AI AND THE REDUCTION OF SOCIAL INEQUALITIES IN A LINGUISTIC PERSPECTIVE

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Abstract. *Artificial intelligence (AI) has the potential to both exacerbate and alleviate social inequalities. In this paper, we investigate AI's impact from a linguistic perspective, focusing on economic disparities, resource allocation, and ethical considerations. Actuality: We examine the current state of AI adoption and its implications for social equity. Recent developments, trends, and challenges related to AI's influence on linguistic and social disparities are highlighted. Purpose: Our research aims to investigate how AI can contribute to reducing inequalities. Specifically, we consider linguistic aspects, such as language bias in AI algorithms, alongside broader societal implications. Research Methods:Our methodology involves a comprehensive literature review. We analyse existing studies, case examples, and empirical evidence related to AI's impact on social inequalities. Results: Preliminary findings suggest that responsible AI design can bridge gaps and dismantle biases. By prioritizing fairness, transparency, and ethical development, we can harness AI's power to create a more equitable society across linguistic boundaries.In summary, this paper advocates for vigilance and empathy in embracing transformative AI technologies to address social disparities.*
Keywords*: artificial intelligence, multilingual interpretation, machine translation system, AI, language inclusivity, social inequalities, biased data, nuanced language, equal access*
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Introduction. Artificial intelligence (AI) has rapidly evolved into a transformative force, reshaping numerous facets of society, from healthcare to education. As AI technologies become more prevalent, they promise to revolutionize the way we live and work. Yet, the dual nature of AI presents both profound opportunities and significant challenges, particularly in relation to social inequalities. While AI holds the potential to reduce disparities by expanding access to essential services and creating new opportunities, it can also amplify existing biases and introduce new forms of discrimination if not developed and applied responsibly. This paper delves into the intricate relationship between AI and social inequalities, with a specific emphasis on linguistic AI. Technologies that process and interpret human language play a pivotal role in shaping social interactions and access to information. However, biases inherent in AI language algorithms pose a serious concern, as they can perpetuate societal prejudices and further marginalize minority communities. The literature review synthesizes insights from a range of academic sources to offer a thorough examination of AI's current adoption, its implications for social equity, and the role linguistic AI plays in addressing - or exacerbating - social disparities. By analyzing both the potential benefits and risks associated with AI, this paper underscores the need for ethical considerations and inclusive growth in AI development and deployment. Ultimately, it aims to contribute to the broader conversation on how AI can be leveraged to foster a more equitable society across linguistic and cultural boundaries.

Literature review. Artificial intelligence (AI) has emerged as a transformative technology with the potential to significantly impact various aspects of society, including social inequalities. The dual nature of AI, where it can both exacerbate and alleviate inequalities, has been a focal point of recent research. This literature review explores the current state of AI adoption, its implications for social equity, and the role of linguistic AI in addressing social disparities.

AI and Social Inequalities. Several studies have highlighted the potential of AI to exacerbate social inequalities. Eubanks (2018) argues that AI systems, when not designed with fairness in mind, can perpetuate existing biases and create new forms of discrimination. This is particularly evident in areas such as hiring practices, where AI algorithms may favor certain demographic groups over others (Raghavan et al., 2020). Similarly, Noble (2018) discusses how search engine algorithms can reinforce racial and gender biases, leading to unequal access to information and opportunities.

On the other hand, AI also holds promise for reducing social inequalities. According to West et al. (2019), AI can be leveraged to improve access to education, healthcare, and other essential services for marginalized communities. For instance, AI-driven educational tools can provide personalized learning experiences, helping to bridge the gap between students from different socio-economic backgrounds (Luckin et al., 2016). In healthcare, AI can assist in diagnosing diseases and recommending treatments, thereby improving health outcomes for underserved populations (Esteva et al., 2017).

Linguistic AI and Language Bias. Linguistic AI, which involves the use of AI technologies to process and understand human language, plays a crucial role in addressing social inequalities. However, language bias in AI algorithms remains a significant challenge. Studies by Blodgett et al. (2020) and Bender et al. (2021)

have shown that AI language models often exhibit biases that reflect societal prejudices. These biases can manifest in various ways, such as favouring dominant languages and cultural norms, which can marginalize minority groups and non-native speakers.

Efforts to mitigate language bias in AI have been explored in recent research. Sun et al. (2019) propose techniques for debiasing word embeddings, which are fundamental components of many AI language models. Similarly, Zhao et al. (2018) suggest methods for reducing gender bias in machine translation systems. These approaches highlight the importance of ethical considerations in the development and deployment of linguistic AI.

Ethical Considerations and Inclusive Growth. The ethical implications of AI are a critical area of study, particularly in the context of social inequalities. Researchers emphasize the need for responsible AI design that prioritizes fairness, transparency, and accountability. Floridi et al. (2018) argue that ethical AI practices are essential to ensure that the benefits of AI are equitably distributed and that potential harms are minimized. This includes addressing biases in AI systems and ensuring that AI technologies are accessible to all, regardless of socio-economic status or linguistic background.

Inclusive growth, which aims to create opportunities for all segments of society, is another key consideration in the deployment of AI. According to the World Economic Forum (2020), AI can contribute to inclusive growth by enabling new forms of economic participation and reducing barriers to entry for marginalized communities. This requires a concerted effort from policymakers, businesses, and researchers to develop AI solutions that are inclusive and equitable.

In summary, the literature highlights the transformative potential of AI in both exacerbating and alleviating social inequalities. Linguistic AI, in particular, plays a crucial role in this dynamic, with language bias and ethical considerations being central to its impact. By prioritizing fairness, transparency, and ethical development, AI can be harnessed to create a more equitable society across linguistic boundaries. Future research should continue to explore the ways in which AI can be designed and deployed to address social disparities, with a focus on inclusive growth and responsible innovation.

Research methodology. Our methodology involved conducting a comprehensive literature review to analyze existing studies, case examples, and empirical evidence related to AI’s impact on social inequalities. We identified and selected relevant academic journals, conference papers, books, and reputable online sources using key databases such as Google Scholar, PubMed, IEEE Xplore, and JSTOR. Inclusion criteria focused on studies addressing AI’s impact on social inequalities, while exclusion criteria filtered out non-empirical or non-peer-reviewed sources.

Data was systematically extracted from the selected sources, focusing on themes such as bias in AI systems, the digital divide, and ethical implications. We analyzed specific case examples that illustrate AI’s impact on social inequalities, providing concrete evidence of both mitigation and exacerbation of social disparities. Empirical evidence was gathered from studies providing quantitative and qualitative data on AI's effects on different social groups.

A critical analysis of the findings was conducted to draw conclusions about the current state of AI adoption and its implications for social equity. Ethical guidelines for AI development, including those established by the European Union and the World Economic Forum, informed our analysis and recommendations.

This methodology provided a comprehensive and insightful analysis of AI's impact on social inequalities, contributing to the broader discourse on ethical AI development.

Main results. The dominance of high-resource languages in AI refers to the overwhelming focus and development of AI technologies in languages that have abundant data and resources, such as English, Chinese, and Spanish. This dominance creates a significant disparity, as AI models trained primarily on these languages tend to perform better in them, while underperforming in low-resource languages that lack extensive datasets and computational resources. Consequently, speakers of low-resource languages face challenges in accessing and benefiting from AI advancements, which can exacerbate existing inequalities and limit the global reach and inclusivity of AI technologies. Addressing this issue requires concerted efforts to collect and curate data for low-resource languages, as well as developing AI models that are more inclusive and equitable. Low-resource languages are those that have limited digital resources, such as text corpora, linguistic databases, and computational tools. Here are a few examples:

Hausa - Spoken in West Africa, primarily in Nigeria and Niger.

Quechua - An indigenous language spoken in the Andean region of South America.

Amharic - The official language of Ethiopia.

Maori - The language of the indigenous people of New Zealand.

Inuktitut - Spoken by the Inuit people in Canada.

Wolof - Widely spoken in Senegal and The Gambia.

Bengali - While it has a large number of speakers, it is still considered low-resource in terms of digital and computational resources compared to languages like English.

These languages often lack extensive datasets and computational tools, making it challenging to develop AI technologies that perform well in them. Efforts to support these languages in AI development are crucial for promoting linguistic diversity and inclusivity.

The article "No Language Left Behind: How to Bridge the Rapidly Evolving AI Language Gap" by Alena Gorbacheva, published on the UNDP (United Nations Development Programme) Eurasia Innovation website, explores the challenges and opportunities associated with AI language representation. It highlights the dominance of high-resource languages in AI technologies, which limits accessibility for speakers of low-resource languages such as Kazakh. This lack of linguistic resources results in poor performance or non-functionality of AI tools for these languages. The article also delves into the struggles faced by speakers of low-resource languages in the digital world, emphasizing the need for more inclusive AI development. It suggests that bridging the AI language gap requires collective efforts from researchers, governments, educational institutions, and private companies through joint development of technologies, educational programs, and pilot projects.

Improving AI Research for Low-Resource Languages. Improving AI research for low-resource languages is essential for promoting linguistic diversity and inclusivity. Here are some strategies to achieve this:

– *Data Collection and Annotation*: gather and curate large datasets for low-resource languages. This can involve collaborating with native speakers, linguists, and local communities to collect text, speech, and other linguistic data. Annotation efforts should also be prioritized to create high-quality labeled datasets.
– *Transfer Learning*: utilize transfer learning techniques to leverage knowledge from high-resource languages. Pre-trained models on high-resource languages can be fine-tuned on low-resource language data to improve performance.
– *Multilingual Models*: develop and train multilingual models that can handle multiple languages simultaneously. These models can share knowledge across languages, benefiting low-resource languages through cross-lingual transfer.
– *Community Involvement*: engage local communities and native speakers in the development process. Their insights and expertise are invaluable for creating culturally and linguistically appropriate AI solutions.
– *Open-Source Initiatives*: Support and contribute to open-source projects focused on low-resource languages. Open-source tools and resources can accelerate research and development efforts by providing a collaborative platform for researchers and developers.
– *Funding and Support*: secure funding and institutional support for research on low-resource languages. Governments, NGOs, and private organizations can play a crucial role in providing the necessary resources and infrastructure.
– *Cross-Disciplinary Collaboration*: foster collaboration between linguists, computer scientists, and AI researchers. Interdisciplinary approaches can lead to innovative solutions and a deeper understanding of the linguistic challenges involved.

By implementing these strategies, we can make significant progress in improving AI research for low-resource languages and ensure that AI technologies are accessible and beneficial to all linguistic communities.

The implications of improving AI research for low-resource languages are profound for global linguistic diversity:

Preservation of Languages: enhanced AI research can help document and preserve endangered languages by creating digital records, speech recognition systems, and translation tools. This is crucial for maintaining cultural heritage and linguistic diversity.

Increased Accessibility: AI technologies that support low-resource languages can make information and services more accessible to speakers of these languages. This includes educational resources, healthcare information, and government services, thereby promoting inclusivity.

Cultural Representation: by incorporating low-resource languages into AI systems, we ensure that diverse cultures and perspectives are represented in the digital world. This can lead to more culturally sensitive and relevant AI applications.

Economic Opportunities: supporting low-resource languages in AI can open up new economic opportunities for communities. It can enable local businesses to reach a broader audience and participate in the global digital economy.

Equitable AI Development: addressing the dominance of high-resource languages in AI research promotes equity in technological development. It ensures that the benefits of AI are distributed more evenly across different linguistic communities.

Enhanced Communication: AI-powered translation and communication tools can bridge language barriers, fostering better understanding and collaboration between different linguistic groups.

Overall, improving AI research for low-resource languages is essential for promoting linguistic diversity, cultural preservation, and global inclusivity. It ensures that AI technologies serve the needs of all linguistic communities, not just those with abundant resources. There have been several successful examples of AI research in low-resource languages. Here are a few notable ones:

Meta's No Language Left Behind (NLLB) Project: Meta developed the NLLB-200 model, which can translate between 204 languages, including many low-resource languages. This project aims to improve translation quality for underrepresented languages and make AI more inclusive (Adelani, 2024). NLLB is a pioneering AI project focused on Multilingual Language Models (MLLMs). The project has released open-source models capable of delivering high-quality translations across 200 languages, improving translations for low-resource languages on platforms like Facebook and Instagram. The NLLB-200 model, integrated into the Wikimedia Foundation's Content Translation tool, helps Wikipedia editors translate content into their preferred languages, enriching Wikipedia's language diversity. The open-source nature of the NLLB-200 model also empowers the research community and Wikipedia editor groups to build upon their findings.

adaptMLLM: this project focuses on fine-tuning multilingual language models for low-resource languages. For example, it has shown significant improvements in translation performance for language pairs like English to Irish (EN ↔ GA) and English to Marathi (EN ↔ MR). As an open-source application, adaptMLLM is freely available for the research community and practitioners in the field of MT (machine translation). This encourages further development and collaboration (Lankford, Afli, & Way, 2023).

AfriBERTa: this multilingual language model covers 11 African languages, including the first language model for four of these languages. It demonstrates that competitive multilingual language models can be trained on less than 1 GB of text (Ogueji, Zhu, & Lin, 2021).

ASR Models for Tujia Language: researchers from the University of Beijing developed a speech recognition model for the Tujia language, a Sino-Tibetan language spoken by the Tujia people in Hunan Province, China. This model helps preserve the language, which is at risk of extinction (Bogdanoski, Mishev, Simjanoska, & Trajanov, 2023). Tujia is a Sino-Tibetan language spoken by the Tujia people in Hunan Province, China.

ASR (Automatic Speech Recognition) models are crucial for preserving endangered languages like Tujia by creating digital records and facilitating language learning. One approach to improving ASR for Tujia involves integrating visual information, such as lip movements, with audio data. This fusion enhances the model's ability to recognize speech accurately, even with limited data (Yu, Yu, Qian, & Tan, 2023).

These models combine LSTM (Long Short-Term Memory) networks with Transformer architectures to improve the accuracy of speech recognition. The AVSR (Audiovisual Speech Recognition) approach has shown a significant reduction in character error rate compared to traditional models.

These examples highlight the potential of AI research to support and preserve low-resource languages, making technology more accessible and inclusive for diverse linguistic communities.

Discussion and conclusions. The ethical implications of AI, especially in the context of social inequalities, are a crucial area of study. Here are some key points to consider:

Bias and Discrimination. AI systems can inadvertently replicate and even amplify existing biases related to race, gender, and other social factors. This can lead to discriminatory outcomes in areas such as hiring, lending, and law enforcement.

Accessibility and Inclusivity. The digital divide, or disparities in access to technology, can exacerbate existing inequalities. Ensuring that AI technologies are accessible and inclusive is essential to prevent further marginalization of disadvantaged groups.

Psychological and psychosocial impacts. It is crucial to incorporate ethical considerations into the design and development of AI systems to prevent harm and ensure fairness of AI technologies and to develop ethical guidelines to mitigate potential risks. AI algorithms used by social media platforms to recommend content, for example, can create echo chambers and contribute to the spread of misinformation. This can impact users' mental health by reinforcing negative beliefs and increasing anxiety.

Data Privacy and Security. AI systems often rely on vast amounts of data, raising concerns about data privacy and security. Ensuring that data is collected and used ethically is critical to protect individuals' rights and prevent misuse.

Accountability and Transparency. There is a need for clear accountability and transparency in AI systems. This includes understanding how decisions are made by AI and ensuring that there are mechanisms in place to address any harmful outcomes.

Potential for Positive Impact. Despite these challenges, AI also holds the potential to reduce unfairness and promote social justice if developed and deployed responsibly. For example, AI can be used to identify and mitigate biases in decision-making processes. Addressing these ethical implications requires a collaborative effort from researchers, policymakers, and communities to ensure that AI benefits all members of society equitably.

Importance in AI Research. Ethics committees are essential for ensuring that AI research is conducted responsibly and ethically, protecting both participants and society at large.

The European Union has established guidelines to ensure that AI development is ethical and trustworthy, emphasizing a human-centric approach (*Ethics Guidelines for Trustworthy AI*). These guidelines include supporting human autonomy and decision-making, ensuring technical robustness and safety, protecting data privacy, maintaining transparency, promoting diversity and fairness, contributing positively to society, and ensuring accountability. Organizations can follow practical steps to build ethical AI, such as leveraging existing ethical frameworks, creating tailored risk frameworks, learning from healthcare practices, providing ethical guidelines for product managers, promoting organizational awareness, incentivizing ethical behavior, and continuously monitoring impacts while engaging stakeholders.

The World Economic Forum outlines general ethical AI principles that are applicable across various cultural and geographical contexts, including ensuring accountability, protecting data privacy, and supporting human decision-making and autonomy. These guidelines and principles help ensure that AI development is conducted responsibly and ethically, minimizing potential risks and maximizing benefits for society.

Our findings underscore the importance of addressing linguistic and social disparities in AI development. Ensuring greater linguistic representation in AI training data, developing ethical AI frameworks, and engaging with diverse communities are essential steps toward creating a more equitable digital ecosystem. AI linguistic technologies hold significant potential to promote multilingualism and preserve endangered languages. By leveraging advanced natural language processing (NLP) techniques, AI can facilitate the development of translation tools, language learning applications, and digital resources that support a wide range of languages, including those with limited resources (Santorelli & Catullo, 2023). For instance, AI-powered translation systems can bridge communication gaps between speakers of different languages, fostering greater linguistic diversity and cultural exchange. Additionally, AI can assist in documenting and revitalizing endangered languages by creating digital archives, generating educational content, and providing real-time translation and transcription services. These efforts not only help preserve linguistic heritage but also empower communities to maintain and celebrate their unique cultural identities. As AI continues to evolve, its role in promoting multilingualism and safeguarding endangered languages will become increasingly vital, contributing to a more inclusive and diverse global society. By prioritizing ethical considerations and promoting inclusive practices, we can ensure that AI technologies contribute positively to society and help bridge the gap in social inequalities.

REFERENCES

Adelani, D. I. (2024). Meta's AI translation model embraces overlooked languages. *Nature*, *630*(8018), 821-822. https://doi.org/10.1038/d41586-024-00964-2

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021, March 3-10). On the dangers of stochastic parrots: Can language models be too big? In: *FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 610-623). New York, NY United States: Association for Computing Machinery.

Bhagat, H. V., & Singh, M. (2023). Machine Learning and Deep Learning Techniques in Social Sciences. In: *Machine Learning Algorithms for Signal and Image Processing* (pp. 409-428). IEEE. https://doi.org/10.1002/9781119861850.ch23

Blodgett, S. L., Barocas, S., Daumé, III H., & Wallach, H. (2020, July 5-10). Language (technology) is power: A critical survey of "bias" in NLP. In: *The 58th Annual Meeting of the Association for Computational Linguistics: Proceedings of Conference* (pp. 5454-5476). Stroudsburg: Association for Computational Linguistics. https://aclanthology.org/2020.acl-main

Bogdanoski, K., Mishev, K., Simjanoska, M., & Trajanov, D. (2023). Exploring ASR Models in Low-Resource Languages: Use-Case the Macedonian Language. In: D. Conte, A. Fred, O. Gusikhin, & C. Sansone (Eds.), *Deep Learning Theory and Applications. DeLTA 2023. Communications in Computer and Information Science* (Vol. 1875). Cham: Springer. https://doi.org/10.1007/978-3-031-39059-3_17

Capraro, V., Lentsch, A., Acemoglu, D., Akgund, S., Akhmedova, A., Bilancini, E., Bonnefon, J. F., Brañas-Garza, P., Butera, L., Douglas, K. M., Everett, J. A. C., Gigerenzer, G., Greenhow, C., Hashimoto, D. A., Holt-Lunstad, J., Jetten, J., Johnson, S., Kunz, W. H., Longoni, C., … & Viale, R. (2024). The impact of generative artificial intelligence on socioeconomic inequalities and policymaking. *PNAS Nexus*, *3*(6), 191. https://doi.org/10.1093/pnasnexus/pgae191

Drushlyak, M., Lukashova, T., Sabadosh, Y., Melnikov, I., & Semenikhina, O. (2024). Using ChatGPT for the development of critical thinking in youth: Example of inequality proof. In: *47th MIPRO ICT and Electronics Convention* (pp. 334-339). Opatija, Croatia. https://doi.org/10.1109/MIPRO60963.2024.10569759

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542, 115-118. https://doi.org/10.1038/nature21056

Eubanks, V. (2018). Automating inequality: How high-tech tools profile, police, and punish the poor. *Law, Technology and Humans, 1*, November, 162-164. https://doi.org/10.5204/lthj.v1i0.1386

European Union. (n.d.). *Ethics Guidelines for Trustworthy AI. Retrieved from.* https://ec.europa.eu/digital-strategy/our-policies/european-approach-artificial-intelligence

Gorbacheva, A. (2023, September 14). *No language left behind: How to bridge the rapidly evolving AI language gap. UNDP Eurasia Innovation*. https://www.undp.org/kazakhstan/blog/no-language-left-behind-how-bridge-rapidly-evolving-ai-language-gap

Hello Future. (2024, March 4). *How AI Can Help Reduce Inequalities. Hello Future.* https://hellofuture.orange.com/en/how-ai-can-help-reduce-inequalities/

https://www.davidluxton.com/Luxton-Watson-Super-Disruptive-AI.pdf

Lankford, S., Afli, H., & Way, A. (2023). AdaptMLLM: Fine-tuning multilingual language models on low-resource languages with integrated LLM playgrounds. *Information*, *14*(12), 638. https://doi.org/10.3390/info14120638

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education.* London: Pearson. https://static.googleusercontent.com/media/edu.google.com/ru//pdfs/Intelligence-Unleashed-Publication.pdf

Luxton, D. D., & Watson, E. (2023). Psychological and Psychosocial Consequences of Super Disruptive A.I.: Public Health Implications and Recommendations. In: *Proceedings of the Stanford Risks Conference* (pp. 60-74). https://doi.org/10.25740/mg941vt961

Noble, S. U. (2018). *Algorithms of oppression: How search engines reinforce racism*. New York: Published NYU Press. https://doi.org/10.2307/j.ctt1pwt9w5

Ogueji, K., Zhu, Y., & Lin, J. (2021). Small data? No problem! Exploring the viability of pretrained multilingual language models for low-resourced languages. In: *Proceedings of the 1st Workshop on Multilingual Representation Learning* (pp. 116-126). Punta Cana, Dominican Republic: Association for Computational Linguistics. https://doi.org/10.18653/v1/2021.mrl-1.11

Park, S. (2024). AI chatbots and linguistic injustice. *Journal of Universal Language*, *25*(1), 99-119. https://doi.org/10.22425/jul.2024.25.1.99

Practical Guide to Building Ethical AI. (n.d.). https://www.weforum.org/reports/a-practical-guide-to-building-ethical-ai

Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. In: *FAccT '20: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 469-481). New York, NY United States: Association for Computing Machinery.

Santorelli, M., & Catullo, D. (2023, May 18-19). Artificial intelligence and global English: An ongoing challenge for sustainable tourism. In: *Tourism for a*

Sustainable Future: Proceedings of the International Scientific Conference (pp. 795-803). Bulgaria: Avangard Prima.

Santorelli, M., & Catullo, D. (2023, October 12-13). Human mobility and language: towards new multilingual approaches with ai. In: *Economic growth in the conditions of globalization*. Scientific session "Migration and demographic change: challenges and public policies": conference proceedings: international scientific-practical conference (17 edition, Vol. 3, pp. 153-163). Chișinău: SEP ASEM. https://doi.org/10.36004/nier.cdr.V.2023.17.16

Sun, T., Gaut, A., Tang, S., Huang, Y., ElSherief, M., Zhao, J., Mirza, D., Belding, E., Chang, K-W., & Wang, W. Y. (2019). Mitigating gender bias in natural language processing: Literature review. In: *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics* (pp. 1630-1640). Florence, Italy: Association for Computational Linguistics.

West, S. M., Whittaker, M., & Crawford, K. (2019). Discriminating systems: Gender, race, and power in AI. AI Now Institute. https://www.acc.com/sites/default/files/2019-11/2019-11-06%20HANDOUT%202%20-%20AI%20and%20Diversity%20Whitepaper.pdf

World Economic Forum. (n.d.). *9 ethical AI principles for organizations to follow*. https://www.weforum.org/agenda/2020/10/ethical-ai-principles/

Yu, C., Yu, J., Qian, Z., & Tan, Y. (2023). Improvement of Acoustic Models Fused with Lip Visual Information for Low-Resource Speech. *Sensors*, *23*(4), 2071. https://doi.org/10.3390/s23042071

Zajko, M. (2022). Artificial intelligence, algorithms, and social inequality: Sociological contributions to contemporary debates. *Sociology Compass*, *16*(3), e12962. https://doi.org/10.1111/soc4.12962