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AI Powered Social Communication: A Qualitative Investigation in to Social and Ethical Concerns

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ABSTRACT

Social media has become an integral part of modern day lifestyle of new generation. The social media penetration in day to affairs is to such an extent that, there hardly is any day that goes without having any social media interaction. Although an easy way of distant communication and entertainment are the driving force behind emergence of social media platforms, in recent times it has been used to fulfil the undesired motives. Many instances of fake news, bias, spreading of hatred, deep fakes have been noticed. This paper is an attempt to conduct a conceptual analysis of AI technology alongwith the literary survey of impact of AI on social communication. Based on the qualitative literary survey, the author has proposed some recommendations, some of which includes, inclusion of social media ethics in school curriculum, international norms for use of social media platform etc.

Keywords: Artificial intelligence, Social communication, Ethics, Algorithm

RESEARCH METHODOLOGY

This paper contains qualitative literary analysis of AI and its possible impact upon social communications. Cole observes that, qualitative literary analysis involving the in depth reading and content analysis is increasingly used method (Cole, 2018). Qualitative content analysis (as done in the present paper) helps in drawing the valid inferences from existing literature (Weber, 1990). It is "a technique for making inferences by objectively and systematically identifying specified characteristics of messages" (Holsti, 1969). Qualitative content analysis has been lauded as powerful analytical method for subjective analysis of qualitative data (Schreier, M., 2014).

INTRODUCTION

Concept of AI

AI is defined as the simulation of human intelligence in machines, enabling them to learn, reason, and make decisions. It encompasses various subfields, including machine learning, natural language processing, computer vision, and robotics (Russell, S., & Norvig, P., 2016).

Different types of AI include narrow or weak AI, which is designed for specific tasks, and general or strong AI, which aims to replicate human-level intelligence (Bostrom, N., 2014).

One of the foundational works in the field of AI is the paper titled "Computing Machinery and Intelligence," published by Alan Turing in 1950. In this influential paper, Turing proposed the idea of a test, now known as the Turing Test, to determine whether a machine can exhibit intelligent behavior indistinguishable from that of a human (Turing, A. M., 2012).

Another significant milestone in AI research is the Dartmouth Conference, held in 1956, which is considered the birth of AI as a field of study. During the conference, leading researchers, including John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon, gathered to discuss and explore the possibilities of creating artificial intelligence and coined the term "Artificial Intelligence" (McCarthy, J., et al., 2006).

Machine Learning (ML)

Machine learning is a subset of AI that focuses on algorithms and statistical models that enable computers to learn and improve from data without explicit programming (Bishop, C. M., & Nasrabadi, N. M., 2006).

Machine learning algorithms can be broadly categorized into three types: supervised learning, unsupervised learning, and reinforcement learning.

1. Supervised Learning: Supervised learning algorithms learn from labelled training data, where each data instance is associated with a known output or target value. The goal is to train a model that can predict the correct output for new, unseen inputs. Examples of supervised learning algorithms include decision trees, random forests, support vector machines (SVM), and neural networks (Bishop, C. M., & Nasrabadi, N. M., 2006) (Hastie, T., et al., 2009).

2. Unsupervised Learning: Unsupervised learning algorithms deal with unlabeled data, where the task is to discover hidden patterns or structures in the data. These algorithms aim to find meaningful representations or groupings of the data without any predefined notions of what to look for. Clustering algorithms, such as k-means and hierarchical clustering, and dimensionality reduction techniques like principal component analysis (PCA) and t-SNE, and density-based spatial clustering of applications with noise (DBSCAN) are some of the common examples of unsupervised learning (Bishop, C. M., & Nasrabadi, N. M., 2006) (Hastie, T., et al., 2009).

3. Reinforcement Learning: Reinforcement learning involves training an agent to interact with an environment and learn from feedback in the form of rewards or punishments. The agent takes actions in the environment to maximize its cumulative reward over time. Reinforcement learning has been successfully applied to tasks such as game playing, robotics, and autonomous driving (Sutton, R. S., & Barto, A. G. 2018) (Kaelbling, L. P., et al., 1996).

Deep Learning (DL)

Deep learning is a subfield of machine learning that uses artificial neural networks with multiple layers to extract high-level features from data, enabling more complex learning and representation capabilities (Goodfellow, I., et al., 2016). It focuses on the development and application of artificial neural networks. These neural networks are designed to mimic the structure and function of the human brain, enabling computers to learn and make decisions in a manner similar to humans. Deep learning algorithms are capable of automatically learning hierarchical representations of data from raw input, without relying on explicit feature engineering (Goodfellow, I., et al., 2016) (LeCun, Y., et al., 2015).

Impact of AI on Social Interaction

AI has brought numerous advancements and benefits to society. It has also had significant impact on how people interact with each other. Below given are some of the key impacts of AI on social interaction:

Changing Communication Patterns
The rise of AI-powered communication platforms, such as social media and messaging apps, has changed the way people interact with each other (Boulianne, S., 2015). AI algorithms in social media platforms play a role in content curation and recommendation systems, which can influence the content people consume and the interactions they have (Tufekci, Z., 2014).

AI has significantly enhanced cross-cultural communication by improving language translation capabilities. Technologies like neural machine translation, powered by deep learning algorithms, have made it easier for individuals and businesses to communicate across language barriers (Johnson, M., et al., 2017) (Zhang, J., & Zong, C., 2020).

Advancements in NLP, a branch of AI, have led to improved communication between humans and machines. NLP enables machines to understand and generate human language, making interactions more seamless. It has applications in chatbots, sentiment analysis, voice recognition, and more (Jurafsky, D., 2000) (Coleman, J., & Coleman, J. S., 2005).

AI algorithms are extensively employed in social media platforms to analyze user behavior, preferences, and interactions. This data-driven approach enables personalized content curation, targeted advertising, sentiment analysis, and social network analysis, transforming the dynamics of online communication (González-Bailón, S., et al., 2011). Platforms like Facebook and Twitter heavily rely on AI to suggest relevant posts, articles, videos, and advertisements (Sadiku, M., et al., 2021). AI algorithms are used to perform sentiment analysis on social media data, helping companies and organizations gauge public opinion about their products, services, or events. By analyzing user sentiments expressed in posts and comments, businesses can gain valuable insights, improve customer satisfaction, and adapt their strategies accordingly (Pak, A., & Paroubek, P., 2010).

AI technologies, including natural language processing and machine learning, are leveraged to combat the spread of fake news on social media. These algorithms analyze the credibility, source, and context of information shared to identify potential misinformation, helping users make informed judgments and reducing the impact of false narratives (Shu, K., et al., 2017). From the aforementioned discussions, one can conclude that, AI has certainly transformed the way individuals interact in their social communication. However, AI is a double edged sword and also comes with certain limitations and concerns. AI enabled technology has increased the virtual communication and presence of human being, resulting into their distancing from each other in the real world. Family members are hardly having any in person communication, leading to creating vacuum interpersonal relations within a family. It is further posing a social challenge such as increased cases of divorce (Widiantari, M., et al. 2019), neglect of old age citizens, psychological issues etc. (Chandra Guntuku, et al. 2019) as a result of lack of real world direct social interaction.

Personalization and Filter Bubbles

AI algorithms can personalize content and recommendations based on users' preferences and behavior, which can lead to the creation of "filter bubbles" where individuals are exposed to limited perspectives and echo chambers (Pariser, E., 2011). This can impact social interaction by reducing exposure to diverse opinions and narrowing the range of conversations (Bakshy, E., et al. 2015).

These AI algorithms are used by various online platforms, including social media, search engines, and news aggregators, to tailor content recommendations to individual users. While AI filter bubbles aim to enhance user experience by presenting relevant and engaging content, they can also have unintended consequences, such as reinforcing biases, limiting exposure to diverse perspectives, and creating echo chambers (Pariser, E., 2011).

Filter bubbles can contribute to decreased civic engagement and a narrowing of public discourse. When individuals are exposed only to content that aligns with their existing beliefs, they may become disengaged from political or social issues that are outside their filter bubble. This can hinder informed decision-making, public deliberation, and the functioning of democratic societies (Sunstein, C. R., 2018). Filter bubbles limit serendipitous encounters with diverse ideas and content. By customizing information based on users' preferences, AI algorithms may inadvertently restrict exposure to new and unexpected information that may be outside their typical interests. This can hinder creativity, intellectual growth, and the discovery of new ideas (Bruns, A., 2019).

AI-Powered Assistants

Virtual assistants and chatbots powered by AI have become increasingly common, altering the way people seek and receive information, as well as interact with technology. These AI assistants can provide instant responses, potentially reducing the need for human-to-human interaction in certain situations (Balakrishnan, J., & Dwivedi, Y. K., 2021).

Voice-based virtual assistants such as Amazon Alexa, Google Assistant, Apple Siri, and Microsoft Cortana have become widely adopted in homes, smartphones, and other devices. These assistants can understand spoken commands, answer questions, provide recommendations, and control smart home devices. They enable hands-free interaction and have become an integral part of daily routines, allowing users to perform tasks and access information effortlessly (Voorveld, H. A., & Araujo, T. 2020) (Silva, A. et al., 2020). These, virtual assistants bring an ease in most of the day to day activities, which particularly has had a significant impact on the lifestyle of old age persons and children's.

AI-powered chatbots have revolutionized customer service and online messaging platforms. They can engage in text-based conversations, understand user queries, and provide relevant information or assistance. Chatbots are commonly used in customer support, e-commerce, and social media platforms, enabling businesses to handle large volumes of inquiries effectively and provide 24/7 support (Luger, E., & Sellen, A., 2016).

Automation and Job Displacement

The automation of certain tasks through AI and robotics has raised concerns about job displacement and changes in the workforce (Frey, C. B., & Osborne, M. A. (2017). This can affect social interactions in workplaces and communities, as well as lead to economic disparities and social challenges (Autor, D. H., 2019). AI powered development now has given a push for new age skill based workforce which has resulted in development of new programs in educational world. As a result, in country like India, the computer based branches are attracting more students whereas the other domain such as civil, mechanical, electrical have no takers. This will have an adverse in form of lack of skilled manpower in civil and other industrial domains wherein complete reliance on AI is not possible.

Ethical Considerations and Bias

The use of AI in decision-making processes, such as hiring or resource allocation, raises ethical concerns and the potential for biased outcomes (O'neil, C., 2017). AI-powered social communication platforms collect vast amounts of user data, including personal information, conversations, and behaviour patterns. This raises concerns about privacy and data protection. Unauthorized access, data breaches, and misuse of user information can have serious consequences (Acquisti, A., et al., 2015).

Biases in AI algorithms can perpetuate social inequalities and impact social interactions in various contexts, including education, employment, and criminal justice (Eubanks, V., 2018). These biases can lead to discriminatory outcomes, affecting user experiences and reinforcing social inequalities. Addressing algorithmic bias is crucial for ensuring fairness and inclusivity in social communication (Caliskan, A., et al., 2017).

AI-powered social communication platforms can inadvertently amplify the spread of misinformation and fake news. Automated algorithms may struggle to identify and moderate false content, leading to the dissemination of inaccurate information, which can have detrimental effects on public discourse and decision-making processes (Lewandowsky, S., et al., 2017) (Pennycook, G., et al., 2020).

AI algorithms used in social communication platforms often operate as black boxes, making it challenging for users to understand how decisions are made. Lack of transparency and explainability can undermine trust, as users may question the fairness and reliability of AI-driven social communication systems (Mittelstadt, B. D., et al., 2016).

RECOMMENDATIONS

- Social media ethics should be made a part of school curriculum. Students should be sensitized about the use of social media for exchange of innovative ideas and for the betterment of society.
- Social media platform operators should be held responsible for keeping vigil on likely misuse of their platform and take appropriate action in case of violation of ethical norms. The ones failing to do that should be held vicariously liable for any damage arising on account of misuse of platform.
- UN and other International bodies should develop a set of international principles/norms for ethical usage of social media platform. An international law against the crimes resulting from usage of social media platform should be adopted.
- In case of AI powered social media platforms, the developers should be held accountable for any instance of bias, violation of privacy, hallucination and AI powered spreading of misinformation etc. Such platforms should not be floated open for public usage unless they are thoroughly checked and vetted by the panel of neutral experts, preferably appointed by the respective governments.

Governmental policies should protect, promote and incentivize the ethical technological innovations.

CONCLUSION

Every technology is a double edged sword and its efficacy by and large depends on how it is being used. Social media, as observed herein above, has been used in recent times for creating a social hatred, circulating fake news, developing a defamatory and hateful trend against an individual, pushing the social and in particular political agenda etc. The best solution to ensure the wise usage of social media platforms is to sensitise the users about its ethical usage and promoting a cultural of respectful social (media) communication. The roots of it again lies in the age old cultural teachings (often referred to as *Sanskaras* in native Indian language). The grooming of children's, both in families and at schools should centre around 'respect for others and ethical behaviour in the society'. Law should play a role of deterrence and the ethical upbringing and sensitisation should be used as a driving force for preventing the misuse of social media.

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