AI for Social Good: A Review Report

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I. Introduction

Artificial intelligence (AI) represents the emergence of a new form of intelligence, one that transcends human cognition and biological limitations. At its core, AI refers to machines that can simulate human-like abilities such as learning, reasoning, and even problem-solving [1]. In the early stages of its development, much of the focus was on commercial interests where AI was exercised to maximize business operations, streamline manufacturing, augment customer experiences, and automate repetitive tasks. Industries such as finance, entertainment, and e-commerce saw the promise for AI to drive profits and create new business models. This profit-driven approach to AI innovation sparked tremendous growth in the private sector [2].

As the power of AI became more evident, it was clear that its reach extended far beyond the confines of economic interests. The ability of AI to examine extensive datasets, recognize patterns, and offer insights at a speed and scale unimaginable for humans opened new possibilities for addressing complex global challenges. This awareness led to a fundamental shift in thinking, reflecting a growing recognition that AI must be guided to prioritize the welfare of all people and the health of the environment [3].

In response to this increasing awareness, the concept of AI for Social Good (AI4SG) began to take shape. AI4SG represents the collective effort to leverage AI technologies in ways that contribute to solving urgent global issues, ensuring that the benefits of AI are distributed more equitably across society. With a strong commitment to the 17 United Nations Sustainable Development Goals (as shown in Figure 1), AI4SG aims to drive AI innovation towards creating a more just, sustainable, and prosperous future for all [4].

This review report focuses on the field of AI4SG, with the goal of exploring how AI is being leveraged to address societal issues and promote sustainable development. It first identifies and examines the contributions of influential individuals, organizations, and initiatives that have significantly elevated AI in this field. In addition, their leading research is also discussed to illustrate how AI has already made a difference in areas like healthcare, education, and environmental protection.

Next, the review shifts to recognizing and discussing the various AI methods being adopted in the context of social good. It explores techniques such as machine learning, natural language processing, computer vision, and reinforcement learning, interpreting how each method is applied to address societal impediments. Additionally, real-world studies are also provided in this section to demonstrate the practical applications of these methods.

Fig. 1. SDGs of the United Nations. Adapted from [5]
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In the final section, the review delves deeper into a specific sub-area of AI for social good: natural language processing (NLP) in the field of mental health. This section provides a thorough assessment of the current state of research and the practical applications of this technology in addressing mental health challenges. Moreover, the review highlights key gaps in the current body of research and proposes solutions to overcome the identified obstacles.

Ultimately, this review report aims to deepen the understanding of how AI can be a force for good, providing both theoretical insights and practical examples of its application. As AI continues to evolve, so does the possibility of solving some of the world's most critical social problems. Through the lens of past achievements and the discovery of areas for improvement, this review seeks to contribute to the ongoing conversation on how AI can best serve humanity and foster a more sustainable and just future.

II. Review of Influential Work

The potential of AI to drive societal benefits has attracted the attention of a diverse range of individuals, organizations, and initiatives. Each of these actors brings a unique perspective and set of resources to the table, contributing to a collaborative ecosystem essential for addressing the multifaceted challenges of modern society. Within this growing field, one figure stands out for his interdisciplinary contributions: Peter E. Friedland. During his tenure at National Aeronautics and Space Administration, he made substantial contributions to the scientific community, most notably by leading the development of BIONET, which marked a significant milestone in biological science by facilitating the integration of AI with bioinformatics. It has subsequently played a fundamental role in improving drug discovery processes, enabling the identification of new drug candidates and accelerating the development of therapies for genetic disorders [6].

As technological innovations like BIONET continue to transform the healthcare sector, other researchers have shifted their focus towards social development. One prime example is the work of Ana Paiva, who has concentrated her efforts on exploring the feasibility of AI in this area. Her research challenges the traditional view of AI as purely utilitarian and self-serving, proposing instead that it can be designed to encourage prosocial behaviors. She has fostered this idea through the development of intelligent agents that engage children in interactive games and simulations designed to mimic real-life social interactions. The goal of these AI-driven agents is to serve as a powerful tool for fostering emotional intelligence, cooperation, and conflict resolution, which can have lasting societal effects. Children who grow up learning the importance of these values are more likely to contribute positively to society later in life [7].

The significance of AI, however, extends beyond medical and social contexts; it is also influencing governance and public administration. James A. Hendler is another notable figure in this field, with contributions spanning across government, academia, and policy-related arenas. He has been a vocal advocate for the responsible use of AI, particularly within governmental bodies. His pioneering work with the Semantic Web has revolutionized the way large volumes of online data are organized, interpreted, and utilized. This advancement has enabled governments to harness extensive data more effectively, leading to more informed and accurate policy formulation [8].

Yet, while data-driven governance is revolutionizing how public initiatives are shaped, high-stakes decision-making still requires sound judgment, more so under conditions of uncertainty. This is an area where Eric Horvitz has made a profound impact. He led the development of the Decision-Theoretic Reasoning System, which can operate robustly in uncertain environments. Through probabilistic reasoning, it enables AI to predict outcomes and make informed decisions, even when faced with incomplete or ambiguous information [9]. These capabilities have broad applications in areas where real-time predictions are crucial for efficiently allocating resources during rapidly evolving crises.

Organizations, too, are instrumental in expanding the reach of AI4SG. The United Nations (UN) has been at the forefront of promoting this movement through its focus on the Sustainable Development Goals (SDGs). Working alongside diverse stakeholders, the UN has made considerable progress in harnessing AI to combat global adversities. One notable example of this is the application of AI in disaster management efforts. In partnership with private organizations and regional governments, the UN successfully employed machine learning algorithms to predict and mitigate the repercussions of natural disasters in high-risk areas of Southeast Asia. This initiative has since drastically contributed to reducing casualties and minimizing property damage in vulnerable communities [4].

The Association for the Advancement of Artificial Intelligence (AAAI) is another organization that plays a vital part in showcasing the wide-reaching societal benefits of AI through its projects that focus on areas such as public safety, healthcare, and sustainability. One striking example of AAAI's efforts can be seen in their research on utilizing AI algorithms to manage real-time traffic data effectively. This study aimed to reduce traffic congestion and minimize carbon emissions in densely populated urban areas, such as Los Angeles, where traffic is a significant challenge. Leveraging AI's capabilities, this experiment not only improved commuting times but also had notable environmental consequences through reducing vehicle idling and carbon footprints [10].

Parallel to these efforts, the Computing Community Consortium (CCC) has also made substantial strides, primarily during the height of the COVID-19 pandemic. Amid this global crisis, CCC-supported AI models processed patient data, infection rates, and hospital capacity to ensure that pivotal resources were deployed where they were needed most. These models helped prevent hospital overcrowding and ensured that life-saving equipment, such as ventilators, was available in regions with the greatest need [10]. The success of this project underscores the aptitude of AI to save lives in real-time, high-pressure situations.

Climate change, another pressing global challenge, has also seen the transformative power of AI through the efforts of the United Nations Development Programme (UNDP). In one notable investigation, UNDP partnered with governments in sub-Saharan Africa to develop models capable of predicting droughts and providing early warnings to farmers. This AI experiment has had a major impact on agricultural communities in drought-prone regions, improving food security and protecting livelihoods [4].

Furthermore, the success of AI4SG is closely tied to well-planned and carefully executed initiatives as well. A noteworthy example of this is the 'Unusual Suspects' project under the Cambridge Conservation Initiative. The experiment involved using AI to detect illegal logging activities in rainforests. The AI framework analyzed satellite imagery to identify patterns of deforestation, allowing conservationists to intervene before it was too late. This technology was then deployed in countries like Brazil to curb illegal deforestation and protect biodiversity [11]. This exemplifies the power of AI in preserving the environment and supporting global biodiversity.

Transitioning from conservation to education, the STEAM for Social Good Innovation Challenge empowers young students to become problem solvers for real-world issues. This initiative fosters a new generation of thinkers and innovators who are directly engaged in contributing to the achievement of the SDGs. In one research instance, students designed an irrigation mechanism to improve water usage in farming. The integration of AI into soil moisture sensors optimized water distribution, minimizing waste and enhancing crop yields, thereby demonstrating the capability of this technology in addressing agricultural challenges [12].

Lastly, shifting focus to healthcare, the AI for Health Equity in Least Developed Countries initiative demonstrates how AI can boost healthcare delivery in underserved regions. One of their experiments involved using AI to predict outbreaks of diseases such as malaria and cholera, based on weather, mobility, and environmental data. This early-warning algorithm enabled healthcare workers to allocate resources more effectively, reducing the spread of disease and improving outcomes in vulnerable populations [13].

In summary, it is visible that AI4SG continues to evolve, propelled by the dedication of individuals, organizations, and global initiatives. Whether it is improving healthcare, fostering empathy in education, protecting wildlife, or combating climate change, AI's transformative potential is being harnessed to address some of the world's most pressing matters. Through interdisciplinary collaborations and a focus on ethical, sustainable development, AI is proving to be a powerful tool in supporting the well-being of humanity and the planet alike.

III. Discussion of AI Methods

Building on the contributions of influential individuals, organizations, and initiatives in the area of AI4SG, it is clear that AI is actively driving innovation across numerous sectors, offering solutions that once seemed unattainable. Central to this progress are the AI methodologies that enable these breakthroughs. Among these, Machine Learning (ML) stands as a fundamental approach. This technique enables machines to learn from data and make decisions without requiring explicit programming at each step. ML models continuously improve their performance as they are exposed to more data [14]. One sector where ML is making a remarkable social impact is public health. Predicting and managing disease outbreaks has always been a major challenge in regions where resources are limited and healthcare infrastructure is insufficient. In Malaysia, Salim and his team of researchers applied ML to address the issue of dengue fever outbreaks. Using supervised learning models, they integrated climate-related data to forecast surges in dengue cases with a high degree of reliability [15]. This portrays how ML can be leveraged to address public health crises, potentially saving lives and reducing the burden on healthcare organizations.

The benefits of ML extend well beyond public health, with disaster preparedness emerging as another imperative area where ML has become indispensable. Natural disasters such as floods, hurricanes, and heatwaves have devastating consequences on communities, often with little to no warning. Nevertheless, researchers like Jain and his collaborators have demonstrated that interpreting environmental datasets allows ML models to predict severe weather events with extraordinary precision. [16]. This predictive capability empowers governments and disaster relief agencies to act sooner and mitigate the damages associated with these catastrophic events.

The impact of ML does not stop with disaster management and public health; in education, it is fostering a revolution in personalized learning. Traditional classroom models often struggle to meet the unique needs of individual students, but ML is changing that through the facilitation of adaptive learning arrangements. For instance, Kochmar and contributors developed an intelligent tutoring model that showed a 22.95% improvement in student outcomes compared to traditional teaching methods [17]. This approach guarantees that students receive the tailored support they need to thrive, making education more equitable and accessible.

As ML revolutionizes sectors like public health, disaster preparedness, and education, natural language processing (NLP) is redefining how machines interact with human language. It is a field of AI focused on assisting machines to comprehend and produce human language in ways that are both meaningful and useful [18]. One outstanding application of NLP is in content moderation on social media platforms where hate speech and harmful content are prevalent. Davidson and his team built an NLP model capable of detecting hate speech with 90% accuracy. It processed thousands of social media posts and identified patterns associated with hateful content [19]. Similarly, Mosqueda and Sulayes constructed another NLP model that achieved an astonishing 98% accuracy in identifying comments associated with gender and LGBTQ+ violence [20]. These progressions can substantially improve the speed at which offensive content is identified and removed from online platforms.

Additionally, NLP has shown tremendous promise in addressing the growing mental health crisis. Inkster and colleagues harnessed this technology to develop a chatbot designed to provide cognitive behavioral therapy for individuals suffering from anxiety and depression. In a study involving 1,000 participants, the chatbot demonstrated its proficiency, with 68% of users reporting improved mental health outcomes after just six weeks of use [21]. This innovative application of NLP not only makes mental health support more accessible, but also diminishes barriers for individuals who may struggle to access traditional therapy services.

While NLP is making waves in language-based tasks, computer vision (CV) is another AI technique making a mark through accommodating machines to interpret and understand visual data. This technology mimics human vision, but with the added ability to process vast amounts of visual data quickly and accurately [22]. CV has been exceptionally prominent in environmental conservation efforts, where it has been administered to monitor deforestation and wildlife populations. McCallum and his team applied deep learning and crowdsourcing techniques to classify satellite images of the Amazon rainforest, achieving over 90% precision in detecting areas of deforestation [23]. Similarly, CV models like VGG16 and ResNet50 have been employed in wildlife conservation efforts. These models have achieved up to 87% correctness in establishing animal species from camera trap images, aiding researchers in monitoring endangered species and assessing biodiversity with greater precision [24].

In addition to environmental monitoring, CV has proven to be a valuable tool in disaster response as well. For example, following the 2016 Kumamoto earthquake in Japan, Zhan and his team applied a modified Mask R-CNN model to assess the damage to residential buildings by analyzing aerial imagery. Their solution achieved an impressive 95% validity in extracting building data and over 92% reliability in classifying buildings based on the level of damage sustained [25]. This high level of certainty is crucial in the aftermath of a disaster, as it enables authorities to prioritize recovery efforts more systematically.

While ML, NLP, and CV address a variety of tasks across different domains, reinforcement learning (RL) represents a more specialized AI technique. In RL, an AI agent learns by interacting directly with its environment, receiving feedback in the form of rewards or penalties based on its actions. This trial-and-error approach enables the agent to continuously improve its performance. Unlike traditional supervised learning, where the model learns from a fixed dataset, RL relies on the agent's ability to adapt and learn from real-time feedback. It is well-suited for dynamic scenarios that involve sequential decision-making, where decisions made at one stage affect future outcomes [26].

In energy management, for instance, RL is being applied to optimize the operation of renewable energy grids, which is crucial as the world transitions to more sustainable energy approaches. RL helps manage the distribution and storage of energy in grids that rely on intermittent renewable sources like solar and wind power [27]. By optimizing the distribution and storage of energy, it significantly contributes to building more resilient and efficient energy networks.

Moreover, it is also transforming traffic management in smart cities. In urban areas where traffic congestion is a major issue, Wan and Hwang demonstrated the effectiveness of RL-based traffic control techniques. They deployed deep reinforcement learning agents at busy intersections to optimize traffic flow, reduce delays, and minimize emissions. The system learned and adapted to changing traffic patterns in real-time, resulting in smoother traffic flow and a reduction in overall congestion [28].

RL has proved noteworthy in the healthcare sector too, refining the allocation of critical resources. For instance, researchers like Bertsekas and his team have successfully employed RL agents to manage the distribution of hospital beds, ventilators, and other essential medical equipment. Utilizing them to make real-time, data-driven decisions, they achieved 18% increase in treatment capacity, enabling hospitals to serve more patients with the same resources [29].

In summary, these AI methodologies are fueling remarkable transformations across multiple sectors. As these technologies continue to evolve, their applications for social good are also expanding. The future of AI is filled with immense potential, and it is up to society to harness it in ways that promote inclusivity, equity, and sustainability.

IV. Highlighted Topic and Identification of Gaps

As discussed in the previous section, AI methodologies, including ML, NLP, CV, and RL, each contribute uniquely to addressing critical social challenges. However, one sub-area that stands out and warrants further exploration is NLP, particularly its role in mental health support. Mental health is a cornerstone of overall well-being, profoundly influencing how individuals think, feel, and navigate their daily lives. However, in recent years, mental health has noticeably declined worldwide [30].

Factors such as social isolation, uncertainty about the future, and increasing economic pressures have led to a sharp rise in mental issues [31]. This growing crisis is compounded by two major challenges: limited access to mental health care and the persistent stigma that discourages many people from seeking help. While numerous mental health apps have emerged as valuable alternatives to traditional services, these solutions still face limitations regarding scalability and professional oversight. This is where innovations in technology, specifically NLP, offer promising opportunities for mental health care [32].

One of the most impactful applications of NLP in this context is AI-powered therapeutic interventions. Digital health platforms are increasingly leveraging chatbots that use NLP to provide accessible and scalable mental health support to individuals experiencing issues such as depression, anxiety, and stress. These chatbots are designed to engage users in natural, empathetic conversations that mimic the tone and approach of human therapists. In doing so, they create a supportive environment where users feel comfortable sharing their thoughts and emotions [33].

Beyond individual therapeutic applications, NLP has expanded its influence in clinical settings through the analysis of electronic health records. For years, valuable diagnostic information buried in unstructured clinician notes went untapped because conventional systems were unable to parse the complexity of natural language [34]. However, NLP can now extract symptoms from these notes. For example, at one of the largest mental health institutions in Europe, the South London and Maudsley Trust, researchers applied NLP to its vast repository of clinical records to extract data on mood instability. This approach provided healthcare professionals with a more nuanced understanding of patient outcomes and hospitalization risks [35].

Interestingly, mental health signals are not confined solely to medical records; they are also embedded in the language people use in everyday communication on social media platforms. With the rise of online communication, platforms like X, Facebook, Instagram, and Reddit have become digital spaces where individuals often share their thoughts, feelings, and experiences. Studies have shown that specific language patterns on these platforms, such as increased use of first-person pronouns, negative sentiment, or shifts in language, are linked to several mental conditions [36]. Building on these insights, developments in NLP techniques have facilitated the detection of early signs of emotional distress and suicidal thoughts through the evaluation of user posts. By evaluating the language used in user posts, NLP tools can analyze the nuances of communication and flag concerning trends [37].

Furthermore, the true transformation occurs when NLP is combined with ML. Through ML models, NLP can go beyond merely detecting whether an individual is struggling with mental issues; it can also evaluate the severity of the condition with greater precision. One compelling example of this is a recent experiment that involved detecting the severity of depression through Bengali-language social media posts. In this study, researchers constructed a labeled dataset in collaboration with mental health experts and applied different ML models. Among these, the Gated Recurrent Units model achieved 81% accuracy, demonstrating how it is possible now to assess mental health severity from text data. [38].

Despite these leaps, there still remain some gaps that must be addressed, one of the most urgent being the inherent biases introduced when training NLP models on social media data. These platforms are often dominated by specific demographic groups, resulting in skewed datasets that fail to capture the diversity of mental health experiences across diverse geographic backgrounds. Models built on such unrepresentative data exacerbate existing cognitive disorders rather than reduce them [39].

Equally challenging is the absence of standardization across different mental health care systems, which complicates efforts to create models that function consistently in various clinical environments. Mental health data, by its very nature, tends to be unstructured as it involves subjective experiences and the nuanced language of emotional well-being. Unlike data in other medical fields, which rely on standardized test results, data in this domain is often rooted in narrative descriptions provided by patients and clinicians. This variability in how data is recorded poses a substantial hurdle for NLP models [40].

In addition to technical and operational constraints, ethical issues further complicate the implementation of NLP in emotional well-being. One of the most immediate ethical concerns centers around the use of social media data for mental health analysis. NLP models are increasingly being used to scan social media posts to detect signs of mental distress. While this approach holds promise for early intervention, it often occurs without the explicit consent or knowledge of the users whose posts are being scrutinized. Many individuals may be unaware that algorithms are mining their social media posts for mental health signals, raising serious concerns about privacy and informed consent [41]. AI-driven chatbot therapists present another ethical challenge as they risk causing unintended harm if their responses are not rigorously monitored and evaluated under the guidance of trained professionals. A poorly designed or inadequate response could worsen a user's mental state, leading to harmful outcomes [42].

Nevertheless, there are some promising solutions that can be implemented to address these challenges. One effective approach to mitigating bias can be fine-tuning transfer learning models, such as BERT and GPT, on diverse and representative datasets. Training these models on data from diverse demographic groups can significantly help reduce biases in predictions. This would result in more neutral mental health tools that perform effectively across diverse populations.

Moreover, the issue of standardization can be tackled using advanced deep learning models, which are capable enough to manage and interpret unstructured mental health data. These models have been proven to recognize intricate patterns within documentation that includes informal language, medical abbreviations, and inconsistent symptom descriptions. They possess the power to generate more accurate, reliable, and consistent analyses across various healthcare settings and contexts. Consequently, they would facilitate better-informed decisions in mental health treatment, leading to improved outcomes for individuals receiving care.

In addressing privacy concerns, federated learning can be applied as a powerful solution. This technique opens the door for models to be trained across decentralized devices without transferring sensitive user data. In the context of mental health, it can enable mental health apps to improve their performance using user interaction data while ensuring that the data remains stored locally on their devices. This would lessen the risk of privacy breaches and consistently safeguard sensitive personal information.

Lastly, to address the broader ethical problems associated with AI in mental health, dedicated ethical oversight committees can be established. These committees, consisting of ethicists, clinicians, mental health professionals, and AI experts, would be responsible for continuously monitoring and evaluating the safety, validity, and ethical implications of AI-powered mental health tools, such as apps and chatbots. Through their adherence to strict ethical standards, these committees would ensure that patient well-being is always protected.

In the end, it can be noted that the input of NLP in this field represents an exceptional revolution, reshaping the very foundation of how mental health support is accessed, delivered, and experienced. Although barriers such as bias, data standardization, and ethical dilemmas remain, solutions are becoming increasingly tangible. Merging innovative technology with careful human guidance, NLP has the potential to revolutionize mental health care, ensuring that it becomes more accessible, inclusive, and effective for all.

V. Conclusion

This review report has thoroughly explored the rapidly evolving field of AI4SG. By examining the contributions from key individuals, influential organizations, and significant initiatives, it has demonstrated how AI has made substantial impacts across multiple sectors, including healthcare, education, and environmental protection. The research discussed not only illustrates the immense potential AI holds to drive positive change, but also emphasizes the significant strides that have already been made by pioneers in this area.

Additionally, the review provided a comprehensive examination of the AI methodologies currently employed to tackle pressing social challenges. It focused on techniques such as ML, NLP, CV, and RL, showcasing how they are being utilized to solve real-world problems. The practical examples presented in this section underscore the versatility and adaptability of AI methodologies in addressing a wide range of social impediments.

Delving deeper, the review highlighted the role of NLP within the context of mental health, offering an in-depth analysis of how it is being used to address various mental health challenges. This section also critically assessed the limitations in the existing research, identifying significant gaps such as issues with data quality, concerns around ethical standards, and challenges related to privacy and bias. These obstacles were discussed in detail, and the report proposed potential solutions to overcome these barriers, advocating for improvements that could refine the role of NLP in mental health care.

Essentially, the review report aimed to deepen the understanding of AI's potential as a force for social good. At last it becomes evident that AI stands poised to play a critical role in fostering a more sustainable, equitable, and just future. The field of AI4SG is currently at a pivotal juncture, where continued technological innovation, cross-disciplinary collaboration, and ethical vigilance will be essential to ensuring that the benefits of AI are distributed equitably across all segments of society, especially to those who are most vulnerable or underserved.

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