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REVIEW

Algorithmic Bias and Data Justice: ethical challenges in Artificial Intelligence Systems

Sesgo Algorítmico y Justicia de Datos: desafíos éticos en los Sistemas de Inteligencia Artificial

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ABSTRACT

This article examines the critical ethical challenges posed by algorithmic bias in artificial intelligence (AI) systems, focusing on its implications for social justice and data equity. Through a systematic review of case studies and theoretical frameworks, we analyze how biased datasets and algorithmic designs perpetuate structural inequalities, particularly affecting marginalized communities. The study highlights key examples, such as gender and racial biases in facial recognition and hiring algorithms, while exploring mitigation strategies rooted in data justice principles. Additionally, we evaluate regulatory responses, including the European Union's AI Act, which proposes a risk-based governance framework. The findings underscore the urgent need for interdisciplinary approaches to develop fairer AI systems that align with ethical standards and human rights.

Keywords: Algorithmic Bias; Data Justice; Artificial Intelligence Ethics; Machine Learning Fairness; AI Regulation.

RESUMEN

Este artículo analiza los desafíos éticos críticos planteados por el sesgo algorítmico en los sistemas de inteligencia artificial (IA), centrándose en sus implicaciones para la justicia social y la equidad de datos. Mediante una revisión sistemática de casos de estudio y marcos teóricos, examinamos cómo los conjuntos de datos sesgados y los diseños algorítmicos perpetúan desigualdades estructurales, afectando especialmente a comunidades marginadas. El estudio destaca ejemplos clave, como los sesgos de género y raciales en algoritmos de reconocimiento facial y contratación, mientras explora estrategias de mitigación basadas en principios de justicia de datos. Además, evaluamos respuestas regulatorias, incluyendo el Reglamento de IA de la Unión Europea, que propone un marco de gobernanza basado en riesgos. Los hallazgos subrayan la necesidad urgente de enfoques interdisciplinarios para desarrollar sistemas de IA más justos que cumplan con estándares éticos y derechos humanos.

Palabras clave: Sesgo Algorítmico; Justicia de Datos; Ética de la Inteligencia Artificial; Equidad en Aprendizaje Automático; Regulación de IA.

INTRODUCTION

Artificial Intelligence (AI) has now established itself as a catalyst for transformation in multiple sectors. According to recent research, technologies such as machine learning, computer vision, and smart IoT devices are revolutionizing the most diverse sectors of society. These tools identify hazards more accurately, optimize complex protocols and tasks, and contribute to knowledge management, including a few of their applications.[1,2]

Language models (LLM) and other machine learning techniques are redefining information management processes based on more developed AI systems. From accelerated data analysis to automated creation of reports, graphs, or even code, these tools streamline tasks that previously required hours of manual work. Their adoption, however, requires critical evaluation to ensure accuracy and ethics in their results.[3,4]

Machine learning relies on data of a diverse nature, from images, audio, and text to complex networks, GPS coordinates, or tabular structures. Any digital representation of information can become raw material for these models. This fundamental principle - that systems learn patterns directly from data - explains why machine learning is at the core of what we commonly call "artificial intelligence" in contemporary applications. Indeed, most of the disruptive technologies of the 21st century that are marketed as AI are, in essence, sophisticated implementations of machine learning techniques.[5,6]

Multiple paradigms coexist in machine learning, with supervised learning being one of the most widespread. In this approach, models are trained on labeled data that act as a guide, establishing a systematic relationship between intrinsic features of the data and their corresponding predefined categories. This seemingly technical process underpins critical applications ranging from medical diagnostic systems to image recognition platforms.[5,7,8,9]

However, these same algorithms that drive innovations carry with them a latent risk: their intrinsic biases can amplify existing social inequalities when implemented on a mass scale. Focusing on data, models, and people can serve to build a "fairer" artificial intelligence.[5,8]

AI systems are not neutral: their ability to replicate or amplify social inequalities through algorithmic bias makes them a priority ethical challenge. This phenomenon, defined as systematic errors that disadvantage marginalized groups, arises from data reflecting historical biases and inadvertently discriminatory algorithmic designs. These issues lead to a focus on aspects so critical to the level of generalisability achieved by AI.[10,11]

This article aims to critically systematize the mechanisms that generate algorithmic bias in AI systems. This approach is necessary for supervised learning models and LLMs to assess their ethical implications in sensitive applications (health, justice, and employment) and propose strategies based on data justice to mitigate them.[4]

METHOD

This study adopts a qualitative critical review approach to systematize the theoretical and empirical references on algorithmic bias and data justice in artificial intelligence systems. An analytical-synthetic method was used to organize, evaluate, and interpret the available evidence, ensuring rigor in the selection and analysis of sources.

An exhaustive search was conducted in academic databases: Scopus, SciELO, PubMed/Medline, Semantic Scholar, and Google Scholar. The key terms used were 'Algorithmic bias,' 'Ethics of artificial intelligence,' 'Fairness in machine learning,' and 'AI regulation.' The inclusion criteria covered studies published between 2021 and 2025 in English, Spanish, and Portuguese addressing ethical aspects of bias in AI. Qualitative analysis and triangulation of sources allowed us to contrast findings and validate consistency in conclusions.

DEVELOPMENT

In the Fourth Industrial Revolution context, the AI debate has moved beyond technical, academic, and business circles into the global public sphere.[12] This popularisation is evidenced by recurrent media and social media coverage highlighting how AI is reshaping everyday life and economic systems at national and international scales.[13]

Algorithms have been identified as having a dual materiality: digital in their constitution and cultural in their functionality, as expressed by Sued.[14] In this sense, technology must be understood as reflecting social relations inscribed in a specific historical context, invalidating any claim to technical neutrality. This contingent nature of intelligent systems demands a critical analysis of their design. Such an understanding is fundamental to studying the socio-technical processes of technology transfer and appropriation, where algorithms emerge as artifacts that materialize power dynamics, cultural preferences, and institutional biases.

This inevitably implies the emergence of biases in AI algorithms. Algorithmic bias is a systemic phenomenon that reproduces injustices through data-driven systems, disproportionately affecting historically marginalized communities. These are technical errors and manifestations of structural inequalities encoded in technology. It reveals the urgency of an interdisciplinary debate that addresses.[15]

- The socio-historical roots of biases (data reflecting past discrimination).
- The technical mechanisms that perpetuate them (model design and metrics).
- Mitigation strategies focused on algorithmic justice.

Algorithmic bias is conceptualized as an equity issue, requiring an approach prioritizing fairness over equity in unfair contexts. This framework advocates governance strategies, including improving data quality and modeling structural injustice to improve fairness and equity.[16,17]

Biases are caused by systematic errors in data or decision-making processes, which affect equity. Mitigating them is essential to promote fairness and justice in machine learning applications, ensuring responsible AI practices that minimize harm and improve fairness in outcomes.[18]

According to the literature, they arise when training data reflects social inequities, which can perpetuate discrimination. Data justice seeks to address these biases through technical solutions, social justice initiatives, and governance measures, emphasizing the need for comprehensive approaches to mitigate biases in AI systems.[19]

The concept of algorithmic bias emerged as an analytical category from pioneering studies of facial recognition and predictive surveillance technologies, revealing how these systems not only reproduce structural inequalities but intensify them through new forms of neo-colonial control. These technologies - deployed predominantly on black, Indigenous, and racialized communities - update historical mechanisms of oppression under the guise of technical neutrality.[20]

As Singer points out,[21] the discussion of algorithmic biases has transcended the technical and moved into applied ethics, a field traditionally marginalized in engineering education. This tension exposes a foundational paradox: while AI systems are implemented globally, their designs often ignore specific socio-political contexts, thus naturalizing systemic violence under the rhetoric of technological progress.

Cases of algorithmic bias derived from datasets are numerous and heterogeneous, mainly resulting from databases that do not reflect population diversity. These limitations respond to a structural problem: the available data are partial representations that reproduce the perspectives and experiences of historically privileged groups. Thus, AI systems end up codifying and amplifying the dominant views of those who have occupied hegemonic positions in the production of knowledge.[4,22]

Delegating to algorithmic tools-specific decision-making processes in societies central to society allows public and private institutions to transfer ethical responsibilities to technology. However, this apparent technical objectivity masks a critical problem: many of these systems reproduce and amplify patterns of structural inequality, increasing the vulnerability and exclusion of historically disadvantaged groups. Far from being neutral, algorithms institutionalize bias under the guise of technological impartiality.[4]

Inclusion in the statistical patterns identified by generative AI systems determines access to critical social resources. This automated selection, presented as objective, sets up invisible barriers that can exacerbate the vulnerability of those left out of these models.[4]

The supposedly fine line between algorithmic assessment and human analysis reveals itself as a social fracture when it amplifies pre-existing inequalities. Data-driven systems prioritize efficiency over equity, displacing values such as contextual rationality and interpersonal communication in critical decisions. This phenomenon evidences a double injustice: algorithmic (in design) and epistemic (in knowledge production).[23,24]

The massive implementation of these technologies poses urgent challenges, particularly in public policy and labor processes. Algorithms not only replicate historical biases but reinforce them through feedback loops. A paradigmatic example is automated hiring systems that perpetuate gender discrimination (as shown in Dastin's 2018 research on Amazon's recruitment tools).[4,25,26]

In Amazon's recruitment system, the simple introduction of the term 'women's' in the CV generated a bias against women. It showed a particular bias against women graduates of non-coeducational women's colleges, systematically demeaning their profiles in the assessment process. Although the team initially identified this discriminatory behavior as a priority problem to correct, the mitigation project was eventually abandoned. The decision was made when it was realized that technical interventions could simply shift the bias to other dimensions without ensuring true neutrality in the selection process.[25,26]

In the face of examples such as this, it has been pointed out that AI-enhanced technologies have patterns that deepen social divisions and social inequalities. This is with more emphasis on historically disadvantaged, marginalized, and vulnerable groups. This pattern exists on a global scale and suggests that low- and middle-income countries may be more vulnerable to the negative social impacts of AI and, thus, less likely to benefit from the concomitant gains.[27]

In the same ethics debates, a significant vulnerability in artificial intelligence systems is revealed due to methods such as data poisoning. This abuse technique allows a social actor, such as a programmer, to alter the training data of algorithms, which changes the decisions a system makes. This poisoning procedure can have serious consequences, including the violation of the privacy of individuals and their data and the risk of accessing, altering, and using personal information against users.

These technical vulnerabilities highlight a deeper ethical challenge: the structural fragility of AI systems to intentional manipulation. Data poisoning - when malicious actors inject biased or false information during the training phase - distorts algorithmic results and can turn these tools into weapons of large-scale discrimination.[28]

The performance of a neural network can be affected by the presence of adversarial samples in the data.

These involve the network's ability to perform through their presence during use.[28]

Recent studies reveal a worrying pattern in the design of intelligent voice assistants (Siri, Alexa, Cortana), whose female identities and mythological names reinforce traditional gender stereotypes. This trend reflects a dynamic of technological feminization, where qualities such as submissiveness and helpfulness are associated with communicative roles historically attributed to women. These platforms intentionally incorporate docile and compliant personalities, perpetuating what some scholars call the 'domestication of artificial intelligence.[27,29]

UNESCO has extensively documented how gender biases embedded in training data and algorithmic structures can amplify harmful stereotypes. These biases, introduced during various technological development phases, from initial design to automated decision-making, represent a tangible threat to gender equity. Their manifestation in intelligent systems could deepen the marginalization of women in multiple spheres (occupational, political, and social), creating new obstacles to progress toward an egalitarian society.[30]

Algorithmic biases often originate in datasets that do not adequately reflect population diversity. Commercial facial recognition systems have significant disparities in accuracy by gender and skin tone and are particularly flawed for black women. This technical flaw stems directly from the under-representation of this demographic in the training data.[5]

In addition, real-time monitoring through smart sensors and wearable devices has proven to be an effective tool for early detection of health-related risk factors. These devices can monitor physiological indicators such as heart rate, body temperature, and exertion level, facilitating intervention in case a worker is in a potentially dangerous situation.[31,32,33] However, recent studies reveal that these systems can have significant biases. For example, fatigue detection algorithms show lower accuracy in dark-skinned workers due to limitations in optical sensors. Physiological 'normal' thresholds are often based on mostly male data, underestimating risks in women.[1,34,35,36]

The above has raised concerns among international organizations, who warn about the ethical risks of handling personal data. Using sensitive information by companies and government agencies could exacerbate systemic discrimination and social inequality patterns, particularly when algorithms reinforce existing biases.[37]

The growing relevance of artificial intelligence on the European policy agenda has materialized in concrete actions. Following the initial strategy developed by the European Commission in 2018, progress has been made toward a proposal for a Regulation that seeks to establish the first harmonized legal framework for this technology. This pioneering legislative instrument aims fundamentally to balance technological innovation with the protection of citizens' rights, implementing a governance system based on risk classification, proportionate assessment, and oversight.[38]

The European Commission has established a tiered system classifying artificial intelligence applications according to their potential impact on fundamental rights and public security. At the strictest level are 'impermissible risk' systems, whose absolute prohibition covers uses that violate basic human rights, such as subliminal manipulation techniques or biometric mass surveillance systems. For 'high-risk' technologies - such as those used in criminal justice or critical infrastructure management - rigorous pre-deployment controls are required, including independent audits, thorough technical documentation, and permanent human oversight mechanisms.[37,38]

At an intermediate step, 'limited risk' AIs (e.g., commercial chatbots) must ensure information transparency towards users, while 'minimal risk' applications are mainly subject to voluntary self-regulatory schemes. This proportional model, embodied in Articles 5-7 of the Draft Regulation (COM/2021/206), seeks to balance technological innovation with adaptable legal safeguards, establishing differentiated obligations according to the actual harmfulness of each system. The structure allows regular updates incorporating new technological developments while maintaining regulatory clarity.[37,38]

The growing importance of moral dilemmas in artificial intelligence has led to the development of Machine Ethics. This specialized field examines how autonomous systems interpret, apply, and eventually modify existing ethical principles in human societies. Recent research by Manasi et al.30 reveals a fundamental paradox. While these systems project an image of technical objectivity, seemingly free of social bias, they lack a genuine capacity to assess the moral correctness of their decisions. This structural limitation raises questions about the feasibility of delegating ethical judgments to entities without a fundamental understanding of underlying human values despite identifying functionally optimal solutions.

The ethical challenges posed by the negative impacts of artificial intelligence systems call for rethinking legal and social responsibility frameworks. This reassessment could provide the basis for new legal and socio-technical precedents and fundamental debates about the role of technologies in protecting the common good and the equitable distribution of its benefits.[34,37,39]

Solving the problem of bias in AI requires a dual approach that examines both the data and the models themselves. First, it is crucial to assess the representativeness of the training datasets, identifying and correcting possible biases before implementation. In parallel, the architecture of the algorithmic model must be analyzed, specifically how its different variables operate and are weighted, applying principles of metric fairness to ensure fairness in its internal processes.[32,33]

The effectiveness and fairness of AI systems depend directly on the quality of their training data. These sets must be comprehensive, accurate, and sufficiently diverse to adequately capture the complexity of the real-world context in which they will be implemented. Only data that accurately reflects all relevant variables - quantity and quality - can develop models capable of operating fairly and accurately in complex scenarios. The testing phase must also ensure that biased results are not fed back into the system through feedback mechanisms.[37]

CONCLUSION

This study shows that algorithmic bias in AI systems is a systemic problem that reproduces and amplifies structural inequalities, where historically marginalized groups are disproportionately affected under a false appearance of technical objectivity. Addressing this dual challenge—technical and ethical—requires improvements in data quality and representativeness, algorithmic justice metrics and continuous audits, and a profound rethinking that incorporates intersectional perspectives and human rights from the very design of algorithms.

The future of ethical AI will depend on the ability to prioritize fairness over efficiency, democratize auditing tools, and continuously adapt regulatory frameworks in the face of emerging risks, such as those posed by generative AI, to ensure that these technologies serve the common good and do not deepen existing injustices.

REFERENCES

1. Simancas LLC, Tous NO, Mendoza LMC, Ramirez CC, Sierra CAS. Artificial intelligence tools for safety and health systems at work. Metaverse Basic and Applied Research 2024;3:.129-.129. https://doi.org/10.56294/mr2024.129.

2. Medina-Barahona CJ, Mora GA, Calvache-Pabón C, Salazar-Castro JA, Mora-Paz HA, Mayorca-Torres D. PROPUESTA DE ARQUITECTURA IOT ORIENTADA A LA CREACIÓN DE PROTOTIPOS PARA SU APLICACIÓN EN PLATAFORMAS EDUCATIVAS Y DE INVESTIGACIÓN. RCTA 2023;1:118-25. https://doi.org/10.24054/rcta.v1i39.1405.

3. Van Noorden R, Perkel JM. AI and science: what 1,600 researchers think. Nature 2023;621:672-5. https://doi.org/10.1038/d41586-023-02980-0.

4. Perdomo Reyes MI. Injusticia epistémica y reproducción de sesgos de género en la inteligencia artificial. CTS: Revista iberoamericana de ciencia, tecnología y sociedad 2024;19:89-100.

5. Ferrante E. Inteligencia artificial y sesgos algorítmicos ¿Por qué deberían importarnos? Nueva Sociedad 2021:27-36.

6. Inastrilla CRA, Santana ML, Vera DG, Madrigal M del CR, Urrutia AR, Inastrilla AA. Systematic review on Artificial Intelligence in the editorial management of scientific journals. EAI Endorsed Transactions on AI and Robotics 2024;3.

7. Espinosa RDC, Caicedo-Erazo JC, Londoño MA, Pitre IJ. Inclusive Innovation through Arduino Embedded Systems and ChatGPT. Metaverse Basic and Applied Research 2023;2:52-52. https://doi.org/10.56294/mr202352.

8. Jurado-Vásquez HA, Ultreras-Rodríguez A, Herrera GWG. Immersive education in the metaverse: bridging the gap between technology and social collaboration. Metaverse Basic and Applied Research 2024;3:.93-.93. https://doi.org/10.56294/mr2024.93.

9. Rodríguez DTG, Hernández JVB. Innovative technology transfers systems in agricultural sciences: social networks and algorithms. Metaverse Basic and Applied Research 2024;3:.130-.130. https://doi.org/10.56294/mr2024.130.

10. Zhang W. Blockchain-based solutions for clinical trial data management: a systematic review. Metaverse Basic and Applied Research 2022;1:17-17. https://doi.org/10.56294/mr202217.

11. Vitón-Castillo AA, Quesada AJF, Valdes Y de la CR, Rivero LB. Metaverse: an emerging research area. Metaverse Basic and Applied Research 2022;1:3-3. https://doi.org/10.56294/mr20223.

12. Sandoval Carrero NS, Acevedo Quintana NM, Santos Jaimes LM. LINEAMIENTOS DESDE LA INDUSTRIA 4.0 A LA EDUCACIÓN 4.0: CASO TECNOLOGÍA IoT. RCTA 2023;1:81-92. https://doi.org/10.24054/rcta.v1i39.1379.

13. Polak P. Welcome to the Digital Era—the Impact of AI on Business and Society. Soc 2021;58:177-8. https://doi.org/10.1007/s12115-021-00588-6.

14. Sued GE. Algorithmic Cultures: Concepts and Methods for their Social Study. Revista Mexicana de Ciencias Políticas y Sociales 2022;67:43-73. https://doi.org/10.22201/fcpys.2448492xe.2022.246.78422.

15. Algorithmic Bias and Data Injustice: Dark Side or Dark Matter? Proceedings - Academy of Management 2023;2023. https://doi.org/10.5465/amproc.2023.16682symposium.

16. Vredenburgh K. Fairness s. f.

17. Leyva MEP, Herrera MCM, Beruvides M del RR, Valido DEE, Escalona ARP. Calidad de la información sobre servicios diferenciados para poblaciones clave mediante la herramienta DataSoft. Revista Cubana de Tecnología de la Salud 2024;15:e4342.

18. Disambiguating Algorithmic Bias: From Neutrality to Justice | Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society. ACM Conferences s. f. https://doi.org/10.1145/3600211.3604695.

19. Data, Power and Bias in Artificial Intelligence. arXiv: Computers and Society 2020.

20. Govia L. Coproduction, Ethics and Artificial Intelligence: A Perspective from Cultural Anthropology. Journal of Digital Social Research 2020;2:42-64. https://doi.org/10.33621/jdsr.v2i3.53.

21. Singer N. When Apps Get Your Medical Data, Your Privacy May Go With It. The New York Times 2019.

22. Inastrilla AA, Inastrilla CRA, Madrigal M del CR, Chacón AL, Medina DMG. Script de visualización de grafos para Matemática Aplicada a Sistemas de Información en Salud. Revista Cubana de Tecnología de la Salud 2024;15:4267.

23. Quisphe MWV, Moreano JAC, Chisag JCC. Artificial intelligence: prototype of an automated irrigation system for the cultivation of roses in Cotopaxi. Data and Metadata 2024;3:398-398. https://doi.org/10.56294/dm2024398.

24. Boussouf Z, Amrani H, Khal MZ, Daidai F. Artificial Intelligence in Education: a Systematic Literature Review. Data and Metadata 2024;3:288-288. https://doi.org/10.56294/dm2024288.

25. El algoritmo de Amazon al que no le gustan las mujeres. BBC News Mundo s. f.

26. Sabán A. Amazon desecha una IA de reclutamiento por su sesgo contra las mujeres. Genbeta 2018. https://www.genbeta.com/actualidad/amazon-desecha-ia-reclutamiento-su-sesgo-mujeres

27. Ramirez Autran R. Sesgos y discriminaciones sociales de los algoritmos en Inteligencia Artificial: Una revisión documental. Entretextos 2023;15:4.

28. Alvarez Rodríguez C, Cárdenas Montes M, Pesudo Fortes V. Redes neuronales robustas frente al envenenamiento de datos aplicadas al problema de la discriminación de los eventos de cuello en DEAP-3600 2022.

29. Barrios Tao H, Díaz Pérez V, Guerra Y, Barrios Tao H, Díaz Pérez V, Guerra Y. Subjetividades e inteligencia artificial: desafíos para 'lo humano'. Veritas 2020:81-107. https://doi.org/10.4067/S0718-92732020000300081.

30. Manasi A, Panchanadeswaran ,Subadra, Sours ,Emily, and Lee SJ. Mirroring the bias: gender and artificial intelligence. Gender, Technology and Development 2022;26:295-305. https://doi.org/10.1080/09718524.2022.2128254.

31. Estrada-Araoz EG, Manrique-Jaramillo YV, Díaz-Pereira VH, Rucoba-Frisancho JM, Paredes-Valverde Y,

Quispe-Herrera R, et al. Assessment of the level of knowledge on artificial intelligence in a sample of university professors: A descriptive study. Data and Metadata 2024;3:285-285. https://doi.org/10.56294/dm2024285.

32. Oliveira TA de, Perugino M. Bibliographic Review on Compartment Syndrome: Critical Evaluation of the 6 P's, Diagnostic Methods and Treatment Algorithms in Unconscious Patients. South Health and Policy 2024;3:136-136. https://doi.org/10.56294/shp2024136.

33. Estrada-Araoz EG, Quispe-Aquise J, Malaga-Yllpa Y, Larico-Uchamaco GR, Pizarro-Osorio GR, Mendoza-Zuñiga M, et al. Role of artificial intelligence in education: Perspectives of Peruvian basic education teachers. Data and Metadata 2024;3:325-325. https://doi.org/10.56294/dm2024325.

34. Araujo Inastrilla A, Araujo Inastrilla CR, Llosa Santana M, Gutiérrez Vera D, Soret Espinosa BL, González García TR. Emerging technologies in Health Information Systems: transformation towards intelligent systems. Seminars in Medical Writing and Education 2024;3:9.

35. Padrón MS. The improvement of preschool educators in communication skills: describing and narrating from an interdisciplinary perspective. Community and Interculturality in Dialogue 2023;3:92-92. https://doi.org/10.56294/cid202392.

36. Moreno MCC, Castro GLG. Unveiling Public Information in the Metaverse and AI Era: Challenges and Opportunities. Metaverse Basic and Applied Research 2023;2:35-35. https://doi.org/10.56294/mr202335.

37. Martín López J. Inteligencia artificial, sesgos y no discriminación en el ámbito de la inspección tributaria. Artificial intelligence, biases and non-discrimination in tax assessment procedure 2022. https://doi.org/10.47092/CT.22.1.2.

38. El Reglamento de Inteligencia Artificial entra en vigor: - Comisión Europea s. f. https://commission.europa.eu/news-and-media/news/ai-act-enters-force-2024-08-01_es

39. Guerra DJO, Velazco AE, Heredia YH. Las Tecnologías de la Información y las Comunicaciones en la formación de Competencias Informacionales. Revista Cubana de Tecnología de la Salud 2023;14:e4058-e4058. https://revtecnologia.sld.cu/index.php/tec/gateway/plugin/pubIdResolver/ark:/83111/urn:ISSN:2218-6719rcts.v14i4.40584.

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