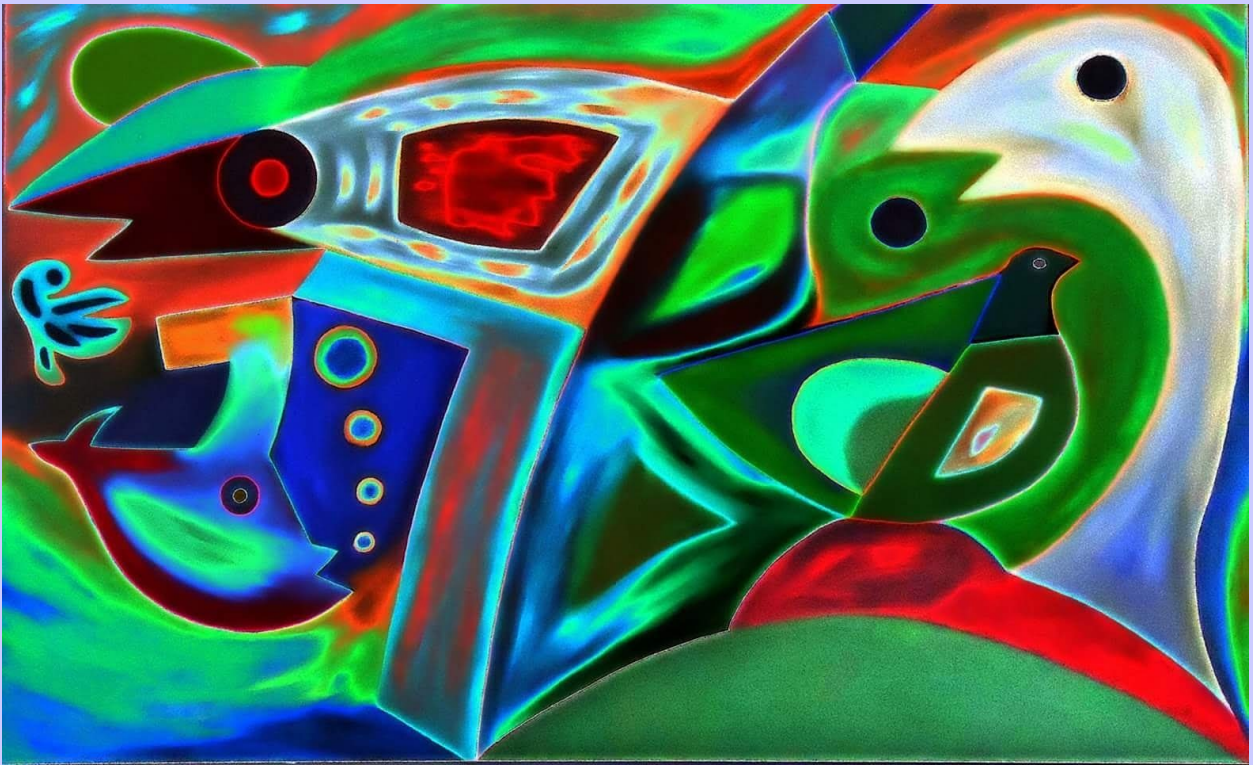


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Ethical Challenges in Explainable AI: A Review on Cultural and Social Bias

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Abstract: Explainable Artificial Intelligence (XAI) has emerged as a critical domain within AI research, aiming to enhance system transparency and user trust. While technical advancements in XAI have improved algorithmic interpretability, ethical concerns, particularly cultural and social biases, remain underexplored. This study adopts a semi-systematic literature review approach to examine how ethical challenges, particularly cultural and social biases, are addressed in Explainable AI (XAI) research, based on papers published between 2017 and 2025, focusing on how current XAI systems recognize, reinforce, or attempt to address such biases. The findings indicate a predominant focus on Western user populations, minimal engagement with underrepresented communities, and a lack of participatory or culturally responsive design strategies. By analyzing themes across healthcare, education, and decision-support systems, the review highlights the limitations of existing models and the need for inclusive, user-centered approaches. The paper concludes by proposing research directions centered on localized explanation models, participatory design, and expanded evaluation metrics that account for cultural relevance and social equity. These insights contribute to the ongoing effort to align XAI development with ethical principles and ensure equitable AI outcomes across diverse user groups.

Keywords: Explainable Artificial Intelligence (XAI), Ethical AI, Social Bias, Cultural Bias

1. Introduction

Explainable Artificial Intelligence (XAI) has become a vital component in the pursuit of transparent, trustworthy, and accountable AI systems. As AI technologies continue to permeate critical domains such as healthcare, education, and decision support, the ability for users to understand and question AI-generated outcomes has become increasingly essential. This relevance extends to business and enterprise applications as well, where the integration of explainable AI helps build trust, ensure accountability, and support ethical data-driven decisions [1],[2]. Classify XAI into opaque, interpretable, and comprehensible systems, each offering varying levels of algorithmic transparency and user involvement. Fig. 1 demonstrates this fact. This distinction underscores the growing need to develop AI systems that are not only functional but also understandable.

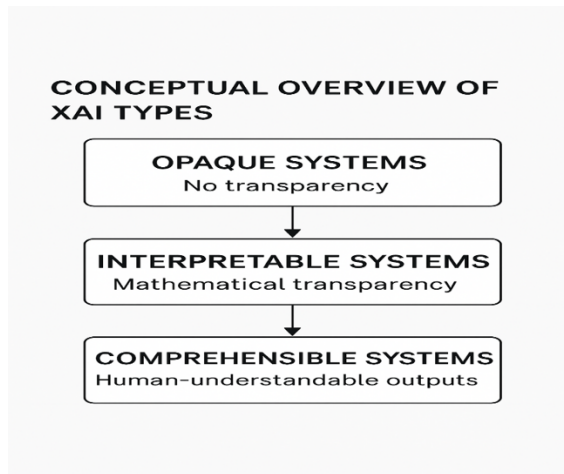


Fig. 2. Conceptual Overview of XAI Types. Source: based on [2] .

Research in XAI has increasingly emphasized human-centered approaches. [3] advocate for integrating insights from the social and behavioural sciences to enhance explainability from the user’s perspective. Similarly, [4] extend the conversation to design-centered and symbolic reasoning contexts, suggesting that effective explanation must go beyond model transparency to reflect how users actually interpret AI behavior.

Despite these advancements, the majority of XAI literature remains focused on technical optimization, often neglecting ethical challenges such as cultural and social bias. Studies by [5] reveal a Western-centric orientation in XAI research and call for the inclusion of marginalized perspectives. Additionally, [6] highlight the significance of culturally sensitive AI in healthcare, where contextual understanding can impact user trust and system effectiveness.

This paper will look to addresses these ethical gaps by conducting a semi-systematic review of recent XAI literature, with a specific focus on how cultural and social biases are identified, addressed, or overlooked. In doing so, it aims to support the development of more inclusive, transparent, and ethically grounded XAI frameworks.

2. Literature Review

Explainable Artificial Intelligence (XAI) has become a critical focus in AI research, driven by the need to enhance transparency, interpretability, and user trust in increasingly complex algorithmic systems. [2] Propose a foundational classification of XAI systems, opaque, interpretable, and comprehensible, highlighting varying levels of algorithmic transparency and user involvement. These distinctions illustrate the breadth of approaches in making AI systems understandable to human users. To improve effectiveness, [3] argue for integrating social and behavioural science insights into XAI design, promoting a shift toward human-centered evaluation. Similarly, [4] have emphasised tailoring AI explanations to real-world user needs, whether in design or decision support contexts. [7] extends the relevance of XAI beyond machine learning, noting its potential across symbolic AI domains.

Within high-stakes sectors like healthcare, the demand for transparency has led to further frameworks and applications [8]. Advocates for “glass box” systems and domain-specific XAI approaches to foster responsible AI use [9]. Provide an overview of available XAI methods, reinforcing the importance of informed technique selection. In line with this, [10] highlighted the role of XAI in addressing black-box challenges and promoting accountability, trust, and ethical deployment of AI models.

AI's rapid growth across sectors has introduced crucial ethical challenges, such as bias, transparency, and accountability. Ethical AI plays a vital role in ensuring responsible development and building trust, aligning AI systems with societal values [11]. It emphasizes principles like fairness, inclusiveness, and human-centered design to prevent harm and promote equitable outcomes. As AI becomes more embedded in decision-making, ethical frameworks are essential to guide its deployment in socially sensitive contexts.

Further, some of the past research works show significant concerns regarding cultural biases in XAI, particularly a predominant focus on Western populations. In [12] conducted a systematic analysis that highlights this bias, indicating a critical gap in understanding how diverse cultural backgrounds influence user interactions with XAI systems. Their findings suggest that existing research often overlooks the needs and responses of non-Western users, which could lead to ineffective or even harmful AI applications in diverse contexts. Further supporting this, [13] emphasize the importance of incorporating marginalized cultural perspectives into AI systems, arguing that enhancing transparency and control, especially when working with underrepresented datasets, can help mitigate deep learning bias. Similarly, [6] explore the implications of AI in palliative and hospice care for underrepresented groups, highlighting the need for culturally sensitive AI applications in healthcare. Together, these studies underscore a pressing ethical concern: without attention to cultural and social diversity, XAI systems risk reinforcing existing inequalities and failing the very users they are meant to serve.

This paper conducts a semi-systematic literature review to examine how ethical challenges, particularly cultural and social biases, are recognised, addressed, or overlooked in current Explainable AI (XAI) research. By analysing recent literature, the review aims to highlight the limitations of technically focused XAI models and emphasise the need for culturally inclusive and socially aware explainability frameworks.

4. Methodology

This study adopts a semi-systematic literature review approach to explore how ethical challenges, particularly cultural and social biases, are addressed in Explainable Artificial Intelligence (XAI) research. A targeted search was conducted across three academic databases: Google Scholar, Scopus, and IEEE Xplore.

The search utilised combinations of the following keywords: "Explainable AI", "Ethical AI", "Bias in AI", "Social bias in AI", "Cultural bias in machine learning", and "Fairness and explainability." The inclusion criteria were:

- Peer-reviewed articles,
- Published between 2017 and 2025,
- Focused on XAI and its ethical, cultural, or social dimensions,
- Written in English.

The screening process began with an initial review of titles and abstracts to assess relevance, followed by a thorough full-text evaluation of the selected articles. To minimize potential bias and enhance interdisciplinary insight, all three authors participated in the review process, bringing together expertise from both social science and technical backgrounds alongside their contributions to the overall

development of the paper. The final set of papers was analyzed thematically, with particular attention to how cultural and social biases are identified, represented, or addressed within the context of XAI systems. This approach is consistent with established practices in semi-systematic and mapping reviews, which allow for flexible but rigorous exploration of under-researched themes [14]

5. Results and Discussion

5.1 Cultural Biases in Explainable AI

Cultural biases in explainable AI (XAI) have garnered increasing attention in recent years, as researchers seek to understand how these biases affect the design, implementation, and user experience of AI systems. A significant body of literature highlights the need for a more nuanced approach to XAI that considers cultural differences and the implications of these biases.

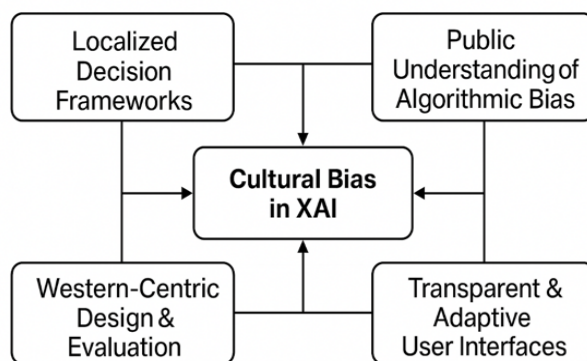


Fig. 3. Key Dimensions of cultural biases in explainable AI systems, based on [12].

[15] Propose a conceptual framework for developing human-centered, decision-theory-driven XAI, emphasizing the importance of understanding human decision-making processes. Their work suggests that integrating insights from philosophy and psychology can enhance the empirical application of XAI, potentially addressing cultural biases by tailoring explanations to diverse user needs.

In a related vein, [16] conducted in-depth interviews with stakeholders to explore user perceptions of biases in AI applications. Their findings indicate that the general public often lacks the understanding necessary to navigate the complexities of black-box algorithms, particularly in high-stakes situations. This underscores the necessity for XAI systems to be designed with cultural contexts in mind, ensuring that explanations resonate with users from various backgrounds.

Further emphasizing the cultural dimension, [5] conducted a systematic analysis of cultural bias in XAI research. They found a predominant focus on Western populations, which raises concerns about the applicability of XAI systems across culturally diverse user groups. Their analysis highlights a critical knowledge gap that future research must address to ensure that XAI is equitable and effective for all users.

Additionally, [17] advocate for the development of transparent and explainable models from the outset, which could mitigate some of the biases identified in existing systems. By prioritizing transparency, the EVOTER framework aims to build trust in AI systems, potentially reducing cultural biases by making the reasoning behind AI decisions more accessible to a broader audience.

[18] highlight the role of biases in exacerbating healthcare inequalities, particularly in radiology. Both studies emphasize the need for XAI to address these biases to promote fairness and equity.

Finally, [19] explore the potential of wearable AI systems to enhance human reasoning, suggesting that such technologies could serve as symbiotic counterparts to users. This approach may offer a pathway to develop culturally sensitive AI systems that adapt to the reasoning styles and explanatory needs of diverse populations.

In summary, there is a pressing need to address cultural biases in explainable AI through user-centered design, transparency, and an understanding of diverse cultural contexts. Future research should focus on developing frameworks and methodologies that account for these biases, ensuring that XAI systems are equitable and effective across different cultural landscapes.

5.2 Social Biases and Inequality in XAI

The exploration of social biases in explainable artificial intelligence (XAI) has become crucial in the recent years, highlighting the intricate relationship between human cognition, algorithmic decision-making, and the interpretability of AI systems. A critical aspect of this discourse is the recognition that while XAI aims to enhance user trust and understanding, it is not immune to the biases that can influence both the design and evaluation of these systems.

According to [20], who provide a heuristic map linking cognitive biases to XAI techniques. They identify that cognitive biases can distort the evaluation of XAI methods in user studies and that certain biases may be mitigated or exacerbated by XAI techniques. This duality underscores the complexity of integrating human cognitive factors into the design of XAI systems.

Further complicating the landscape, [21] argue against a purely technical approach to XAI, positing that understanding and addressing algorithmic bias requires a broader epistemological framework, such as feminist philosophy. This perspective challenges the notion that technical experts can independently manage bias without considering the social and ethical implications of their work. Similarly, [22] advocate for a genealogical approach to algorithmic bias, critiquing existing methodologies for their assumptions about protected characteristics and discriminatory outcomes. This critique highlights the need for a more nuanced understanding of how biases are embedded within algorithmic processes.

[23] explores these concerns within the civil justice system, emphasizing how AI-driven decision tools risk undermining due process and legal fairness when not paired with meaningful explainability. Her discourse analysis highlights structural power imbalances exacerbated by opaque AI models and urges that any XAI deployment in justice settings must ensure transparency, procedural equity, and contestability.

The ethical dimensions of XAI are further explored by [24], who discusses the moral implications of explainability in AI systems. [25] argue that ethical responsibility in AI development cannot be delegated to the systems themselves, especially when addressing social bias. They caution against framing AI as moral agents and emphasise that designers and policymakers must maintain accountability for ethical outcomes. This perspective reinforces the idea that explainability should clarify human agency, rather than suggest machine autonomy.

The study emphasizes the necessity of transparency in AI decision-making processes, which is crucial for users to comprehend the rationale behind AI judgments. This ethical lens is echoed in the work of [26], who investigate how XAI can reduce opacity and address bias in algorithmic models. They argue that by elucidating the predictive processes of algorithms, XAI can play a pivotal role in mitigating biases that may arise from opaque decision-making.

In the context of specific applications, [27] provide a systematic review of XAI challenges in clinical decision support systems, highlighting the need for explainability to ensure equitable healthcare outcomes. This is particularly relevant given the potential for biases in medical AI systems to exacerbate existing disparities in healthcare access and treatment.

Overall, the literature indicates that while XAI holds promise for improving transparency and trust in AI systems, it is essential to critically examine the social biases that can influence both the development and implementation of these technologies. Addressing these biases requires a multifaceted approach that incorporates ethical considerations, cognitive psychology, and a commitment to understanding the broader societal implications of AI. Figure 02, demonstrates the common social bias challenges in XAI explanations.

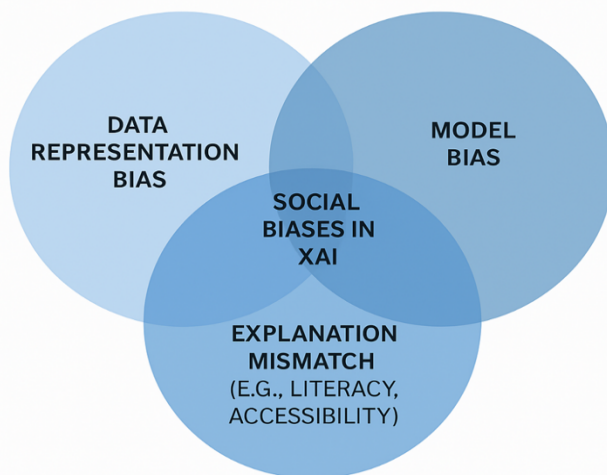


Fig.4. Common Social bias challenges in XAI explanations. Source: [6].

5.3 Current Efforts to Address Bias

There have been some research efforts in the recent past tried to address both social and cultural bias of explainable AI(XAI), highlighting both the potential and limitations of XAI tools in mitigating bias and enhancing fairness in AI systems.

The importance of user backgrounds and impressions in shaping interactions with AI systems is examined by [28]. Their study highlights how anchoring bias can influence users' mental models during initial interactions with intelligent systems. They argue that effective explanations can play a crucial role in mitigating such biases, underscoring the need for XAI to consider user diversity in its design and implementation.

Cultural bias in XAI research is critically analyzed by [12] who point out the predominance of Western-centric perspectives in existing studies. Their systematic analysis reveals a significant gap in understanding how culturally diverse users engage with XAI systems, suggesting that future research should prioritize inclusivity to address these biases effectively.

[29] contribute to the discourse by proposing a genealogical approach to understanding algorithmic bias. They argue that examining the conditions that enable bias can provide valuable insights into the assumptions underlying various XAI

methodologies, thereby fostering a more nuanced understanding of bias in AI systems.

[26] discuss the transformative potential of XAI in reducing opacity in algorithmic models. They assert that XAI can elucidate decision-making processes and help mitigate bias, thereby enhancing the accountability of AI systems. This perspective aligns with the broader goal of making AI more transparent and equitable.

In the context of healthcare, [30] systematically review the impact of XAI on clinicians' trust in AI applications. Their findings indicate that while XAI can enhance trust by providing clarity, it also poses risks of over-reliance, which can lead to adverse outcomes when AI recommendations conflict with clinical judgment. This highlights the delicate balance required in fostering trust without compromising critical decision-making processes.

Overall, the literature underscores the complexity of addressing bias in XAI. While XAI holds promise for improving transparency and fairness, significant challenges remain in ensuring that these tools effectively detect and mitigate bias across diverse user populations and contexts. Future research must continue to explore these dimensions to enhance the efficacy and equity of AI systems.

6. Gaps and Research Directions

Despite notable progress in the development of Explainable AI (XAI), current systems continue to exhibit unconscious cultural and social biases. Much of the existing research prioritizes technical accuracy and general usability, often overlooking the diverse cultural contexts in which AI systems operate. As highlighted in the reviewed literature, the predominance of Western-centric data, design assumptions, and evaluation frameworks raises concerns about the inclusivity and equity of XAI applications.

One critical gap is the lack of localized and community-centered explanation models. Current approaches rarely consider how explanations are interpreted differently across cultural groups, potentially leading to misunderstandings, mistrust, or exclusion. Addressing this requires future research to move beyond one-size-fits-all solutions and instead develop explanation methods that are tailored to specific user communities.

Moreover, there is a clear need for the adoption of participatory design methods in XAI. Rather than designing explanations for users based on assumed preferences, future systems should be developed with input from diverse users, including those from underrepresented or marginalized backgrounds. This participatory approach can help ensure that explanations align with the values, expectations, and cognitive models of intended user groups.

A similar emphasis on contextual sensitivity is seen in domain-specific XAI research, such as cybersecurity, where ethical challenges extend beyond fairness to include risks of adversarial misuse. Scholars caution that exposing internal mechanisms of AI systems, even for transparency, may lead to security vulnerabilities if explanations are accessed by malicious actors [31]. This reinforces the importance of carefully balancing explainability with contextual constraints, particularly in culturally or politically sensitive domains.

Finally, existing evaluation metrics in XAI largely focus on technical correctness or understandability from a system's perspective, while overlooking dimensions such as cultural relevance, fairness, and social inclusivity. Future work should expand the criteria for evaluating XAI to include these ethical and contextual factors, enabling more holistic assessments of system effectiveness and impact. Supporting this direction, [32] review the use of AI Impact Assessments (AI-IAs) as structured tools to anticipate ethical and social risks. Their analysis of 38 AI-IAs reveals their potential

to stimulate proactive reflection and broaden stakeholder engagement. Incorporating such frameworks into XAI evaluation processes can help ensure that explainability efforts address not only technical clarity but also cultural relevance and ethical accountability.

In summary, advancing equitable and ethical XAI requires a shift in both design and evaluation, from technically centered models to those that prioritize cultural sensitivity, user engagement, and social responsibility.

7. Conclusion

Explainable AI (XAI) has emerged as a crucial area in artificial intelligence, aiming to improve transparency, trust, and interpretability in complex systems. While the field has made technical strides, this review highlights a significant ethical gap: the persistent neglect of cultural and social dimensions in XAI design and evaluation. Many current systems remain shaped by Western-centric assumptions and overlook the diverse needs of global user populations.

Through a semi-systematic review of recent literature, this paper examined how cultural and social biases are manifested—and sometimes challenged—in XAI research. Findings reveal a lack of inclusive frameworks, limited representation of marginalized communities, and minimal use of participatory approaches. These limitations not only reduce the effectiveness of AI explanations but also risk reinforcing existing inequalities.

To move toward more equitable and responsible AI, future XAI research must prioritize culturally sensitive, user-centered design, adopt participatory methodologies, and broaden evaluation metrics to include social inclusivity and cultural relevance. Embedding these considerations into the core of XAI development is essential for building systems that serve diverse populations ethically, transparently, and effectively.

References

1. Thalpage N. The Integration of Machine Learning and Explainable AI in Business Digitization: Unleashing the Power of Data – A Review. *JDS*, **6**(1), (2024). <https://doi.org/10.33847/2686-8296.6.1.2>.
2. Doran, D.; Schulz Sarah S.; Besold, T. R. What Does Explainable AI Really Mean? A New Conceptualization of Perspectives. DOI: 10.48550/arXiv.1710.00794, 2017.
3. Miller, T. P.; Sonenberg, Howe and L. "Explainable AI: Beware of Inmates Running the Asylum Or: How I Learnt to Stop Worrying and Love the Social and Behavioural Sciences," no. 10.48550/arXiv.1712.00547, 2017.
4. Zhu, J.; Liapis, A.; Risi, S.; Bidarra R.; Youngblood, G. M. "Explainable AI for Designers: A Human-Centered Perspective on Mixed-Initiative Co-Creation," no. 10.1109/CIG.2018.8490433, 2018.
5. Peters U. ; Carman, M. Cultural Bias in Explainable AI Research: A Systematic Analysis," *Journal of Artificial Intelligence Research*, **79** (2024) 971-1000, 2024. <https://doi.org/10.1613/jair.1.14888>.
6. Xu T.; Rose, G. Opportunities and Barriers to Artificial Intelligence Adoption in Palliative/Hospice Care for Underrepresented Groups A Technology Acceptance Model-Based Review," *Journal of Hospice & Palliative Nursing*, no. DOI: 10.1097/NJH.0000000000001120, 2025.
7. Lecue, F. On the role of knowledge graphs in explainable AI. DOI: 10.3233/SW-190374, 2019. DOI: 10.3233/SW-190374, 2019.
8. Rai, A. Explainable AI: from black box to glass box," *Journal of the Academy of Marketing Science*,,, no. DOI: 10.1007/s11747-019-00710-5, 2019.
9. Holzinger, A. et al. Explainable AI Methods - A Brief Overview," *Lecture Notes in Computer Science*, no. DOI: 10.1007/978-3-031-04083-2_2, 2022.

10. Thalpage N.S. Unlocking the Black Box: Explainable Artificial Intelligence (XAI) for Trust and Transparency in AI Systems. *J. Digit. Art Humanit.* **4**(1), 31-36, (2023). <https://doi.org/10.33847/2712-8148.4.1.4>.
11. Akinrinola, O. et al. Navigating and reviewing ethical dilemmas in AI development: Strategies for transparency, fairness, and accountability. *GSC Advanced Research and Reviews*, no.DO: 10.30574/gscarr.2024.18.3.0088, 2024.
12. Peters U.; Carman, M. Cultural Bias in Explainable AI Research: A Systematic Analysis. *The Journal of Artificial Intelligence Research (JAIR)*, no. <https://doi.org/10.1613/jair.1.14888>, 2024.
13. Bryan-Kinns N.; Li, Z. Reducing Barriers to the Use of Marginalised Music Genres in A. *Explainable AI for the Arts*. <https://doi.org/10.48550/arXiv.2407.13439> , 2024.
14. Thalpage N. S.; Nisansala, T. A. D. Exploring the Opportunities of Applying Digital Twins for Intrusion Detection in Industrial Control Systems of Production and Manufacturing – A Systematic Review. *Data Protection in a Post-Pandemic Society*, DOI: 10.1007/978-3-031-34006-2_4 , 2023.
15. Wang, D.; Yang, Q.; Ashraf A.; Lim, B. Designing Theory-Driven User-Centric Explainable AI. 2019. DOI: <https://doi.org/10.1145/3290605.3300831>
16. Yuan, C. W.; Bi, N.; Lin Y.-F.; Tseng, Y.-H. Contextualizing User Perceptions about Biases for Human-Centered Explainable Artificial Intelligence in CHI '23: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, 2023. <https://doi.org/10.1145/3544548.3580945>
17. Shahrzad, H.; Hodjat B.; Miikkulainen, R. EVOTER: Evolution of Transparent Explainable Rule-sets. *ACM Transactions on Evolutionary Learning and Optimization*, 2025. <https://doi.org/10.1145/3702651>
18. De-Giorgio, F. et al. The need for balancing 'black box' systems and explainable artificial intelligence: A necessary implementation in radiology," *European Journal of Radiology*, 2025. DOI: [10.1016/j.ejrad.2025.112014](https://doi.org/10.1016/j.ejrad.2025.112014)
19. Danry, V.; Pataranutaporn, P.; Mao Y.; Maes, P. Wearable Reasoner: Towards Enhanced Human Rationality Through A Wearable Device With An Explainable AI Assistant, in *AHs '20: Proceedings of the Augmented Humans International Conference*, 2020. <https://doi.org/10.1145/3384657.3384799>
20. Bertrand, A.; Belloum, R.; Eagan J. R.; Maxwell, W. How Cognitive Biases Affect XAI-assisted Decision-making: A Systematic Review, in *AIES '22: Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society*, 2022. DOI: [10.1145/3514094.3534164](https://doi.org/10.1145/3514094.3534164)
21. Huang, L. T.-L.; Chen H.-Y.; Lin Y.-T. Ameliorating Algorithmic Bias, or Why Explainable AI Needs Feminist Philosophy in *Feminist Philosophy Quarterly*, 2022. DOI: [10.5206/fpq/2022.3/4.14347](https://doi.org/10.5206/fpq/2022.3/4.14347)
22. Ziosi, M.; Watson D.; Floridi, L. A Genealogical Approach to Algorithmic Bias. *SSRN Electronic Journal*, 2024. DOI: [10.1007/s11023-024-09672-2](https://doi.org/10.1007/s11023-024-09672-2)
23. Roozafzai, Z. Navigating Ethical Complexities of Artificial Intelligence in Civil Justice: A Discourse Analysis. *Journal of Digital Arts and Humanities*. <https://doi.org/10.33847/2712-8149.5.2.2>.
24. Yadav, B. "The Ethics of Understanding: Exploring Moral Implications of Explainable AI," *International Journal of Science and Research (IJSR)*, 2024. DOI: [10.21275/SR2452912281](https://doi.org/10.21275/SR2452912281)
25. Etzioni A.; Etzioni, O. "Incorporating Ethics into Artificial Intelligence," *The Journal of Ethics*. DOI: [10.1007/s10892-017-9252-2](https://doi.org/10.1007/s10892-017-9252-2)
26. Andrade O. M. d.; Alves, M. A. S. "From 'black box' to 'glass box': using Explainable Artificial Intelligence (XAI) to reduce opacity and address bias in algorithmic models," *Revista Thesis Juris*, 2024. DOI: [10.5585/13.2024.26510](https://doi.org/10.5585/13.2024.26510)
27. Antoniadi, A. M.; et al. "Current Challenges and Future Opportunities for XAI in Machine Learning-Based Clinical Decision Support Systems: A Systematic Review," *Applied Sciences*, 2021. <https://doi.org/10.3390/app11115088>
28. Mahsan Nourani, C. R.; Block, J. E.; Honeycutt D. R.; Rahman, T. "On the Importance of User Backgrounds and Impressions: Lessons Learned from Interactive AI Applications," *ACM Transactions on Interactive Intelligent Systems*, 2022. DOI: [10.1145/3531066](https://doi.org/10.1145/3531066)
29. Ziosi, M.; Watson D.; Floridi, L. "A Genealogical Approach to Algorithmic Bias," *SSRN Electronic Journal*, 2024. [10.1007/s11023-024-09672-2](https://doi.org/10.1007/s11023-024-09672-2)
30. Rosenbacke, R.; Melhus, A.; Mckee, M.; Stuckler, D. "How Explainable Artificial Intelligence Can Increase or Decrease Clinicians' Trust in AI Applications in Health Care: Systematic Review," *JMIR AI*, 2024. <https://doi.org/10.2196/53207>

31. Zhang, Z. H. Al and HamadiHussam, "Explainable Artificial Intelligence Applications in Cyber Security: State-of-the-Art in Research," IEEE Access, 2022. DOI: [10.1109/ACCESS.2022.3204051](https://doi.org/10.1109/ACCESS.2022.3204051)
32. Stahl, B. C.; et al. A systematic review of artificial intelligence impact assessments. Artificial Intelligence Review, 2023. <https://doi.org/10.1007/s10462-023-10420-8>

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