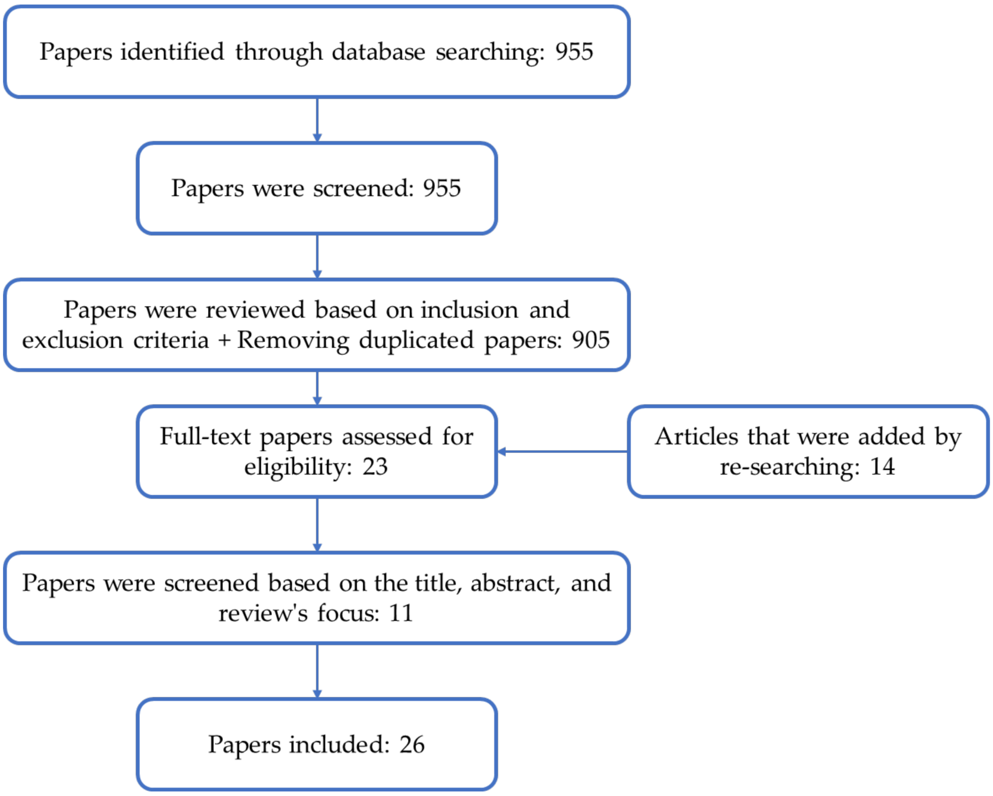

Figure 3. Process of selecting articles.

3.6. Data Synthesis

The selected papers' findings were summarized and structured to suit the review's study question and aim. To provide a complete understanding of the social implications related to machine learning and neural networks, common themes, patterns, and insights were uncovered.

4. Analysis of the Literature

4.1. Synthesis of Findings

Out of 955 articles, 26 were chosen. Machine learning and neural networks are two topics of AI that have received significant interest in recent years because of their potential to automate decision making and enhance accuracy in a variety of applications. Machine learning is the process of teaching computers to learn from data, and neural networks are a form of machine learning algorithm inspired by the structure of the human brain. Machine learning and neural networks have had a profound impact on reducing costs, improving user engagement, and enhancing decision-making processes. By leveraging large volumes of data and sophisticated algorithms, machine learning techniques enable businesses to automate processes, optimize resource allocation, and identify cost-saving opportunities. Additionally, neural networks have revolutionized user engagement by powering personalized recommendations, targeted advertisements, and interactive chatbots, thus enhancing the overall user experience. Moreover, these technologies enable data-driven decision making, providing organizations with valuable insights, predictive analytics, and actionable recommendations that facilitate more informed and efficient choices, leading to improved outcomes and competitive advantages in today's fast-paced and data-driven world.

According to the included studies, machine learning and neural networks are increasingly being utilized to tackle complicated problems and make more accurate and efficient decisions. These technologies can automate human-performed jobs such as picture identification, language translation, and even car driving. According to several of the featured papers, machine learning and neural networks are also being utilized to improve the safety and security of various systems. The study by Karayiğit et al. [50] looked at using machine learning to detect abusive comments on Instagram, while another considered utilizing neural networks to construct an intrusion detection system for cloud environments.

Other studies have claimed that machine learning and neural networks can help to improve healthcare results. The study by Komatsu et al. [51] covered the use of machine learning to predict the success of psychiatric medicines, whereas another study [52] investigated the use of neural networks to forecast illness risk and improve patient safety. However, the implementation of machine learning and neural networks is not without difficulties. Song et al. [53] examined the need to quantify uncertainty in machine learning models, while Yalur [54] investigated the topic of "naturalness" in machine learning and RNNs. These names imply that, while machine learning and neural networks have the potential to change many disciplines, crucial considerations and constraints need to be considered.

In summary, the included studies demonstrate how machine learning and neural networks can be used to improve decision making, safety, healthcare outcomes, and other elements of modern life. However, it is equally critical to be aware of the constraints and limitations of these technologies, as well as to carefully examine their uses in a variety of contexts.

There has been a considerable increase in the number of publications discussing machine learning and neural networks over the last five years, particularly regarding social networks, media, and related factors (Figure 4). The trend began with a dearth of publications in 2017 and 2018, but gained traction in subsequent years. This rising tendency could be explained by several factors. Firstly, rising interest and investment in AI and machine learning have catapulted these subjects into the mainstream. As a result, there is a greater demand for information and publications that delve into the complexities of these topics. During this time, advances in machine learning and neural networks have also been important. Notably, advancements in these disciplines have occurred in 2019 and beyond with the introduction of novel models and algorithms, such as transformer-based designs. The media has aggressively reported these achievements, which has undoubtedly contributed to the increased quantity of publications. Furthermore, the growing use of machine learning and neural networks in a variety of fields, including social networks and media, has attracted attention. Furthermore, the pattern may have been impacted by the spread of knowledge and the demand for awareness.

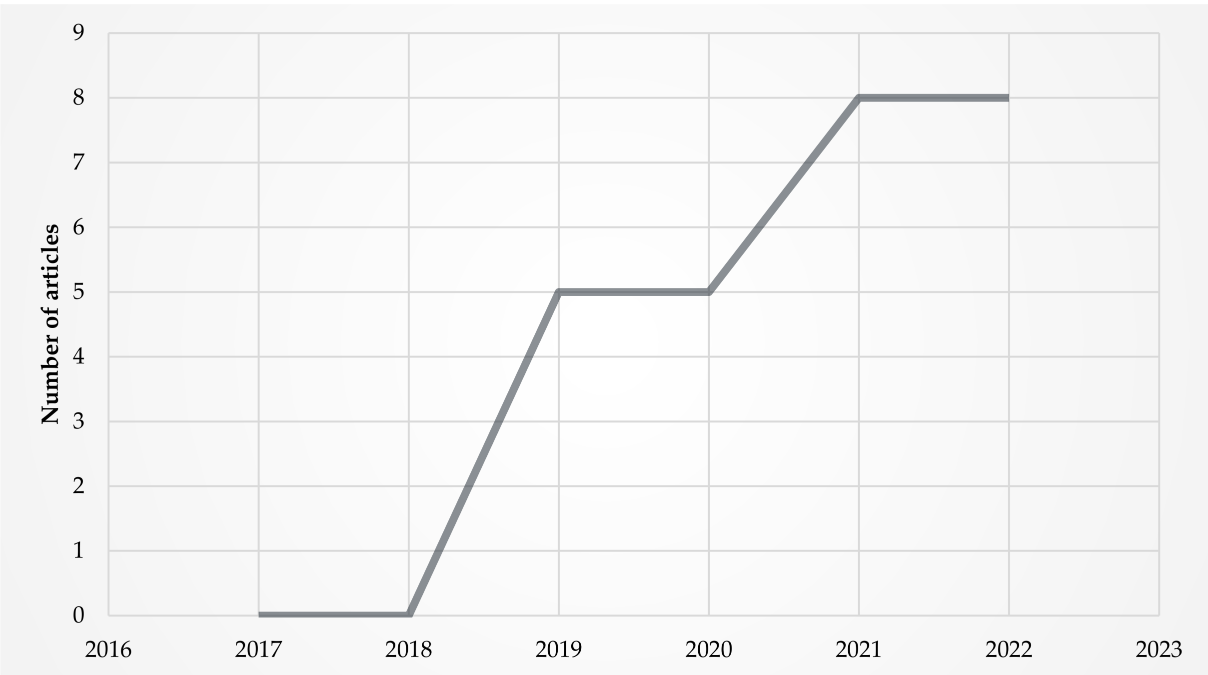

Figure 4. Number of included papers over the past five years (2017–2022).

The distribution of the authors' countries in the included articles on machine learning and neural networks is significant because it provides valuable information about global participation in and contributions to these research fields (Figure 5). This distribution sheds light on the geographical distribution of researchers, highlighting the regions which are actively engaged in the advancement of machine learning and neural networks. Understanding this distribution can facilitate knowledge sharing, collaboration, cross-cultural perspectives, and advancements in these fields.

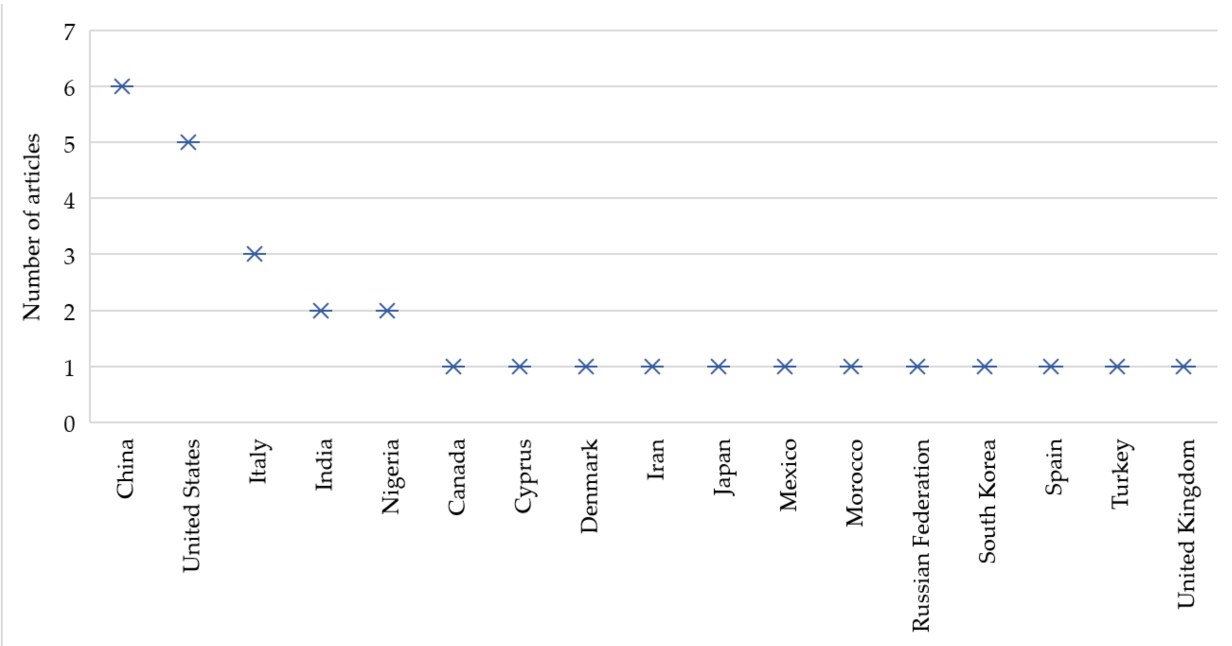

Figure 5. Authors' country distribution.

Several factors can influence the distribution of authors' countries in the included articles on machine learning and neural networks. This distribution is significantly influenced by research and development institutions such as those in the United States, China, and the United Kingdom. These nations have established themselves as technological innovation powerhouses, with well-funded institutions and technology companies that actively contribute to the research literature. In addition, countries with renowned academic institutions that emphasize research and innovation are more likely to publish more works. The distribution of authors' countries in the field of machine learning and neural networks is also influenced by factors such as the availability of funding, research resources, and international collaboration.

4.2. Key Themes and Patterns

The included articles demonstrate the diverse applications of machine learning and neural networks in a variety of fields, highlighting the growing interest in employing these technologies to solve difficult problems. This section provides a curated selection of 26 papers, with an emphasis on essential themes and patterns that emerge from the papers. From the included papers, the following themes and patterns emerge:

- Machine learning and neural networks: The application of machine learning algorithms, specifically neural networks, in diverse fields such as education, finance, healthcare, and environmental studies is the subject of numerous publications.
- Hybrid models: Several publications discuss the use of hybrid models that incorporate various machine learning techniques, such as neural networks with support vector machines, random forests, and Gaussian processes, to enhance performance and accuracy.

- Predictive modeling: A common theme is the use of machine learning for prediction and classification tasks, such as predicting academic performance, estimating parameters, mapping landslide susceptibility, recognizing emotions, and forecasting safety risks.
- Interdisciplinary applications: These papers demonstrate the interdisciplinary nature of machine learning, with applications in fields such as sociology, nanotechnology, social sciences, crime prediction, sound design, and molecular activity prediction.
- Explicability and Interpretability: Some papers highlight the importance of understanding and interpreting machine learning models, especially in areas such as automated trading, lecture quality assessment, and molecular activity prediction.
- Comparative studies: Several papers compare different machine learning algorithms or techniques, such as support vector machines, backpropagation neural networks, extreme learning machines, and linear regression, to assess their performance in specific contexts.
- Educational and learning contexts: Several papers mention the application of machine learning in educational settings, including predicting academic performance, building intelligent tutoring systems, and enhancing gifted education.

Table 3 provides a compilation of articles on machine learning and neural networks, highlighting their defining characteristics and themes. This table provides information regarding the social considerations, citations, and machine learning algorithms or neural network varieties associated with each paper. The table illustrates the multidisciplinary character of machine learning as well as its diverse applications and research areas.

Table 3. Key themes and characteristics of machine learning algorithms.

Reference	Social Consideration	Cited by	Machine Learning Algorithm/Neural Network Type
[55]	Education	1	Radial Basis Function
[56]	Sociology	0	Deep Neural Network
[57]	Technology	0	Multilayer Perceptron, Random Forest
[58]	Security, Privacy	1	Gaussian Process Regression, Hybrid Emotional Artificial Neural Network
[59]	Environmental Studies	4	Deep Learning Neural Network, Support Vector Machine Ensemble
[60]	Nanotechnology	2	Artificial Neural Network
[61]	Innovation, Dairy Industry	0	Improved Neural Network
[62]	Fitness, Health	2	Convolutional Neural Network
[63]	Environmental Studies	4	Convolutional Neural Network, Unet
[64]	Film, Audio Design	15	Artificial Neural Network, Regression
[50]	Social Media	13	Convolutional Neural Network
[65]	Substance Abuse	2	Machine Learning Classical, Neural Network
[66]	Social Sciences	47	Machine Learning, Neural Network
[51]	Healthcare	15	Psychiatric Neural Network Precision Therapeutics
[67]	Education	1	Neural Network, Machine Learning
[68]	Crime Prediction	9	Neural Network, Machine Learning
[69]	Technology	0	Semi-Supervised Learning Machine
[54]	AI	2	Recurrent Neural Network
[70]	Blended Learning, Data Science	5	Neural Network, Machine Learning
[71]	Healthcare	21	Support Vector Machine, Backpropagation Neural Network, Extreme Learning Machine
[53]	Environmental Studies	10	Recurrent Neural Network
[72]	Education	7	Neural Network
[52]	Sports Safety	22	Backpropagation Neural Network
[73]	Cloud Computing	88	Deep Neural Network
[74]	Molecular Activity Prediction	30	Deep Neural Network Quantitative Structure–Activity Relationship Models
[75]	Energy	71	Multiple Linear Regression, Artificial Neural Network, Extreme Learning Machine, Support Vector Machine

The diversity of topics covered by these publications is indicative of the dynamic and cross-disciplinary nature of the subject of machine learning and neural networks.

4.3. Gaps and Limitations

Rapid integration of machine learning and neural networks in the social sciences raises ethical concerns regarding the use of these technologies. To assure responsible and equitable use, the field needs to address issues such as bias, privacy, and data protection. In addition, numerous social science studies have focused on particular contexts or data sets, which can limit the generalizability of their findings. Models of machine learning trained on a single population or dataset may not perform well when applied to disparate populations or distinct contexts.

The lack of interpretability and explicability of machine learning and neural networks is one of the major obstacles. The opaque nature of these models makes it difficult to comprehend and interpret the fundamental processes. This lack of transparency hinders researchers' ability to clarify how these models arrive at their predictions or classifications, thereby reducing their usefulness in social science research. The availability and quality of data are also crucial to the success of machine learning models. Nonetheless, the social sciences frequently deal with complex, unstructured, and subjective data, making it difficult to obtain large-scale, high-quality datasets for training accurate models.

The limited capacity of machine learning models to establish causal relationships is another limitation. While these models excel at recognizing patterns, they struggle to infer causation. Typically, social science research seeks to comprehend the underlying causal mechanisms of observed phenomena; however, machine learning techniques are better adapted for correlation analysis than causal inference. Moreover, although machine learning models are effective predictors, the social sciences require more than just accurate forecasts. The discipline attempts to comprehend the underlying processes, mechanisms, and social dynamics, which may not be completely captured by purely predictive models.

Collaboration between data scientists and domain experts is required for the incorporation of machine learning and neural networks in social sciences. However, there is frequently a communication and comprehension divide between these two groups, which hinders the application of machine learning techniques to social science research questions. In addition, social sciences investigate human behavior, society, and culture, which are contextually rich and intricate. Frequently developed without a profound understanding of the social context, machine learning models may neglect crucial social, cultural, and historical factors that influence human behavior and decision making.

Moreover, machine learning models trained on biased data may perpetuate and amplify societal biases. Without careful consideration and mitigation strategies, the application of machine learning and neural networks in the social sciences may reinforce existing social inequalities and prejudices. For the social sciences to realize the full potential of machine learning and neural networks, interdisciplinary collaboration is essential. Collaborations between social scientists, computer scientists, and data scientists can enhance the contextual relevance, ethical responsibility, and social impact of machine learning applications in social science research.

4.4. Recommendations for Future Research

Future trends and emerging technologies in the field of social sciences will transform how researchers investigate human behavior and societal dynamics. Increasing the utilization of big data analytics is one such trend. Social scientists can use advanced analytics techniques to extract meaningful insights and patterns from diverse datasets as a result of the exponential development of available data. This will allow for a deeper comprehension of various facets of human behavior.

NLP is an emerging technology that concentrates on the interactions between computers and human language. NLP can be used to analyze significant amounts of textual data in the social sciences, such as social media posts, interviews, and surveys. NLP can provide valuable insights into social dynamics by distinguishing sentiments, extracting key themes, and revealing concealed communication patterns.

In addition, social network analysis is gaining prominence. Researchers can gain insight into information diffusion, community formation, and social influence by examining the relationships and interactions between individuals or groups. The growing availability of digital data enables the analysis of online social networks, yielding valuable insight into social interactions in the digital domain. The increasing sophistication and precision of machine learning and predictive modeling enable social scientists to make predictions and forecasts. This applies to fields such as public opinion, consumer behavior, and social trends. Such forecasts can assist policymakers and organizations in making data-driven, informed decisions.

As AI continues to advance, ethical considerations in the social sciences become increasingly important. It is essential to address issues such as privacy concerns, algorithmic bias, and lack of transparency in AI systems to ensure the responsible and impartial use of AI technologies in research. For social science research, virtual and augmented reality (VR/AR) technologies offer immersive experiences. These technologies generate virtual environments for the controlled study of human behavior and social interactions. IoT and sensor data are generating vast quantities of data on various facets of human existence, enabling social scientists to gain insight into human behaviors, habits, and interactions.

Social science theories are combined with computer science and data analysis techniques in computational social science. This combines traditional qualitative research methods with quantitative data analysis, allowing researchers to investigate new research questions and tackle complex social problems. Effective data visualization and narratives are essential for disseminating research results to a wider audience. Future tendencies will emphasize the development of interactive and innovative data visualization tools that make research more accessible and influential. By combining quantitative data-driven analysis with in-depth qualitative insights, researchers can provide a more comprehensive understanding of social phenomena.

There are some additional emerging technologies and methodologies that will transform the social sciences. For instance, the prevalence of data mining and data fusion techniques is increasing, enabling researchers to integrate data from multiple sources and extract meaningful insights. This can include combining survey data with administrative data or merging data from various geographic regions to examine regional differences.

Utilizing social media analytics is another emerging trend. With billions of active users on various social media platforms, these platforms provide social scientists with a wealth of data. Utilizing data mining, sentiment analysis, and other techniques, social media analytics extracts insights from social media data. This applies to a vast array of topics, including political polarization, public opinion, and consumer behavior.

Geospatial analysis is an additional technology that is gaining importance in social science research. Integrating spatial data with other data sources enables researchers to identify geographic patterns and spatial relationships, thereby shedding light on topics such as urban planning, public health, and environmental issues.

In social sciences research, causal inference, which concentrates on determining cause-and-effect relationships, is also gaining traction. This involves using statistical methods to determine the effect of an intervention or policy change, enabling researchers to assess the efficacy of social programs and policies. Additionally, the use of mobile and wearable devices is creating new opportunities for social science research. With the widespread adoption of smartphones and other mobile devices, researchers can collect data in real time, enabling a more precise and comprehensive comprehension of human behavior.

In the social sciences, the use of open science practices is gaining momentum. Open science is the practice of making research data, methods, and findings accessible to the general public, thereby fostering greater transparency and reproducibility. This can increase the integrity and credibility of social science research, as well as foster greater collaboration and innovation in the field. Emerging technologies and methodologies are expected to radically alter the future of research in the social sciences. Social scientists will have access to new tools and methodologies to obtain a deeper understanding of human behavior, societal trends, and complex social phenomena due to the growing availability of data, advanced analytics techniques, and innovative technologies. These trends will facilitate more rigorous, innovative, and impactful social science research which has the potential to inform policy and decision making and to enhance the understanding of the world.

Based on the study's findings, practitioners and policymakers can take several actionable recommendations into account. They need to incorporate radial basis function neural networks to predict academic performance in secondary school students; foster transparency and human–machine interactions in deep neural network-based automated trading; and utilize hybrid machine learning models for accurate parameter estimations in specific domains. Additionally, they can explore emotional artificial neural networks and Gaussian process regression-based hybrid models for predicting security and privacy effects in M-Banking, adopt ensemble models for landslide susceptibility mapping, and integrate artificial neural networks into undergraduate experiences. Policymakers can also foster innovation ecosystems in industries such as dairy through machine learning, develop real-time exercise coaching applications using convolutional neural networks, and leverage machine learning for ecological studies and film sound design. These recommendations cover a wide range of fields and offer practical implications for leveraging machine learning and neural networks to drive positive outcomes.

5. Conclusions

Management is aided by network analysis in reducing overall expenses and the maintenance workload. Social media platforms frequently employ neural networks to recommend content that matches user preferences. Machine learning is one of many social network analysis methods. The inputs for machine learning algorithms consist of collections of observable features extracted from user data. Machine learning and neural network-based systems represent an interdisciplinary field of study. Using machine learning, computers can now discern the emotions behind specific content uploaded by users to social media networks.

The capacities of machine learning and neural networks to process vast quantities of data, recognize patterns, and make accurate predictions are remarkable. As their influence permeates society, it becomes essential to investigate the social implications of their deployment, particularly in the context of media and networks. This review examined the social implications of neural networks and machine learning in the media and network domains, with a focus on the resultant challenges, risks, and opportunities. By analyzing the existing literature, this paper sought to provide a comprehensive review of the complex interactions between technology and society in these contexts. In addition, it examined the proposed measures and interventions to address the identified challenges, promoting a nuanced discussion regarding the responsible application of these potent tools.

The accelerated incorporation of machine learning and neural networks into the social sciences presents both opportunities and difficulties. There are numerous applications for these technologies in various disciplines, but ethical concerns, interpretability concerns, and the limitations of causal inference need to be addressed. Collaborations between data scientists and subject matter experts are essential, and emergent technologies such as NLP and social network analysis hold promise. The future of social science research resides in innovations such as virtual reality, big data analytics, and open science practices, which can improve comprehension and inform decisions.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author declares no conflict of interest.

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