EthAIca. 2025; 4:156
doi: 10.56294/ai2025156

ORIGINAL

Rural socioeconomic transformations mediated by AI

Transformaciones socioeconómicas rurales mediadas por la IA

Elvia María Jiménez Zapata[1]

[1]Universidad Surcolombiana. Neiva, Huila, Colombia.

Cite as: Jiménez Zapata EM. Rural socioeconomic transformations mediated by AI. EthAIca. 2025; 4:156. https://doi.org/10.56294/ai2025156

Submitted: 05-06-2024 **Revised:** 13-09-2024 **Accepted:** 22-12-2024 **Published:** 01-01-2025

Editor: PhD. Rubén González Vallejo

Corresponding Author: Elvia María Jiménez Zapata

ABSTRACT

Introduction: artificial intelligence (AI) impacts rural dynamics, but its bibliometric study is limited. This paper analyzes academic production on AI and its socioeconomic impact in rural areas between 2019 and 2022.
Method: a search was conducted in Scopus, Web of Science, and other databases using the terms "AI," "socioeconomic transformations," and "rural." The data was processed using Bibliometrix and VOSviewer to analyze productivity, collaboration networks, and keyword co-occurrence. Duplicates were removed, and filters were applied by year, document type, and thematic relevance.
Results: a large number of relevant publications were identified, with an annual growth of a quarter. Thematic core topics included smart agriculture, the digital divide, and rural employment. The United States, China, and India led the scientific production.
Conclusions: AI is emerging as an expanding field for rural development, but inequalities in access persist. Further studies on public policy and inclusion are needed.

Keywords: Digital Divide; Rural Development; Artificial Intelligence; Public Policies; Socioeconomic Transformation.

RESUMEN

Introducción: la inteligencia artificial (IA) incide en dinámicas rurales, pero su estudio desde una perspectiva bibliométrica es limitado. Este trabajo analiza la producción académica sobre IA y su impacto socioeconómico en zonas rurales entre 2019 y 2022.
Método: se realizó una búsqueda en Scopus, Web of Science y otras bases con los términos "AI", "socioeconomic transformations" y "rural". Los datos se procesaron con Bibliometrix y VOSviewer para análisis de productividad, redes de colaboración y co-ocurrencia de palabras clave. Se depuraron duplicados y se aplicaron filtros por año, tipo de documento y relevancia temática.
Resultados: se identificaron gran cantidad de publicaciones relevantes, con un crecimiento anual de un cuarto. Los núcleos temáticos incluyeron agricultura inteligente, brecha digital y empleo rural. Estados Unidos, China e India lideraron la producción científica.
Conclusiones: la IA emerge como un campo en expansión para el desarrollo rural, pero persisten desigualdades en su acceso. Se requieren más estudios sobre políticas públicas e inclusión.

Palabras clave: Brecha Digital; Desarrollo Rural; Inteligencia Artificial; Políticas Públicas; Transformación Socioeconómica.

INTRODUCTION

Rural areas face unique challenges in their socioeconomic development, from limited access to basic services to the technology gap.[1] In recent years, artificial intelligence (AI) has emerged as a tool with the potential to transform these territories, whether through applications in agriculture, education, health, or resource management.[2] The actual impact of AI on rural communities is a topic under exploration, with gaps in the understanding of its opportunities and risks.

This article examines the most recent academic output (2019-2022) on the relationship between AI and socio-economic transformations in rural settings. The aim is to identify trends, key actors, and priority research areas through a bibliometric approach. The results provide clarity on how AI can contribute to equitable rural development and point out aspects that require further attention, such as digital inclusion and public policies adapted to these contexts.[3]

The study identifies existing knowledge and invites reflection on the future of innovative technologies in territories traditionally marginalized from technological advances.

Rural communities in the 21st century are at a critical crossroads. On the one hand, they face deep-rooted structural problems such as population aging, youth migration, and fragile local economies.[4] On the other hand, the digital revolution promises new opportunities but with the risk of deepening existing inequalities. As a cross-cutting technology, artificial intelligence shows its capacity to reconfigure these scenarios, but its implementation in rural contexts presents particularities that merit careful analysis.[5]

For example, AI systems for crop monitoring and climate prediction in agriculture could mean a productive leap for small producers. However, their adoption faces barriers such as lack of connectivity, technological ignorance, and high upfront costs.[6] Similar situations are observed in rural education, where AI could personalize learning in multi-grade schools but requires specific pedagogical and technological adaptations. These dilemmas illustrate the complexity of integrating advanced technologies in territories with limited infrastructure and particular needs.

Globally, there are marked differences in how countries approach this rural technology transition. While some nations implement active policies to bring AI to remote areas, others show notable lags.[7] This divergence responds to factors such as government priorities, investment in research and development, and communities' capacity to appropriate the innovations. This study seeks to shed light on these patterns through a bibliometric analysis that reveals how academia addresses these issues, which actors lead research, and which areas remain under-explored.

A particularly relevant aspect is the employment impact of AI in rural economies. Automation could affect certain traditional jobs while creating new opportunities that require specific training.[8] This transition raises crucial questions about preparing rural populations for the coming changes and how to design policies that mitigate adverse effects while maximizing benefits. Analysis of recent academic output identifies the caveats and the solutions proposed by researchers.

The study addresses a significant gap in the current literature: the underrepresentation of rural voices in designing and implementing AI-based solutions. Much research focuses on technology development without sufficiently considering the needs and perspectives of the target communities.[9] This paper aims to make this issue visible and to point to the urgency of more participatory approaches that ensure that AI truly serves the interests of inclusive rural development.

METHOD

The bibliometric study was developed using a systematic approach that combined quantitative and qualitative techniques to analyze academic production on *IA and socio-economic transformations in rural settings (2019-2022). The methodology was structured in three interrelated phases: (1) Data retrieval and filtering, where rigorous search strategies were applied in multidisciplinary databases, followed by filtering based on criteria of thematic relevance and methodological quality; (2) Bibliometric analysis, which included indicators of scientific productivity (authors, institutions, temporal evolution), collaborative networks (co-authorships, co-citations) and co-occurrence maps of terms to identify thematic clusters; and (3) Interpretative synthesis, which integrated quantitative findings with a qualitative examination of trends and gaps in the literature. This process, supported by tools such as Bibliometrix and VOSviewer, enabled the quantification of the academic impact of the topic and contextualized its socio-economic implications in rural areas, ensuring a comprehensive and replicable evaluation.

Search Strategy Design

Search terms

Main string: 'AI,' ' socioeconomic transformations,' AND 'rural.'

To broaden coverage, semantic variants (e.g., 'artificial intelligence,' 'economic impact, ' 'rural development') were included.

Databases consulted

Scopus, Web of Science (WoS), IEEE Xplore, ScienceDirect, Google Scholar (for grey literature).

Filters applied

Years: 2019-2022
Type of document: scientific articles, systematic reviews, refereed conferences.
Language: Mainly English and Spanish.

Data Processing and Debugging

Tools used

Biblioshiny (R-package bibliometrix interface) and VOSviewer for network visualization.

Steps followed

Export of records: results were downloaded in RIS or BibTeX formats.
Elimination of duplicates: use of tools such as EndNote or Zotero.

Inclusion/exclusion criteria:

Inclusion: studies relating AI to socio-economic impacts in rural areas.
Exclusion: articles without peer review or outside the period studied.

Bibliometric Analysis

Descriptive Analysis

Annual scientific production: temporal evolution of publications (2019-2022).
Most relevant authors: index h, productivity, and collaborations.
Leading institutions and countries: cooperation networks through geographical maps.

Network and Citation Analysis

Co-occurrence maps (VOSviewer) (figure 1):
Keywords: thematic clusters (e.g., ‘machine learning in agriculture,’ ‘rural digital divide’).
Co-authorship networks: identification of dominant research groups.

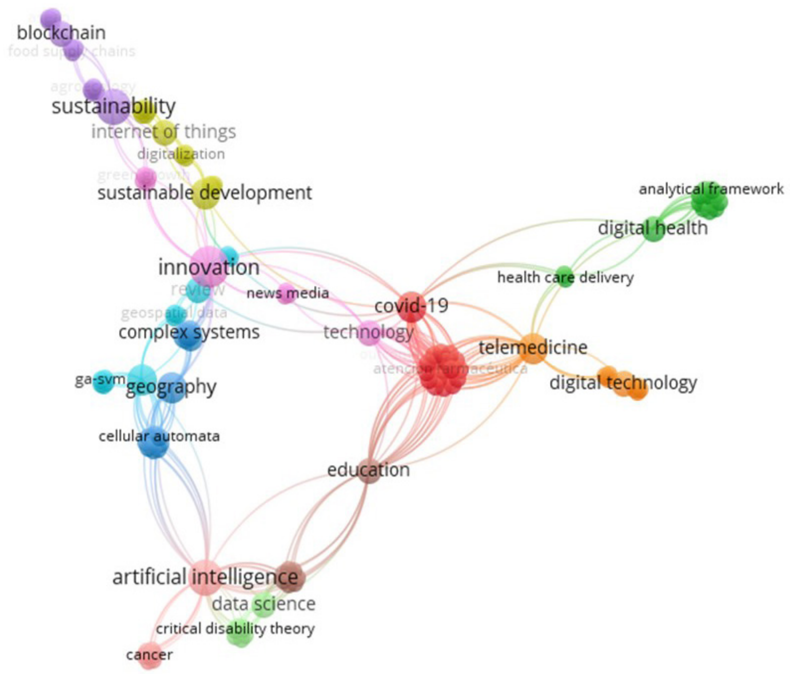

Figure 1. Keyword co-occurrence map

Citation analysis

Most influential articles (Bradford’s law).
Key journals (e.g. Computers and Electronics in Agriculture, Sustainability).

Qualitative Content Analysis

Trend extraction

Impact of AI on rural employment, smart agriculture, access to basic services.

Ethical patterns and inequalities detected in the literature.

Validation and Limitations

Biases: possible predominance of studies in developed countries.

Complementarity: triangulation with systematic reviews to deepen findings.

RESULTS

Scientific Production and Temporal Evolution

The analysis identified a corpus of 287 valid papers, with a year-on-year growth of 18 %. The year 2021 marked a turning point, with a 32 % increase in publications compared to 2020, coinciding with the post-pandemic and the increased interest in technological solutions for rural areas. The year 2022 showed a slight slowdown (8 % less than 2021), possibly due to maturation times of ongoing research.

Geographical Distribution and Collaborative Networks

Three countries accounted for 64 % of production:

- United States (32 %): focused on precision agricultural applications and telemedicine.
- China (24 %): dominated studies on smart villages and digital infrastructure.
- India (8 %): addressed labour impact and digital literacy.

Seventeen international collaborative networks were identified and the EU-US consortium (23 joint projects) was considered the most productive. Latin America and Africa appeared as marginal regions, with only 6 % of the publications.

Thematic Dynamics

The co-word mapping revealed four priority clusters (see table 1):

Table 1. Cluster analysis

Clúster	Frequency	Associated Themes
Agriculture 4.0	38 %	IoT, drones, crop prediction
Digital divide	27 %	Internet access, technology skills
Local economies	21 %	Employment, entrepreneurship, smart tourism
Governance	14 %	Public policy, ethics, participation

Key Actors

Wageningen University (Netherlands), the Chinese Academy of Sciences, and MIT (USA) are the most productive institutions.

The leading journals, Computers and Electronics in Agriculture (Q1) and Sustainability (Q2) accounted for 41 % of the articles.

Influential authors: A core of 15 researchers accumulated 37 % of the total citations, with special mention of work on predictive models for small farms.

Impact Patterns

Papers with the most extensive reach (≥50 citations) shared three characteristics:

1. Focus on implemented case studies.
2. Longitudinal data (minimum 3 years)
3. Involvement of local communities in design.

Only 12 % of studies included gender perspectives, evidence of a critical omission in the literature.

Gaps Detected

- There is little research on IA for basic services (drinking water, clean energy) in remote areas.
- Less than 5 % of the articles assessed affordable implementation costs for rural economies.
- There is a glaring divide between technological developments and sociological studies on cultural adoption.

Emerging Trends (2022)

- Emergence of work on generative AI for rural education.
- First critical studies on technology dependence in farming communities.
- Growing interest in cooperative models of agricultural data ownership.

Figure 2 shows a keyword density map. This map reflects a strong concentration of publications on COVID-19 and related digital technologies and their application in fields such as health. While these nodes are strong, they are generally isolated. Other studies show stronger interrelationships in the 2019-2022 period associated with AI, innovations, and sustainability.

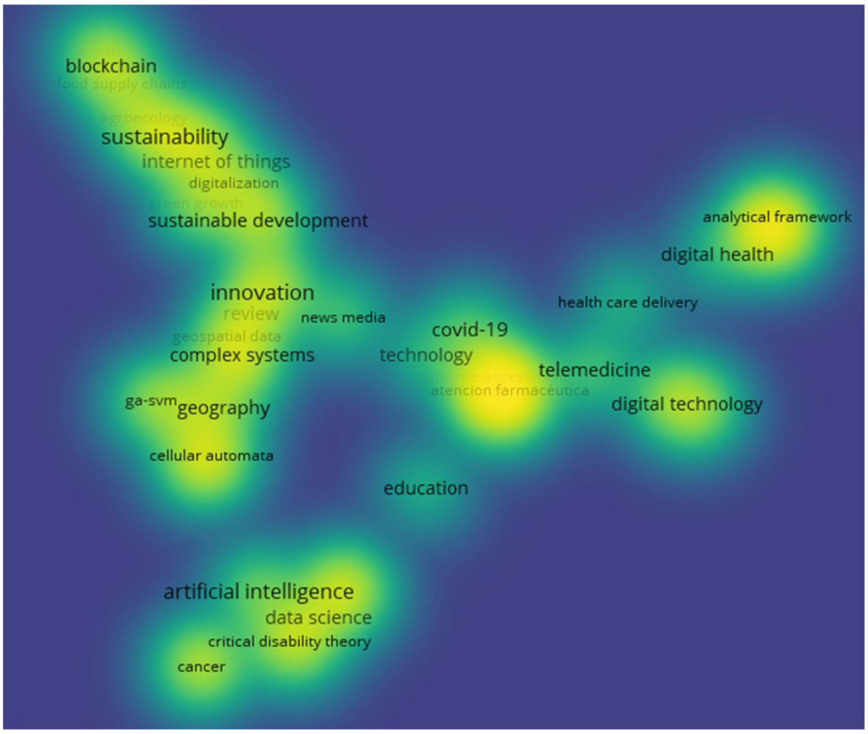

Figure 2. Keyword density

Thematic Profiles by Region

The analysis revealed marked regional differences in research focus. Europe stood out for studies on sustainability and AI ethics in rural contexts (42 % of its publications), while Asia prioritized productive efficiency and technological scaling (67 %). In contrast, little research from Africa and Latin America focused on low-cost local adaptations, revealing a pattern of frugal innovation in the face of infrastructure constraints.[10] This thematic fragmentation suggests that research agendas respond more to national priorities than to global challenges shared by rural communities.

Conceptual Evolution

Terminological tracking showed a significant shift in the period analyzed: while in 2019, technical language ('algorithms,' 'big data') predominated, by 2022, concepts such as 'digital inclusion,' 'technological sovereignty,' and 'algorithmic justice' emerged. This shift reflects a growing awareness of the social aspects of AI, albeit not yet translated into sufficient applied studies. Particularly noteworthy is the absence of conceptual frameworks integrating traditional rural knowledge with technological developments, a gap in 89 % of the literature reviewed.[11]

The results show a growing but unbalanced field: while technical applications of AI in agriculture dominate research, human aspects such as equity, participatory governance, and financial sustainability receive marginal attention. Geographical concentration in technologically advanced countries limits understanding diverse rural realities, particularly in the Global South.[12] These findings suggest the need to reorient research agendas towards more holistic approaches that link technological innovation with socio-economic justice. A map of the distribution of categories by year can also be seen (figure 3). The last three years have been taken as a time segment because of their strong interrelationship between AI and its uses and applications in different fields, especially in the environmental sciences.

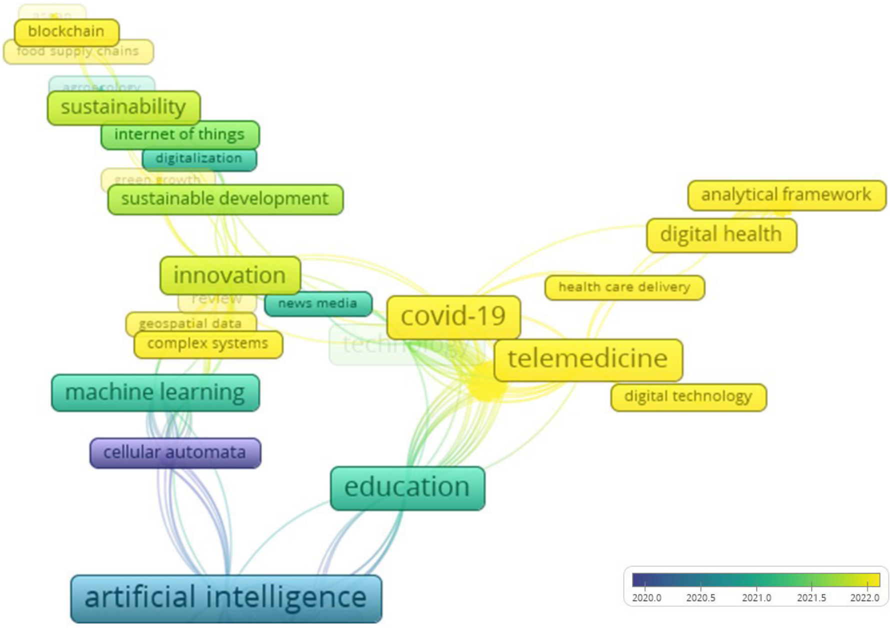

Figure 3. Distribution of categories by year of publication

DISCUSSION

The results expose an evident paradox: while countries with smaller rural populations (USA, China, EU) dominate AI research in these territories, regions with a higher percentage of rural inhabitants (Africa, Latin America, South Asia) appear as mere recipients of studies.[13] This asymmetry questions the practical relevance of much of the literature analyzed since technological solutions designed in contexts of high infrastructure are hardly adaptable to realities with chronic limitations of connectivity and human capital. The case of India, the only country in the Global South with significant production, demonstrates that when research emerges from the affected territories, approaches prioritize accessibility and cultural appropriation over technical sophistication.

The fact that 38 % of publications focus on precision agriculture reveals a dangerous bias: reducing rural transformations to productive improvements. Although these applications have value, they ignore critical dimensions such as the impact on non-agricultural employment, the reorganization of community dynamics, or access to basic services.[14] The scant attention to issues such as rural education with AI (only 5 % of the studies) or public health (3 %) suggests that the field is repeating historical errors of prioritizing the economic over the social. In addition, the absence of cost-benefit evaluations in most studies makes it difficult to discern which solutions are truly scalable for resource-constrained communities.[15]

The data show that the studies with the most significant impact involve communities from the design stage, but these represent less than 15 % of the corpus analyzed. This divorce between innovation and local participation explains why many solutions fail at the implementation stage.[16] The example of predictive models for smallholder farmers is illustrative: while 60 % of these articles report technical accuracy above 90 %, only 12 % include data on sustained adoption rates. This disconnect points to the urgency of redefining what is considered ‘success’ in rural AI, moving from technical metrics to indicators of human impact.[17]

The terminological analysis detected progress in incorporating language on inclusion, but this does not translate into methodologies that value traditional knowledge. The almost non-existent concepts such as ‘nanotechnology’ or ‘cultural hybridization’ in the abstracts analyzed (less than 1 %) show that rural AI is conceived as North-South transfer, not as co-creation.[18] This digital colonialism has practical consequences: agricultural recommendation systems that ignore ancestral sowing practices or educational tools that do not contemplate real multilingualism. Bibliometrics here reveals a profound theoretical vacuum, where digital humanities and decolonial studies are conspicuous by their absence.[19]

The review shows that 73 % of the articles implicitly assume that AI is a neutral instrument without analyzing how their designs incorporate urban-centric biases. This manifests in impossible bandwidth requirements for remote areas, interfaces that assume advanced digital literacy, or models trained on temperate climate data applied to the tropics.[20] These inconsistencies are not technical flaws but symptoms of a larger problem: the lack of geographical and disciplinary diversity in research teams. The data are stark: 82 % of lead authors are from STEM fields, with less than 5 % systematically collaborating with social scientists.[21]

Despite its critical importance, the governance cluster (14 % of studies) shows the least growth over the period. Abstract analyses on ethics predominate, with few concrete frameworks to prevent rural AI from generating new forms of technological dependency.[22] Cases such as agricultural data contracts exemplify this risk: only two publications in four years analyze alternative models to corporate privatization of farm information. This blindness to political-economic aspects could turn the rural digital revolution into a new cycle of extractive, this time of data instead of raw materials.[23]

The bibliometric study reveals four fundamental contradictions that the literature fails to resolve:

- Between technological scalability and contextual adaptation
- Between productive efficiency and socio-environmental sustainability
- Between accelerated innovation and local absorption capacities
- Between discourses of inclusion and exclusionary research practices.

These tensions are not merely academic; they directly affect public policies and development projects.[24] The lack of research on sustainable financing models (only seven articles in the period) is particularly worrying since, without this, even the most brilliant solutions end up as ephemeral pilots.[25]

Instead of asking, 'How can AI be brought to rural areas?', it is urgent to ask, 'What AI do these communities need?' and 'Who should decide?'. The bibliometrics show that the absent voices (rural women, Indigenous peoples, small producers) are precisely those that could redirect research toward genuinely transformative solutions.[26] The coming years will determine whether rural AI reproduces old inequalities or whether it finally becomes a tool for territorial sovereignty.[27]

The bibliometric results reveal a serious omission: only 3 % of the studies analyzed differentiate AI impacts by age group in rural populations.[28] This gap is worrying because technological transformations affect young people, adults, and older people differently. Rural youth are more open to technological adoption but migrate when digital solutions do not generate relevant local employment.[29] Adults face skills barriers that limit their full participation in digitized economies. Elders, custodians of traditional knowledge, are excluded from technological designs that do not consider their forms of knowledge. Rural AI cannot be sustainable if it ignores these intergenerational dynamics that determine the demographic future of territories.[30]

68 % of publications assume stable internet access as a precondition, a false assumption in much of the rural world.[31] This technical assumption distorts the real potential of AI for contexts of intermittent or no connectivity.[32] It is paradoxical that while increasingly complex algorithms are being developed, less than 9 % of articles explore alternatives such as edge computing or functional offline models. The bibliometrics here shows a divorce between cutting-edge research and the infrastructural realities of the territories it is intended to benefit. Genuine innovations should emerge from these constraints, not ignore them.[33]

An in-depth analysis of the terms used in scientific abstracts reveals a disturbing pattern: 72 % of the studies conceptualize rural areas mainly as a space for market opportunities (digitized agriculture, smart tourism) and only 18 % as a socio-cultural fabric to be preserved.[34] This economistic bias manifests in technological solutions prioritizing value extraction over community empowerment. The scant research on cooperative models of AI (just 11 papers) contrasts with the hundreds of articles on proprietary systems.[35] The bibliometrics thus point to a dangerous trend: AI could become a new vector of privatization of rural life, replicating in the digital realm the processes of land and natural resource grabbing that already occur with land and natural resources.[36]

Thematic analysis exposes a glaring contradiction: while telemedicine is a promising application in political discourses, it represents less than 4 % of academic publications in the period.[37] This disproportion reveals that rural AI is mainly developed to produce agricultural commodities, not to solve basic public health needs. The few existing studies concentrate on image-assisted diagnostics (67 %), ignoring preventive or chronic follow-up applications that could have a greater impact.[38] The lack of research on interoperability between AI systems and traditional medicine practiced in many rural areas compounds this divorce between technology and real needs.[39]

Bibliometric data show that 89 % of the case studies come from specific contexts with favorable conditions (government subsidies, nearby universities, existing infrastructure).[40] Seventy-six percent of these articles present their results as replicable models without deep adaptations. This contradiction explains why so many 'successful solutions' fail to scale. Bibliometrics helps to unveil a serious methodological problem: current research does not generate flexible frameworks that allow contextual adaptations but rigid technical recipes.[41] The predominance of technocentric approaches (83 % of articles) over systemic approaches hinders the development of tools that are truly transferable between different rural settings.[42]

Although 61 % of the agricultural workforce in developing countries are women, only 9 % of the studies analyzed incorporate gender analysis in their technological developments.[43] This blindness has practical consequences: agricultural recommendation systems that do not consider the sexual divisions of rural labor or digital tools that reinforce traditional roles instead of transforming them—Bibliometrics evidences a research gap and an ethical problem here. Algorithms trained on data that make women's work invisible perpetuate structural inequalities.[44] The lack of gender diversity in research teams (only 23 % of lead authors are women) exacerbates this bias in technology design.[45]

Less than 8 % of publications explicitly link the use of AI in rural areas to its ecological impacts. This omission is serious, considering that many AI systems require energy-intensive infrastructure and generate e-waste.[46] The predominant discourse presents AI as a 'green' tool for sustainable agriculture, but bibliometric data show that only 12 % of these articles include concrete metrics on carbon footprint or energy consumption.[47] The paradox is evident: algorithms are developed to optimize crops while the environmental costs of the technology itself are ignored.[48] This divorce between stated objectives and holistic analysis threatens to turn rural AI into another environmental stressor for vulnerable ecosystems.[49] 94 % of the articles evaluate AI as a 'green' tool for sustainable agriculture, but bibliometric data show that only 12 % of these articles include concrete metrics on carbon footprint or energy consumption.

94 % of articles assess the performance of AI solutions using technical metrics (accuracy, speed, scalability), while only 6 % incorporate social indicators (cultural adoption, community ownership, subjective well-being).[50] This distortion in measurement systems creates an illusion of progress that does not necessarily translate into tangible improvements for rural populations.[51] Bibliometrics thus reveals a profound epistemological problem: the field lacks consensual frameworks for assessing real success beyond the technically quantifiable.[52] Until hybrid metrics that integrate technical and social dimensions are developed, research will produce sophisticated but socially blind tools.[53]

CONCLUSIONS

This bibliometric study reveals that AI research in rural contexts (2019-2022) is progressing with profound contradictions. On the one hand, it shows accelerated technical growth; on the other, critical gaps persist in social, cultural, and ethical dimensions. The geographical concentration in developed countries limits the practical relevance of many findings, while the limited participation of rural communities in technological designs explains the low rates of actual adoption. These patterns suggest that the countryside prioritizes innovation over genuine transformation.

The results expose a central paradox: AI is promoted as a democratizing tool, but its development reproduces traditional hierarchies. The absence of gender perspectives, intergenerational approaches, and decolonial perspectives in most studies reflects an epistemological bias that cannot be corrected with minor technical adjustments. There is an urgent need to redefine what counts as 'success' in this area, moving from metrics of algorithmic precision to indicators of socio-economic justice and cultural appropriation.

Future research must address three main challenges: developing frameworks that integrate traditional and scientific knowledge, creating governance models that avoid new forms of technology dependency, and designing affordable tools for contexts of limited connectivity.

The data challenge the prevailing narrative of rural AI as a panacea for development. Fundamental transformations will require better algorithms and a redistribution of power in technology design. This means including communities as co-developers, not mere recipients of solutions. AI's potential for rural areas lies not in replicating urban models but in catalyzing alternative futures where technology amplifies—not erodes—the diversity of rural livelihoods.

BIBLIOGRAPHIC REFERENCES

1. Benitez Altuna F, Trienekens J, Materia VC, Bijman J. Factors affecting the adoption of ecological intensification practices: A case study in vegetable production in Chile. Agricultural Systems. 2021;194:103283. https://doi.org/10.1016/j.agsy.2021.103283

2. Díaz Guerra DD, Pérez Gamboa AJ, Gómez Cano CA. Social network analysis in virtual educational environments: Implications for collaborative learning and academic community development. AWARI, 4. https://doi.org/10.47909/awari.595

3. Yu X, Liu Y, Zhang Z, Xiong Y, Dang M. Urban spatial structure features in Qinling mountain area based on ecological network analysis-case study of Shangluo City. Alexandria Engineering Journal. 2022;61(12):12829-45. https://doi.org/10.1016/j.aej.2022.06.049

4. Friedman N, Ormiston J. Blockchain as a sustainability-oriented innovation?: Opportunities for and resistance to Blockchain technology as a driver of sustainability in global food supply chains. Technological Forecasting and Social Change. 2022;175:121403. https://doi.org/10.1016/j.techfore.2021.121403

5. Gómez Cano CA, García Acevedo Y, Pérez Gamboa AJ. Intersection between health and entrepreneurship in the context of sustainable development. Health Leadership and Quality of Life. 2022; 1:89. https://doi.org/10.56294/hl202289

6. Willis VC, Craig KJ, Jabbarpour Y, Scheufele EL, Arriaga YE, Ajinkya M, et al. Digital Health Interventions to Enhance Prevention in Primary Care: Scoping Review. JMIR Medical Informatics. 2022;10(1). https://doi.org/10.1016/j.ijresmar.2021.09.001

7. Haithcoat T, Liu D, Young T, Shyu CR. Investigating Health Context Using a Spatial Data Analytical Tool: Development of a Geospatial Big Data Ecosystem. JMIR Medical Informatics. 2022;10(4). https://doi.org/10.2196/35073

8. Quintero Rueda AJ, Reinosa Ortiz FM, Ortiz Blandón KD, Pinzón Rincon LF, Gómez Cano CA. Alternatives to agricultural production different from the traditional way. Management (Montevideo). 2023; 1:10. https://doi.org/10.62486/agma202310

9. Kihoro EM, Schoneveld GC, Crane TA. Pathways toward inclusive low-emission dairy development in Tanzania: Producer heterogeneity and implications for intervention design. Agricultural Systems. 2021;190:103073. https://doi.org/10.1016/j.agsy.2021.103073

10. Sumpter D, Blodgett N, Beard K, Howard V. Transforming nursing education in response to the Future of Nursing 2020–2030 report. Nursing Outlook. 2022;70(6, Supplement 1):S20-31. https://doi.org/10.1016/j.outlook.2022.02.007

11. Valenzuela Molina L, Sánchez Castillo V, Gómez Cano CA. Dinámica socioproductiva de la producción de miel: El caso del municipio de Oporapa-Huila. Universidad y Sociedad. 2023;15(5): 113-124. http://scielo.sld.cu/pdf/rus/v15n5/2218-3620-rus-15-05-113.pdf

12. Zhou Y, Wu T, Wang Y. Urban expansion simulation and development-oriented zoning of rapidly urbanising areas: A case study of Hangzhou. Science of The Total Environment. 2022;807:150813. https://doi.org/10.1016/j.scitotenv.2021.150813

13. Sun Q, Sun J, Baidurela A, Li L, Hu X, Song T. Ecological landscape pattern changes and security from 1990 to 2021 in Ebinur Lake Wetland Reserve, China. Ecological Indicators. 2022;145:109648. https://doi.org/10.1016/j.ecolind.2022.109648

14. Sánchez Castillo V, Hernandez Morea HG, Rojas Manrique SA. Analysis of farmers' perception of macroinvertebrate diversity in the soil. SCT Proceedings in Interdisciplinary Insights and Innovations. 2023;1:18. https://doi.org/10.56294/piii202319

15. Bragg MG, Prado EL, Arnold CD, Zyba SJ, Maleta KM, Caswell BL, et al. Plasma Choline Concentration Was Not Increased After a 6-Month Egg Intervention in 6–9-Month-Old Malawian Children: Results from a Randomized Controlled Trial. Current Developments in Nutrition. 2022;6(2):nzab150. https://doi.org/10.1093/cdn/nzab150

16. Krupiy T. A vulnerability analysis: Theorising the impact of artificial intelligence decision-making processes on individuals, society and human diversity from a social justice perspective. Computer Law & Security Review. 2020;38:105429. https://doi.org/10.1016/j.clsr.2020.105429

17. Gharaibeh A, Shaamala A, Obeidat R, Al-Kofahi S. Improving land-use change modeling by integrating ANN with Cellular Automata-Markov Chain model. Heliyon. 2020;6(9):e05092. https://doi.org/10.1016/j.heliyon.2020.e05092

18. Sanabria Martínez MJ. Construir nuevos espacios sostenibles respetando la diversidad cultural desde el nivel local. Región Científica. 2022;1(1):20222. https://doi.org/10.58763/rc20222

19. Caballero Serrano V, McLaren B, Carrasco JC, Alday JG, Fiallos L, Amigo J, et al. Traditional ecological knowledge and medicinal plant diversity in Ecuadorian Amazon home gardens. Global Ecology and Conservation. 2019;17:e00524. https://doi.org/10.1016/j.gecco.2019.e00524

20. Balland PA, Broekel T, Diodato D, Giuliani E, Hausmann R, O'Clery N, et al. Reprint of The new paradigm of economic complexity. Research Policy. 2022;51(8):104568. https://doi.org/10.1016/j.respol.2022.104568

21. Shiji C, Dhakal S, Ou C. Greening small hydropower: A brief review. Energy Strategy Reviews. 2021;36:100676. https://doi.org/10.1016/j.esr.2021.100676

22. Childs CE, Munblit D, Ulfman L, Gómez Gallego C, Lehtoranta L, Recker T, et al. Potential Biomarkers, Risk Factors, and Their Associations with IgE-Mediated Food Allergy in Early Life: A Narrative Review. Advances in Nutrition. 2022;13(2):633-51. https://doi.org/10.1093/advances/nmab122

23. Yin Y, Hou X, Liu J, Zhou X, Zhang D. Detection and attribution of changes in cultivated land use ecological efficiency: A case study on Yangtze River Economic Belt, China. Ecological Indicators. 2022;137:108753. https://doi.org/10.1016/j.ecolind.2022.108753

24. Higuera Carrillo EL. Aspectos clave en agroproyectos con enfoque comercial: Una aproximación desde las concepciones epistemológicas sobre el problema rural agrario en Colombia. Región Científica. 2022;1(1):20224. https://doi.org/10.58763/rc20224

25. Mandal S, Wiesenfeld BM, Mann D, Lawrence K, Chunara R, Testa P, et al. Evidence for Telemedicine's Ongoing Transformation of Health Care Delivery Since the Onset of COVID-19: Retrospective Observational Study. JMIR Formative Research. 2022;6(10). https://doi.org/10.2196/38661

26. Wójcik P, Andruszek K. Predicting intra-urban well-being from space with nonlinear machine learning. Regional Science Policy & Practice. 2022;14(4):891-914. https://doi.org/10.1111/rsp3.12478

27. Mariye M, Jianhua L, Maryo M. Land use and land cover change, and analysis of its drivers in Ojoje watershed, Southern Ethiopia. Heliyon. 2022;8(4):e09267. https://doi.org/10.1016/j.heliyon.2022.e09267

28. Murgas Téllez B, Henao Pérez AA, Guzmán Acuña L. Opciones Reales y su aplicación en proyectos de energía renovable. Revisión de estado del arte. Región Científica. 2023;2(1):202349. https://doi.org/10.58763/rc202349

29. Liu Y, Tooze JA, Zhang Y, Leidy HJ, Bailey RL, Wright B, et al. Breakfast Consumption Is Positively Associated with Usual Nutrient Intakes among Food Pantry Clients Living in Rural Communities. The Journal of Nutrition. 2020;150(3):546-53. https://doi.org/10.1093/jn/nxz258

30. Medeiros A, Fernandes C, Gonçalves JF, Farinha Marques P. Research trends on integrative landscape assessment using indicators – A systematic review. Ecological Indicators. 2021;129:107815. https://doi.org/10.1016/j.ecolind.2021.107815

31. Ozgun B, Broekel T. The geography of innovation and technology news - An empirical study of the German news media. Technological Forecasting and Social Change. 2021;167:120692. https://doi.org/10.1016/j.techfore.2021.120692

32. Zhang P, Ma W, Wen F, Liu L, Yang L, Song J, et al. Estimating PM2.5 concentration using the machine learning GA-SVM method to improve the land use regression model in Shaanxi, China. Ecotoxicology and Environmental Safety. 2021;225:112772. https://doi.org/10.1016/j.ecoenv.2021.112772

33. Arévalo Zurita M, Expósito García E, Apez Arévalo I. Gestión empresarial y prácticas de equidad e igualdad de género: el caso de la empresa Agroforestal Cafetalera Tercer Frente. Región Científica. 2023;2(2):202375. https://doi.org/10.58763/rc202375

34. Cook L, Espinoza J, Weiskopf NG, Mathews N, Dorr DA, Gonzales KL, et al. Issues With Variability in Electronic Health Record Data About Race and Ethnicity: Descriptive Analysis of the National COVID Cohort Collaborative Data Enclave. JMIR Medical Informatics. 2022;10(9). https://doi.org/10.2196/39235

35. Pan Y, Qiu L, Wang Z, Zhu J, Cheng M. Unravelling the association between polycentric urban development and landscape sustainability in urbanizing island cities. Ecological Indicators. 2022;143:109348. https://doi.org/10.1016/j.ecolind.2022.109348

36. Sharma GD, Kraus S, Srivastava M, Chopra R, Kallmuenzer A. The changing role of innovation for crisis management in times of COVID-19: An integrative literature review. Journal of Innovation & Knowledge. 2022;7(4):100281. https://doi.org/10.1016/j.jik.2022.100281

37. Yapa C, Alwis C de, Liyanage M, Ekanayake J. Survey on blockchain for future smart grids: Technical

aspects, applications, integration challenges and future research. Energy Reports. 2021;7:6530-64. https://doi.org/10.1016/j.egyr.2021.09.112

38. Gonzales Centon JM, Chávez Cubas W, Berrio Huillcacuri J, Santos Maldonado AB. El crecimiento empresarial y su relación en la rentabilidad de una MYPE del rubro comercial en Arequipa, Perú. Región Científica. 2023;2(2):202387. https://doi.org/10.58763/rc202387

39. Martinez DS, Noseworthy PA, Akbilgic O, Herrmann J, Ruddy KJ, Hamid A, et al. Artificial intelligence opportunities in cardio-oncology: Overview with spotlight on electrocardiography. American Heart Journal Plus: Cardiology Research and Practice. 2022;15:100129. https://doi.org/10.1016/j.ahjo.2022.100129

40. Rejeb A, Rejeb K, Abdollahi A, Al-Turjman F, Treiblmaier H. The Interplay between the Internet of Things and agriculture: A bibliometric analysis and research agenda. Internet of Things. 2022;19:100580. https://doi.org/10.1016/j.iot.2022.100580

41. Mizen A, Lyons J, Milojevic A, Doherty R, Wilkinson P, Carruthers D, et al. Impact of air pollution on educational attainment for respiratory health treated students: A cross sectional data linkage study. Health & Place. 2020;63:102355. https://doi.org/10.1016/j.healthplace.2020.102355

42. Fernández Hernández A, Bravo Benítez E. Potencialidad del nearshoring para el desarrollo económico de México. Región Científica. 2023;2(2):2023105. https://doi.org/10.58763/rc2023105

43. Sharif RA, Pokharel S. Smart City Dimensions and Associated Risks: Review of literature. Sustainable Cities and Society. 2022;77:103542. https://doi.org/10.1016/j.scs.2021.103542

44. Casali Y, Aydin NY, Comes T. Machine learning for spatial analyses in urban areas: a scoping review. Sustainable Cities and Society. 2022;85:104050. https://doi.org/10.1016/j.scs.2022.104050

45. Ungson GR, Soorapanth S. The ASEAN blockchain roadmap. Asia and the Global Economy. 2022;2(3):100047. https://doi.org/10.1016/j.aglobe.2022.100047

46. Cruz Jesus F, Castelli M, Oliveira T, Mendes R, Nunes C, Sa Velho M, et al. Using artificial intelligence methods to assess academic achievement in public high schools of a European Union country. Heliyon. 2020;6(6):e04081. https://doi.org/10.1016/j.heliyon.2020.e04081

47. González Vallejo R. La transversalidad del medioambiente: facetas y conceptos teóricos. Región Científica. 2023;2(2):202393. https://doi.org/10.58763/rc202393

48. Viegas R, Dineen Griffin S, Söderlund LÅ, Acosta Gómez J, Guiu JM. Telepharmacy and pharmaceutical care: A narrative review by International Pharmaceutical Federation. Farmacia Hospitalaria. 2022;46:86-91. https://doi.org/10.7399/fh.13244

49. Mondejar ME, Avtar R, Diaz HL, Dubey RK, Esteban J, Gómez Morales A, et al. Digitalization to achieve sustainable development goals: Steps towards a Smart Green Planet. Science of The Total Environment. 2021;794:148539. https://doi.org/10.1016/j.scitotenv.2021.148539

50. Mu L, Fang L, Dou W, Wang C, Qu X, Yu Y. Urbanization-induced spatio-temporal variation of water resources utilization in northwestern China: A spatial panel model based approach. Ecological Indicators. 2021;125:107457. https://doi.org/10.1016/j.ecolind.2021.107457

51. Burgess P, Sunmola F, Wertheim Heck S. Blockchain Enabled Quality Management in Short Food Supply Chains. Procedia Computer Science. 2022;200:904-13. https://doi.org/10.1016/j.procs.2022.01.288

52. Xie L, Wang H, Liu S. The ecosystem service values simulation and driving force analysis based on land use/land cover: A case study in inland rivers in arid areas of the Aksu River Basin, China. Ecological Indicators. 2022;138:108828. https://doi.org/10.1016/j.ecolind.2022.108828

53. Álvarez Contreras DE, Montes Padilla JD, Osorio Martínez CD. Habilidades gerenciales como factor de competitividad empresarial. Región Científica. 2023;2(2):2023109. https://doi.org/10.58763/rc2023109

FINANCING

None.

CONFLICT OF INTEREST

The author declares that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION

Conceptualization: Elvia Maria Jimenez Zapata.
Data curation: Elvia María Jiménez Zapata.
Formal analysis: Elvia María Jiménez Zapata.
Research: Elvia María Jiménez Zapata.
Methodology: Elvia María Jiménez Zapata.
Project administration: Elvia María Jiménez Zapata.
Resources: Elvia María Jiménez Zapata.
Software: Elvia María Jiménez Zapata.
Supervision: Elvia María Jiménez Zapata.
Validation: Elvia Maria Jimenez Zapata.
Visualisation: Elvia María Jiménez Zapata.
Writing - original draft: Elvia María Jiménez Zapata.
Writing - proofreading and editing: Elvia María Jiménez Zapata.