LatIA. 2025; 3:304
doi: 10.62486/latia2025304
ISSN: 3046-403X

SYSTEMATIC REVIEW

Artificial intelligence in Latin American higher education: implementations, ethical challenges, and pedagogical effectiveness

Inteligencia artificial en la educación superior latinoamericana: implementaciones, desafíos éticos y efectividad pedagógica

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Cite as: González Torres VH, Lucero Baldevenites EV, Ruiz Esparza M de JA, Bracho-Fuenmayor PL, de Lamarque CPC. Artificial intelligence in Latin American higher education: implementations, ethical chal2lenges, and pedagogical effectiveness. LatIA. 2025; 3:304. https://doi.org/10.62486/latia2025304

Submitted: 31-05-2024 **Revised:** 22-12-2024 **Accepted:** 19-05-2025 **Published:** 20-05-2025

Editor: Dr. Rubén González Vallejo

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ABSTRACT

Artificial intelligence is establishing itself as a catalyst for transformation in the regional university sector, generating growing yet uneven academic output. This research conducted a systematic review following the PRISMA methodology on applications of artificial intelligence in Latin American higher education. The results from the 421 studies obtained during the bibliometric stage indicate that research is geographically and institutionally concentrated in a limited set of approaches and practices. In this regard, a notable prevalence of studies on Machine Learning applications, as well as Natural Language Processing, was observed. From a practical standpoint, 30 studies were selected for qualitative analysis. These texts agreed that the implementation process of these technologies continues to face structural challenges. Notably, poor infrastructure conditions, as well as deficiencies in teacher training, were identified as the main obstacles to implementing these technologies. The analyzed studies also concurred on the inadequate treatment of algorithmic biases or data protection in application policies proposed by the literature. Consequently, a key recommendation of this research is the urgent need for studies aimed at evaluating short-term outcomes, as well as analyzing the long-term sustainability of such innovations.

Keywords: Artificial Intelligence; Higher Education; Systematic Review; Technology Adoption; Latin America.

RESUMEN

La inteligencia artificial se consolida como catalizador de transformación en el ámbito universitario regional, generando una producción académica creciente, aunque desigual. En esta investigación se realizó una revisión sistemática de acuerdo a la metodología PRISMA sobre las aplicaciones de la inteligencia artificial en la educación superior latinoamericana. Los resultados de los 421 estudios que se obtuvieron, durante la etapa bibliométrica, indica que las investigaciones se centran tanto geográfica como institucionalmente en un conjunto reducido de enfoques y prácticas. Al respecto de ello, se observó una prevalencia notable de estudios sobre las aplicaciones del *Machine Learning*, así como el Procesamiento de Lenguaje Natural. En este sentido práctico, se seleccionaron 30 estudios para el análisis cualitativo. Dichos textos coincidieron en que el proceso de implementación de estas tecnologías no deja de verse frenado por problemas estructurales.

Tal fue el caso que, las malas condiciones de infraestructura, así como deficiencias en la formación del docente, fueron los principales obstáculos para la implementación de estas tecnologías. Los estudios analizados también coincidieron en el pobre abordaje de los sesgos algorítmicos o de protección de datos en las políticas de aplicación diseñadas desde la literatura. A partir de lo cual, una recomendación esencial de esta investigación la constituye la urgencia de investigaciones destinadas a la evaluación de los resultados a corto plazo, así como el análisis de la sostenibilidad a largo plazo de dichas innovaciones.

Palabras clave: Inteligencia Artificial; Educación Superior; Revisión Sistemática; Adopción Tecnológica; Latinoamérica.

INTRODUCTION

The applications of artificial intelligence[1,2] especially in higher education contexts, constitute a technological revolution of considerable magnitude. As Crompton et al.[1] pointout, this is particularly relevant in Latin America, especially given the heterogeneity of current university structures.

As a result, the scientific community warns in increasingly cited studies[3,4] that the automation being observed in bureaucratic processes invariably brings with it the need to adapt to scenarios involving algorithmic learning. Despite this clear statement, Cope et al.[5] warn in their study that the objective reality presents a palpable fragmentation. According to the authors, this indicates a lack of rigorous systematization in the applications of artificial intelligence, which, at the very least, raises doubts about its viability in developing countries.

For the authors of this research, the foundations of the technological transformation brought about by advances in artificial intelligence have their antecedents in machine learning and natural language processing, with widely documented pedagogical applications.[6] In this complex landscape, intelligent tutors, as well as automated student performance assessment systems, reflect what has been stated above. However, it would be simplistic to reduce the adoption of these technological benefits to a mere technical change.[7]

In this logical order of ideas, the integration of artificial intelligence into education inevitably brings with it the need to reconsider how the very concept of education is designed, all in order to balance the scalability of these technologies with the equity of their adoption.[8] Especially in Latin America, research related to this idea continues to emerge, but anecdotal approaches prevail over documented empirical evidence.[9,10]

This significant gap indicates, according to the authors of this study, a prevailing demand for a theoretical synthesis that goes beyond the description of documented applications.[11] This is in line with the growing body of researchers who point to the urgent need to examine which institutional factors impact and cut across the increasingly observed digital divide or, if so, whether it reproduces existing exclusions in these contexts.[12,13,14]

The viability of this study, therefore, lies clearly in its effort to offer practical utility to Latin American realities and the educational contexts in which they are immersed. Based on this, the authors of the study aim to highlight the main contradictions and opportunities that are diluted in the implementation of artificial intelligence in Latin American educational realities.

METHOD

Study design

To meet the objectives of the study, a theoretical review paradigm was adopted under the assumptions of the PRISMA guidelines. This approach was selected for its proven ability to integrate evidence, knowledge, and practices without compromising scientific rigor.

Information selection process

The search for documentary sources was carried out in the Scopus database as the main bibliographic source. In addition to this, SciELO and Redalyc were consulted as predominantly Latin American sources.

The search strings were constructed through an iterative process that tested multiple combinations of terms ("Artificial Intelligence," "Higher Education," "Latin America," "ethics," "pedagogy," "learning," "ML," "NLP," "educational tools"). They were not limited to literal translations of key concepts, but incorporated linguistic and conceptual variants specific to the Ibero-American context, along with country names and specific terms of application. The strategy was optimized through pilot testing and iterative adjustments.

Finally, a total of 929 publications were identified (figure 1), of which 182 were eliminated prior to bibliometric screening. The remaining 747 were subjected to the pre-established selection and quality assessment criteria, resulting in the elimination of 326 studies. The bibliometric analysis was performed on the remaining 421 studies. For the qualitative stage, an analysis of the most relevant publications was performed on the 421 selected sources, resulting in the retention of 45 studies. After filtering by thematic relevance, 30 studies were retained for qualitative analysis of the literature.

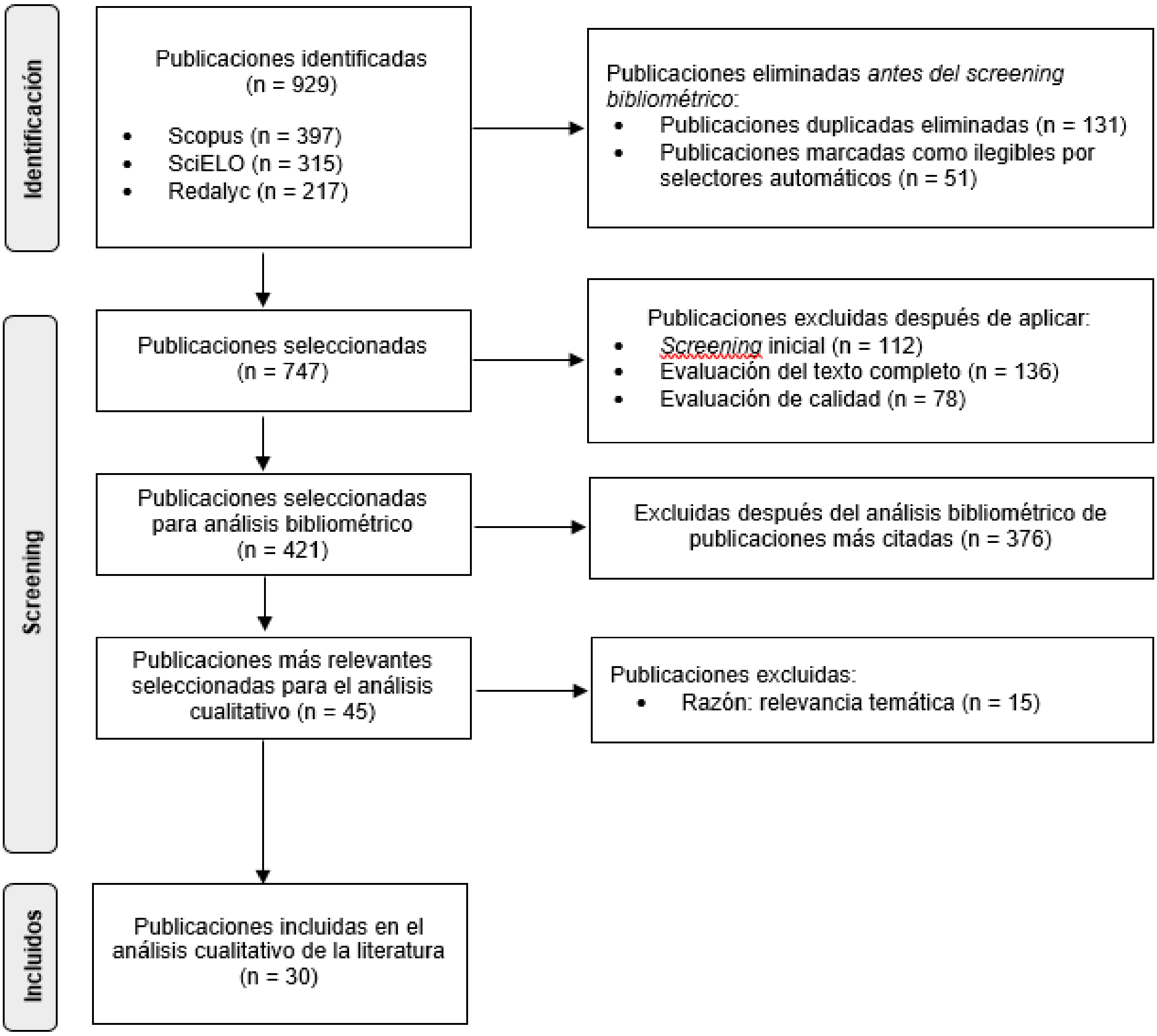

Figure 1. Flow chart for research selection

Eligibility criteria

Clear and operational inclusion and exclusion criteria were established to guide the selection process (table 1).

Table 1. Inclusion and exclusion criteria used

Criteria	Operationalization
Type of study	Primary empirical studies (qualitative, quantitative, mixed) that provided original data; high-quality theoretical studies that proposed conceptual frameworks or adoption models; and previous systematic or scoping reviews.
Context	Research developed or explicitly focused on higher education institutions located in Latin American countries.
Central Topics	Work whose main focus is the description, analysis, or evaluation of: Specific applications of AI in educational, administrative, or research processes. Ethical issues arising from its use (algorithmic bias, data privacy, surveillance, equity, transparency, accountability). Pedagogical impact or effectiveness measured in terms of learning outcomes, engagement, personalization, or teacher development.
Period	Literature published between January 1, 2020, and December 31, 2024.
Focus	Opinion articles without a solid empirical or theoretical basis, studies focused exclusively on non-higher education levels, AI applications without a clear link to the educational context, and literature prior to 2020 were excluded.

Selection and quality assessment procedure

The selection of studies followed a standardized three-phase process (table 2). This process was carried out independently by two reviewers to ensure reliability.

Table 2. Procedure for the selection and quality assessment of studies

Phases	Description of procedures
Initial screening	Elimination of duplicates and evaluation of titles and abstracts against inclusion/exclusion criteria
Full-text evaluation	Critical reading of the preselected articles to verify their suitability for all criteria
Quality assessment	Characterization of the methodological rigor of the evidence and contextualization of its contribution to the synthesis. Discrepancies were resolved by consensus or consultation with a third reviewer

Data extraction and synthesis process

A structured form was developed to collect systematic data from each study, including bibliographic, contextual, and methodological aspects. The instrument also captured specific information on the AI applications examined (from their target population to the ethical dimensions addressed) along with findings on pedagogical effectiveness and reported challenges.

The analysis combined two complementary approaches. First, a *qualitative meta-synthesis* was conducted using an inductive and deductive coding methodology. This process was carried out to identify the thematic patterns that have emerged in the scientific literature around the adoption of artificial intelligence. Next, a quantitative analysis was conducted of the trends observable in the selected data from a statistical point of view. VOSviewer was used for the bibliometric analyses.

RESULTS AND DISCUSSION

Bibliometric and demographic analysis of the document corpus

The bibliometric analysis of annual growth in publications is presented in figure 2. It is noteworthy that after a period of relative stability (22-24 publications per year until 2022), academic output experienced a turning point in 2023, with 85 papers recorded. This upward trend accelerated dramatically in 2024, reaching 260 publications, an increase that reflects both growing scientific interest and the urgency to systematize this emerging knowledge.

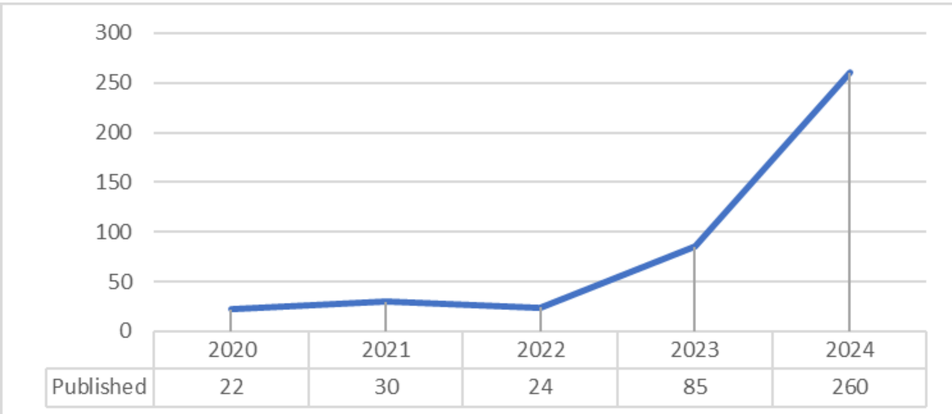

Figure 2. Annual distribution of publications

Geographically, the research shows an uneven distribution concentrated in five countries (figure 3): Mexico (158 documents), Brazil (71), Peru (67), Ecuador (64), and Colombia (47). This disparity suggests that the adoption of AI in higher education varies in its practical implementation and, as a result, in the attention it receives as a subject of study. It is striking that, despite sharing common regional challenges, academic production is not distributed evenly.

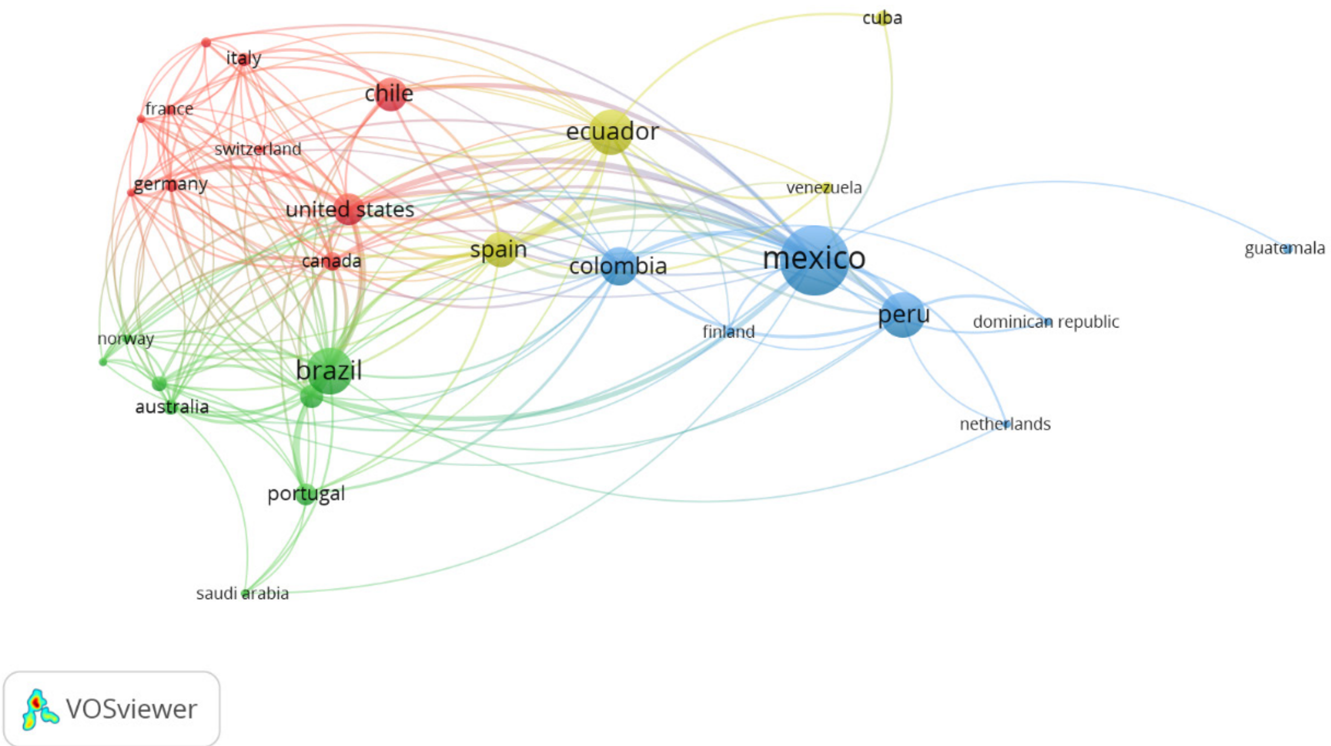

Figure 3. Geographic analysis of scientific production

At the institutional level (table 3), Tecnológico de Monterrey stands out with 114 publications, far surpassing other universities such as Cesar Vallejo University (17) and the University of São Paulo (10). Such concentration raises questions about the epistemological diversity of the corpus analyzed, as it is unclear whether these data truly represent the plurality of educational realities in Latin America or predominantly reflect the research priorities of certain centers.

Table 3. Distribution of publications by institution

Affiliation	Documents
Monterrey Institute of Technology	1
César Vallejo University	17
Technological University of Peru	16
Private University of the North	13
University of São Paulo	10
Private Technical University of Loja	10
Andrés Bello University	9
University of Salamanca	9
Federal University of Santa Catarina	8
Pontifical Catholic University of Chile	8

Thematically (figure 4), a multidisciplinary approach predominates, with an emphasis on Social Sciences (244 documents) and Computer Science (213), followed by Engineering (138) and emerging areas such as Decision Sciences (42). The minority but significant presence of Psychology (25) indicates a growing, albeit still incipient, interest in the cognitive and pedagogical impacts of these technologies. This disciplinary coexistence underscores the need for analytical frameworks that integrate technical dimensions with critical reflections on their educational implementation.

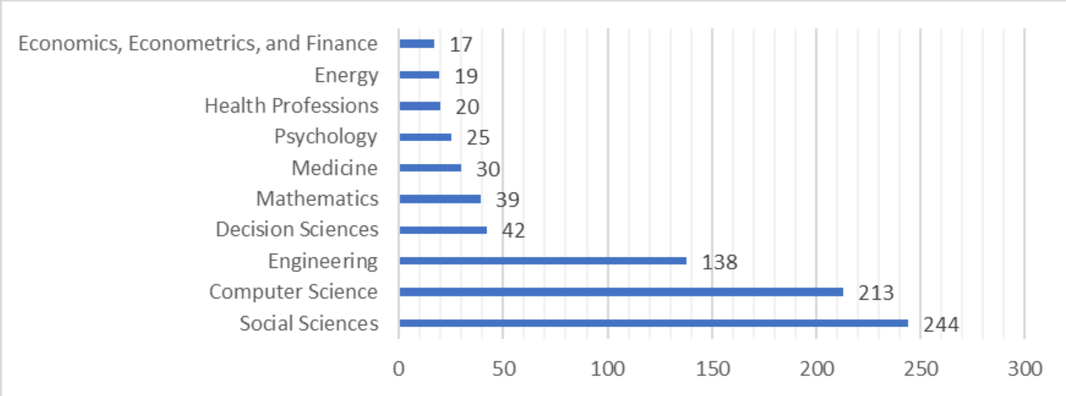

Figure 4. Distribution of data by area of study

Descriptive quantitative analysis of the corpus

The corpus analyzed, consisting of 421 studies, shows clear patterns in the application of artificial intelligence within the Latin American university context. Although technological diversity is represented, certain areas emerge as predominant focuses of research interest.

Types of artificial intelligence applications

Frequency analysis revealed an uneven distribution in the AI applications investigated (table 4). Machine learning (ML) clearly dominated the landscape, accounting for 58 % (244 studies) of the papers analyzed. These studies prioritized three specific uses: learning analytics (112 studies), student performance prediction (87), and training program customization (45).

Table 4. Frequency analysis of types of artificial intelligence applications

Main Category	Subcategory	*f*	%
Machine Learning (ML)	Total ML	244	58
	Learning analytics	11	26,6
	Performance prediction	87	20,7
	Route customization	45	10,7
Natural Language Processing (NLP)	Total NLP	130	31
	Educational Chatbots	98	23,3
	Discourse analysis	22	5,2
	Automated feedback	10	2,4
Other AI tools	Total Other	47	11
	Smart tutors	2	6,7
	Adaptive systems	19	4,5
Hybrid approaches	ML+NLP combination	15	3,6

Natural language processing (NLP) ranked second, with a 31 % (130 studies) presence in the literature. Within this group, educational chatbots captured the spotlight, appearing in 98 papers (75 % of NLP studies). The remaining research was distributed between academic discourse analysis (22) and automated feedback systems (10).

Other AI-based educational tools were significantly less represented, accounting for only 11 % (47 studies) of the total. Intelligent tutors appeared in 28 studies, while complete adaptive systems were analyzed in 19.

An additional finding deserves attention: only 15 studies (3,6 % of the total) explored hybrid applications that combined ML with other technologies. This low representation of integrated approaches could indicate a tendency to research technologies in isolation, potentially limiting the understanding of complex implementations in real educational settings.

Thematic approach

Thematic analysis revealed marked disparities in research approaches (table 5). Technical dimensions accounted for 44,4 % of the studies (187 papers), with the implementation of models (92 studies) and the design of software architectures (67) standing out. This predominance reflects the initial emphasis on the instrumental aspects of technology adoption.

Table 5. Frequency analysis of the thematic focus of the research studies			
Dimension analyzed	**Subcategories**	***f***	**%**
Technical	Total	187	44,4
	Model implementation	92	21,9
	Software architectures	67	15,9
	Effectiveness evaluation	28	6,6
Pedagogical	Total	163	38,7
	Learning outcomes	78	18,5
	Student engagement	59	14,0
	Motivation	26	6,2
Ethics	Total	71	16,9
	Algorithmic biases	32	7,6
	Data privacy	25	5,9
	Equity in access	14	3,3

Pedagogical dimensions accounted for 38,7 % (163 studies), with particular attention to learning outcomes (78) and student engagement (59). However, only 26 studies (6,2 %) delved into motivational aspects, suggesting areas for future research.

In stark contrast, ethical considerations accounted for only 16,9 % of academic output (71 studies). Algorithmic bias (32) and privacy (25) received more attention than equity in access (14), which appears as the most neglected dimension. This distribution highlights a critical gap: while 3 out of 4 studies analyze technical or pedagogical aspects, only 1 in 6 addresses fundamental ethical issues.

Keyword co-occurrence analysis

Dimensions of artificial intelligence adoption

Terminological co-occurrence analysis revealed three intertwined conceptual axes that structure the field of study (figure 5). The technological dimension emerged as the most densely populated, with concepts such as "*machine learning*" and "*natural language processing*" appearing systematically linked to "*artificial intelligence*" and "*e-learning*." This lexical network confirms the predominance of technical approaches as a tendency to conceptualize educational solutions from specific computational paradigms.

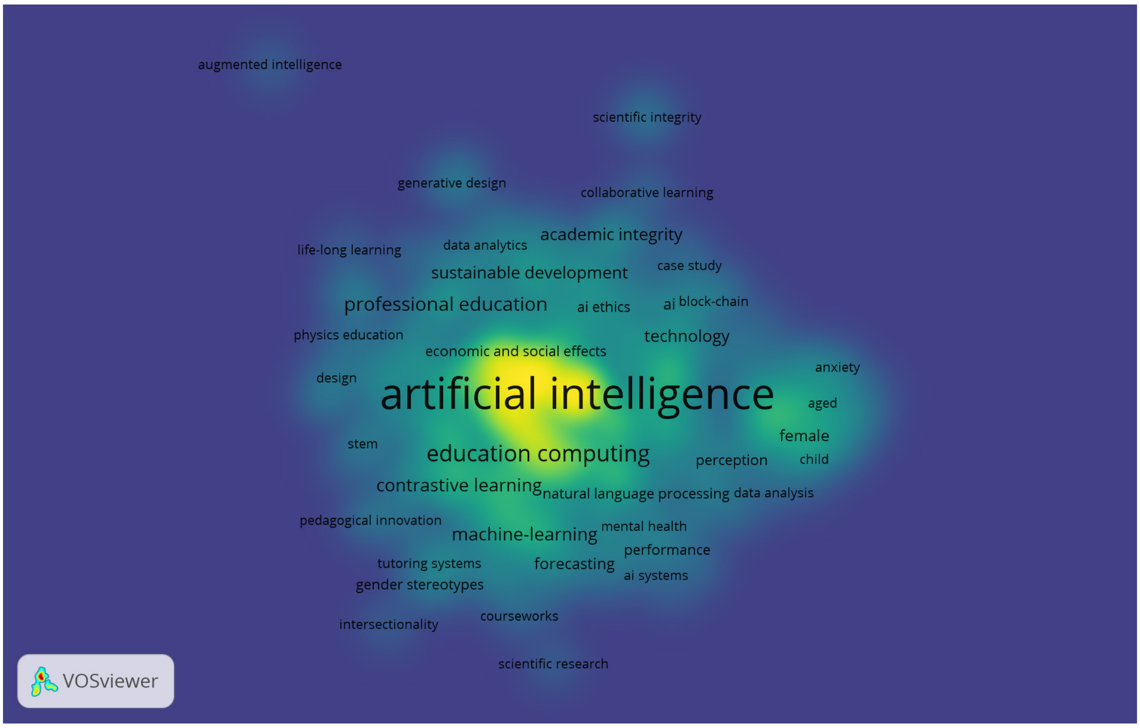

Figure 5. Analysis of the dimensions of artificial intelligence adoption

https://doi.org/10.62486/latia2025304 ISSN: 3046-403X

In contrast, although less dense, the pedagogical dimension showed greater conceptual diversity. Terms such as "*learning*," "*student performance*," and "*teachers*" frequently co-occurred with "*higher education*," indicating that research transcends the merely instrumental to examine concrete impacts on educational processes. Interestingly, while students appear as a recurring focus ("*students*"), teachers ("*teachers*") show a significantly lower presence in the terminological network, which could reflect an imbalance in research attention.

The last dimension contained terms such as "*learning management systems*" and "*digital transformation*." These constructs support the idea that artificial intelligence is conceptualized as a link in deeper institutional processes. It is noteworthy that terms linked to "*educational policies*" or "*technology governance*" are relatively scarce, which could indicate a limited perspective of the organizational and structural factors that cut across these processes.

Relational analysis of the constructs evaluated

An analysis of the co-occurrence of key terms used in the literature was carried out, as shown in figure 6 below. In particular, the concept of "*artificial intelligence*" emerged as a central node, representing the strongest link in the network with 1249. This term has particularly strong connections with "*higher education*" (link strength 1067) and "*education computing*" (283), suggesting that research focuses predominantly on specific applications within the university context.

Specific technologies show interesting patterns of association.

In particular, "*machine learning*" (182) and "*deep learning*" (68) showed a significant link with "*learning analytics*" and "*student performance*." Similarly, concepts such as "*natural language processing systems*" show a weaker connection, with values around 37 points. However, they are strongly associated with "*chatbots*" (56) and "*generative artificial intelligence*" (163).

Terms related to pedagogical constructs also show valuable interactions for the study. In particular, "teaching" (347) and "*learning experiences*" (73) have substantial links with "*educational innovation*" (641). In addition, there is a disregard for ethical requirements when analyzing the weak connections between the concepts of "*critical thinking*" (55) and "*academic integrity*" (47) in this relationship.

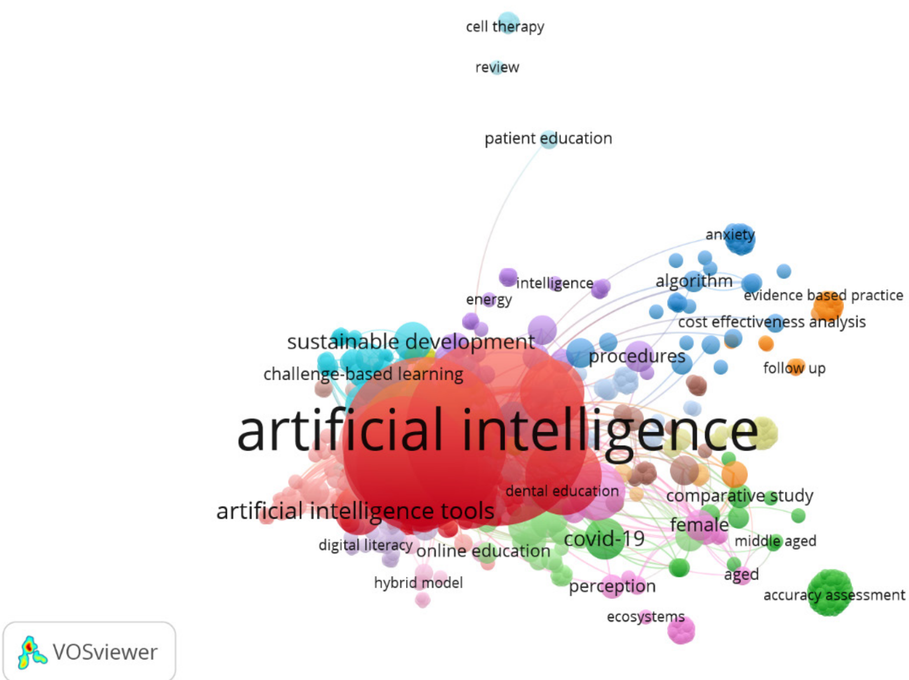

Figure 6. Co-occurrence analysis of terms

Research methodologies appear less developed in the conceptual network. While "*systematic review*" (37) and "*case studies*" (36) have a limited presence, the strong connection between "*higher education*" and "*students*" (837) suggests a predominance of studies focused on the student experience. This trend is tempered by the low representation of "*teachers*" (77) and "*teaching practices*" (37), revealing an imbalance in the attention given to different educational actors.

The conceptual network reveals three major research gaps. First, the relative disconnect between

https://doi.org/10.62486/latia2025304 ISSN: 3046-403X

“*sustainability*” (33) and educational technologies, despite growing interest in sustainable development. Second, the weak integration of concepts such as “*gender stereotypes*” (25) in the prevailing discourse on educational AI. Third, the scarce presence of studies specifically contextualized in “*Latin America*” (32), despite the overall volume of research in higher education.

Qualitative meta-synthesis: interpretative thematic analysis

Models emerging in the literature and their influence on adoption processes

The studies consulted indicate that when artificial intelligence is adopted in university contexts, there is an inherent complexity in its application which in this case is summarized in figure 7. From an initial stage of pilot tests and approaches based on inductive mechanisms, recent progress has been observed towards integration based on Latin American curricula and administrative systems.

Figure 7. Models and processes for the adoption of artificial intelligence in university administration

Classic theoretical frameworks on technology adoption, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM), have been fundamental to the analysis of these technological adoption processes.[20] Despite this, Holmes[21] and Nguyen[22] point out that there are limitations to applying them to artificial intelligence, especially in educational settings.

This is commendable from a general analytical perspective, as these technologies introduce variables that are qualitatively different from the scenarios for which they were designed. Therefore, their application to teaching environments may require conceptual adaptations.[23]

This analysis is particularly relevant when focusing on the actors involved in these dynamics. Such is the case that administrators, who play the role of institutional policy drivers, teachers, and students, are positioned in this analysis as test subjects and evaluators of the effectiveness of these technological implementations.[24,25,26] Opinions are divided on this issue, as policies encourage excessive implementation without taking into account the skepticism (whether justified or not) that the subjects of these applications may have.[27,28,29]

Facilitating mechanisms and barriers identified in the adoption of artificial intelligence in education

The findings reveal a web of systemic barriers that hinder the integration of AI-based solutions in universities (figure 8). Inadequate technological infrastructure—especially in terms of connectivity and basic hardware—is only the most visible layer of a multidimensional problem.[30] As the data show, this technical limitation acts in synergy with equally decisive human challenges.

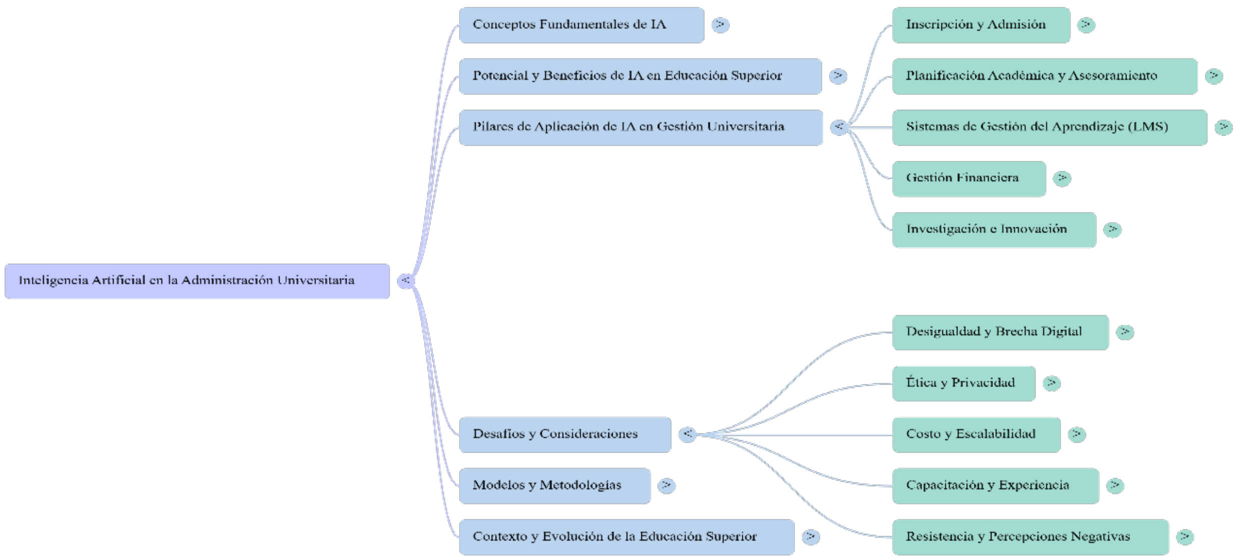

Figure 8. Inhibiting and promoting factors in the implementation of AI in university management

There is a worrying mismatch between technological development and the actual capacity for pedagogical use. Recent research [4,7,31] agrees that there is a training deficit among teachers, who, although they express positive attitudes toward AI, lack specific tools for its educational application. Added to this is the lack of attention paid to the ethical dilemmas involved, an omission that could lead to counterproductive applications if not corrected in time.[32]

Far from being an irrational response, the so-called "*resistance to change*" [21,33] stems from well-founded concerns about the reconfiguration of educational roles and the possible erosion of humanistic aspects in educational processes.[34] This evidence points to the need to design implementation strategies that include spaces for institutional negotiation where these concerns can be articulated.[35]

At the same time, studies such as those by Aljabr[19] and Rehak[31] identify key facilitating factors. The existence of defined institutional policies and the allocation of *ad hoc* resources appear to be necessary—though not sufficient—conditions for progress. The most substantial progress is observed in cases that encourage transdisciplinary collaboration, integrating specialists in pedagogy, engineering, and social sciences from the design phase onwards.[34,35]

Ethical issues and challenges in the implementation of educational AI

The ethical debate surrounding artificial intelligence applied to education, although less developed than other technical or pedagogical approaches, identifies critical issues that require urgent attention (figure 9). Among these, algorithmic biases stand out for their potential to distort key processes such as assessment and admissions.[36] These biases, often a reflection of inequalities present in training data, not only reproduce existing discrimination but in some cases intensify it.[37]

Another central challenge is the management of personal data in educational contexts.[38] The mass collection of student information raises questions, to say the least, about real consent, purpose of use, and protection against possible leaks.[26,39] In this regard, it has been fervently noted that the institutional capacity to safeguard this data does not always match the risks posed by its automated processing.

A notable contradiction is the paradox of technological equity: while AI is promoted as an inclusive tool, its implementation tends to favor institutions with greater resources, thus widening pre-existing educational gaps.[40] This phenomenon calls into question the supposed democratizing nature of technological innovation[41] and calls for redistribution mechanisms that prevent the concentration of advantages.

The absence of standardized protocols for auditing algorithms in higher education is striking.[42,43] The opaque nature of many AI systems makes it difficult to detect or challenge errors or automated decisions, raising serious accountability issues.[44] Some authors interpret this shortcoming as a symptom of a tendency to privilege technical criteria over pedagogical considerations in adoption processes.[45]

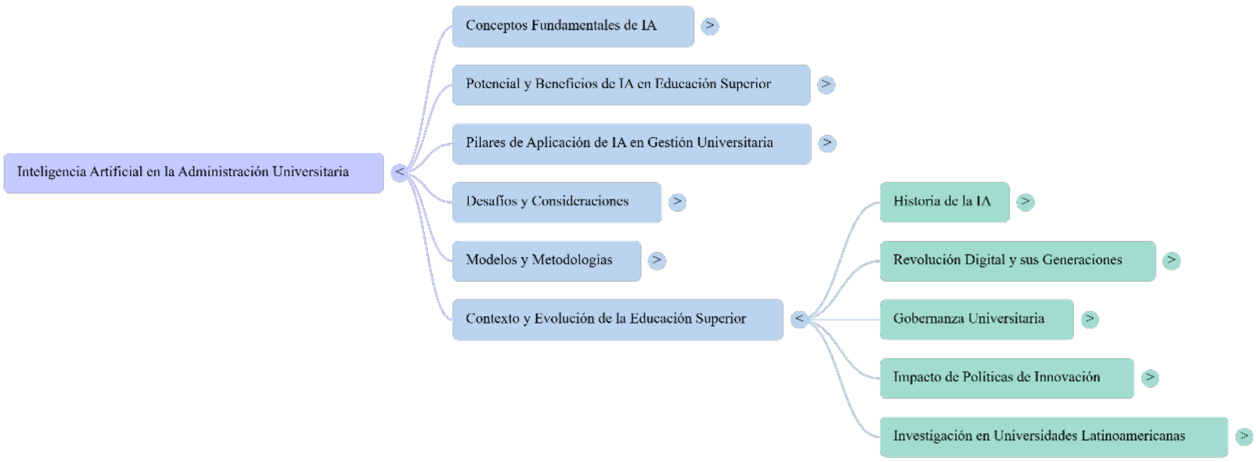

Figure 9. Main ethical dilemmas in the adoption of AI in university settings

Finally, there remains a significant gap between developers and end users. This disconnect often results in tools that are technically advanced but insensitive to the real needs of educational institutions. Moving forward requires operational ethical frameworks that can be translated into concrete guidelines for the design and implementation of these technologies.

Pedagogical impact and practical limitations

Empirical research on AI in education shows tangible benefits, although there are important nuances to consider.[46] Automated feedback systems, for example, have proven particularly effective in areas that require constant practice, such as mathematics or languages, by providing immediate corrections.[47] This advantage is crucial in contexts with high student density, where individualized attention is unfeasible.[48]

Personalization of learning represents another significant contribution. Adaptive platforms that adjust content and pace to individual profiles not only improve academic performance but also increase motivation. However, these capabilities are limited when algorithms work with insufficient data or when institutions lack the infrastructure to deploy advanced solutions.[49]

One of the most transformative effects lies in the redefinition of the role of teachers. By automating routine administrative and evaluative tasks, AI frees up time for higher-value pedagogical activities, such as the development of critical thinking or creative problem solving and skills that still elude the capabilities of machines.[50,51,52]

Despite these advances, a worrying gap remains: most studies measure immediate impacts, but few analyze long-term effects on knowledge retention or metacognitive skills.[53] This methodological limitation makes it impossible to determine whether the reported benefits are sustainable or merely circumstantial.

Synthesis and integration of findings

The initial quantitative analysis revealed exponential growth in academic output on AI in higher education, with a marked geographical concentration in Mexico, Brazil, and Peru.[54,55] This trend was reflected in the qualitative data, which identified certain universities as central nodes of research and practical implementation.[56] Such a distribution suggests a fragmented adoption model, where innovation advances through isolated pockets rather than as an articulated regional movement.[41] The predominant technologies, machine learning and natural language processing, coincide with the most documented pedagogical applications, especially in content personalization and automated feedback systems.[57]

A significant contradiction emerged when analyzing the treatment of ethical issues.[58] While quantitative studies showed little formal attention to these issues, qualitative analysis revealed recurring concerns among educational actors about algorithmic bias, data protection, and equity.[12,25,39] This divergence points to an imbalance in research priorities, where technical advances often overshadow debates about possible unintended consequences.[40,59]

The review identified critical gaps that require immediate attention. The overrepresentation of certain countries in the literature contrasts with the near absence of data on Central America and the Caribbean, which distorts the regional understanding of the phenomenon. Equally problematic is the scarcity of longitudinal studies: most research uses cross-sectional designs that offer only snapshots, unable to capture the evolution of educational impacts.[60,61,62]

These findings point the way for future research. Comparative studies are urgently needed to examine how institutional and national factors mediate the adoption of AI, along with more robust conceptual frameworks for assessing its ethical implications. It is equally crucial to develop mixed methodologies that combine large-scale quantitative analysis with qualitative approaches capable of capturing the concrete experiences of teachers and students.

CONCLUSIONS

This systematic review offers a critical assessment of the current state of AI in Latin American higher education. The field shows rapid growth, dominated by research on machine learning and natural language processing applications. However, these findings must be interpreted considering important methodological limitations, which in turn point to key directions for future studies. The regional adoption process is uneven, ranging from isolated experiments to institutionalized implementations. Despite initial enthusiasm, significant structural barriers remain: insufficient technological infrastructure, inadequate teacher training, and cultural resistance appear as recurring obstacles. These results suggest that success depends less on technical capabilities than on the construction of institutional ecosystems that integrate strategic leadership, coherent policies, and transdisciplinary collaboration. A critical contrast emerges when examining the treatment of ethical dimensions. Although there are isolated acknowledgments of risks such as algorithmic biases or privacy violations, their analysis is marginal compared to the emphasis on technological aspects. This asymmetry represents a considerable vulnerability, as hasty implementations without ethical safeguards could exacerbate inequalities rather than mitigate them. In the educational field, evidence points to concrete benefits, particularly in personalizing learning and automating administrative tasks. However, these conclusions require caution. The predominance of studies with small samples and cross-sectional designs limits both external validity and understanding of long-term effects. This limitation underscores the urgent need for longitudinal research to assess the real sustainability of these innovations.

BIBLIOGRAPHIC REFERENCES

1. Crompton H, Burke D. Artificial intelligence in higher education: the state of the field. International Journal of Educational Technology in Higher Education. 2023;20:1-22. https://doi.org/10.1186/s41239-023-00392-8

2. Ivanov S. The dark side of artificial intelligence in higher education. The Service Industries Journal. 2023;43:1055-1082. https://doi.org/10.1080/02642069.2023.2258799

3. Bates T, Cobo C, Mariño O, Wheeler S. Can artificial intelligence transform higher education? International Journal of Educational Technology in Higher Education. 2020;17. https://doi.org/10.1186/s41239-020-00218-x

4. Keleş P, Aydın S. University Students' Perceptions About Artificial Intelligence. Education 3-13. 2021;9:212-220. https://doi.org/10.34293/EDUCATION.V9IS1-MAY.4014

5. Cope B, Kalantzis M, Searsmith D. Artificial intelligence for education: Knowledge and its assessment in AI-enabled learning ecologies. Educational Philosophy and Theory. 2020;53:1229-1245. https://doi.org/10.1080/00131857.2020.1728732

6. Crawford J, Allen K, Pani B, Cowling M. When artificial intelligence substitutes humans in higher education: the cost of loneliness, student success, and retention. Studies in Higher Education. 2024;49:883-897. https://doi.org/10.1080/03075079.2024.2326956

7. AlAjmi A. Artificial Intelligence and Smart Universities. Studies in Computational Intelligence. 2021;935:295-310. https://doi.org/10.1007/978-3-030-62796-6_17

8. Álvarez-álvarez C, Falcón S. Students' preferences with university teaching practices: analysis of testimonials with artificial intelligence. Educational Technology Research and Development. 2023;71:1709-1724. https://doi.org/10.1007/s11423-023-10239-8

9. Bracho-Fuenmayor PL. Diálogo de saberes como método disruptivo en enseñanza-aprendizaje y evaluación del derecho a través de la investigación. Revista Pedagogía Universitaria Y Didáctica Del Derecho. 2025;12(1):139-154. https://doi.org/10.5354/0719-5885.2025.75475

10. Wang C, Wang H, Li Y, Dai J, Gu X, Yu T. Factors Influencing University Students' Behavioral Intention to Use Generative Artificial Intelligence: Integrating the Theory of Planned Behavior and AI Literacy. International Journal of Human-Computer Interaction. 2024;41:6649-6671. https://doi.org/10.1080/10447318.2024.2383033

11. Sarwari A, Javed M, Adnan H, Wahab M. Assessment of the impacts of artificial intelligence (AI) on intercultural communication among postgraduate students in a multicultural university environment. Scientific Reports. 2024;14 (13849). https://doi.org/10.1038/s41598-024-63276-5

12. Tabuenca B, Uche-Soria M, Greller W, Leo D, Balcells-Falgueras P, Gloor P, et al. Greening smart learning environments with Artificial Intelligence of Things. Internet of Things. 2023;25:101051. https://doi.org/10.1016/j.iot.2023.101051

13. Triberti S, Fuccio R, Scuotto C, Marsico E, Limone P. "Better than my professor?" How to develop artificial intelligence tools for higher education. Frontiers in Artificial Intelligence. 2024;7, 1329605. https://doi.org/10.3389/frai.2024.1329605

14. Lainjo B, Tsmouche H. Impact of Artificial Intelligence On Higher Learning Institutions. International Journal of Education, Teaching, and Social Sciences. 2023;3(2). https://doi.org/10.47747/ijets.v3i2.1028

15. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. Journal of Clinical Epidemiology. 2021;134:178-189. https://doi.org/10.1016/j.jclinepi.2021.03.001

16. Orduña-Malea E, Costas R. Link-based approach to study scientific software usage: the case of VOSviewer. Scientometrics. 2021;126:8153-8186. https://doi.org/10.1007/s11192-021-04082-y

17. Sanusi I, Martin F, Gonzales J, Mahipal V, Oyelere S, Suhonen J, et al. AI MyData: Fostering Middle School Students' Engagement with Machine Learning through an Ethics-Infused AI Curriculum. ACM Transactions on Computing Education. 2024;24:1-37. https://doi.org/10.1145/3702242

18. Klimova B, Pikhart M, Kacetl J. Ethical issues of the use of AI-driven mobile apps for education. Frontiers in Public Health. 2023;10, 1118116. https://doi.org/10.3389/fpubh.2022.1118116

19. Aljabr F, Al-Ahdal A. Ethical and pedagogical implications of AI in language education: An empirical study at Ha'il University. Acta Psychologica. 2024;251:104605. https://doi.org/10.1016/j.actpsy.2024.104605

20. Ranade N, Saravia M. Teaching AI Ethics in Technical and Professional Communication: A Systematic Review. IEEE Transactions on Professional Communication. 2024;67:422-436. https://doi.org/10.1109/TPC.2024.3458708

21. Holmes W, Porayska-Pomsta K, Holstein K, Sutherland E, Baker T, Shum S, et al. Ethics of AI in Education: Towards a Community-Wide Framework. International Journal of Artificial Intelligence in Education. 2021;32:504-526. https://doi.org/10.1007/s40593-021-00239-1

22. Nguyen A, Ngo H, Hong Y, Dang B, Nguyen B. Ethical principles for artificial intelligence in education. Education and Information Technologies. 2022;28:4221-4241. https://doi.org/10.1007/s10639-022-11316-w

23. Weidener L, Fischer M. Teaching AI Ethics in Medical Education: A Scoping Review of Current Literature and Practices. Perspectives on Medical Education. 2023;12:399-410. https://doi.org/10.5334/pme.954

24. Knowles M. Five Motivating Concerns for AI Ethics Instruction. Proceedings of the Association for Information Science and Technology. 2021;58(1), 472-476. https://doi.org/10.1002/pra2.481

25. Huang C, Zhang Z, Mao B, Yao X. An Overview of Artificial Intelligence Ethics. IEEE Transactions on Artificial Intelligence. 2023;4:799-819. https://doi.org/10.1109/TAI.2022.3194503

26. Weidener L, Fischer M. Proposing a Principle-Based Approach for Teaching AI Ethics in Medical Education. JMIR Medical Education. 2023;10. https://doi.org/10.2196/55368

27. Baker B, Mills K, McDonald P, Wang L. AI, Concepts of Intelligence, and Chatbots: The "Figure of Man," the Rise of Emotion, and Future Visions of Education. Teachers College Record. 2023;125:60-84. https://doi.org/10.1177/01614681231191291

28. Zohny H, McMillan J, King M. Ethics of generative AI. Journal of Medical Ethics. 2023;49:79-80. https://doi.org/10.1136/jme-2023-108909

29. Al-Kfairy M, Mustafa D, Kshetri N, Insiew M, Alfandi O. Ethical Challenges and Solutions of Generative AI: An Interdisciplinary Perspective. Informatics. 2024;11:58. https://doi.org/10.3390/informatics11030058

30. Cantelmi R, Di Gravio G, Patriarca R. Reviewing qualitative research approaches in the context of critical infrastructure resilience. Environment Systems & Decisions. 2021;41:341-376. https://doi.org/10.1007/s10669-020-09795-8

31. Rehak D. Assessing and strengthening organisational resilience in a critical infrastructure system: Case study of the Slovak Republic. Safety Science. 2020;123:104573. https://doi.org/10.1016/j.ssci.2019.104573

32. Chester M, Underwood S, Samaras C. Keeping infrastructure reliable under climate uncertainty. Nature Climate Change. 2020;10:488-490. https://doi.org/10.1038/s41558-020-0741-0

33. Nirandjan S, Koks E, Ward P, Aerts J. A spatially-explicit harmonized global dataset of critical infrastructure. Scientific Data. 2022;9(150). https://doi.org/10.1038/s41597-022-01218-4

34. Sonesson T, Johansson J, Cedergren A. Governance and interdependencies of critical infrastructures: Exploring mechanisms for cross-sector resilience. Safety Science. 2021;142:105383. https://doi.org/10.1016/J.SSCI.2021.105383

35. Schweikert A, L'Her G, Deinert M. Simple method for identifying interdependencies in service delivery in critical infrastructure networks. Applied Network Science. 2021;6(44). https://doi.org/10.1007/s41109-021-00385-4

36. Love P, Ika L, Matthews J, Fang W. Curbing Poor-Quality in Large-Scale Transport Infrastructure Projects. IEEE Transactions on Engineering Management. 2020;66(9):1-13. https://doi.org/10.1109/TEM.2020.3031890

37. Hoff R, Helmrich A, Dirks A, Kim Y, Li R, Chester M. Dynamic criticality for infrastructure prioritization in complex environments. Environmental Research: Infrastructure and Sustainability. 2023;3:015011. https://doi.org/10.1088/2634-4505/acbe15

38. Sathurshan M, Saja A, Thamboo J, Haraguchi M, Navaratnam S. Resilience of Critical Infrastructure Systems: A Systematic Literature Review of Measurement Frameworks. Infrastructures. 2022;7(5):67. https://doi.org/10.3390/infrastructures7050067

39. Purwar D, Flacke J, Guzman E, Sliuzas R. A qualitative analysis of cascading effects of critical infrastructure service failure post torrential floods in formal & informal settlement: the study-case of Medellin city, Colombia. Sustainable and Resilient Infrastructure. 2024;9:496-512. https://doi.org/10.1080/23789689.2024.2340924

40. Cárdenas-Mamani Ú, Kahhat R, Magallanes J. Interdependent response of three critical infrastructures in a South American megacity. Environmental Research: Infrastructure and Sustainability. 2022;2:025003. https://doi.org/10.1088/2634-4505/ac6a0a

41. Abouhamad M, Zayed T. Fuzzy Preference Programming Framework for Functional assessment of Subway Networks. Algorithms. 2020;13:220. https://doi.org/10.3390/a13090220

42. Alizadeh H, Sharifi A. Assessing Resilience of Urban Critical Infrastructure Networks: A Case Study of Ahvaz, Iran. Sustainability. 2020;12:3691. https://doi.org/10.3390/su12093691

43. Agrawal K, Durbha S, Talreja P, Nukavarapu N. Deep Reinforcement Learning Driven Critical Infrastructure Protection During Extreme Events. IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium. 2023:2540-2543. https://doi.org/10.1109/IGARSS52108.2023.10282089

44. Robson C, Barr S, Ford A, James P. The structure and behaviour of hierarchical infrastructure networks. Applied Network Science. 2021;6:1-25. https://doi.org/10.1007/s41109-021-00404-4

45. Gao X, Ye Y, Gong S, Chen L, Wang T. Empirical patterns of interdependencies among critical infrastructures in cascading disasters: Evidence from a comprehensive multi-case analysis. International Journal of Disaster Risk Reduction. 2023;103862. https://doi.org/10.1016/j.ijdrr.2023.103862

46. Karakoc D, Barker K, Zobel C, Almoghathawi Y. Social vulnerability and equity perspectives on interdependent infrastructure network component importance. Sustainable Cities and Society. 2020;57:102072. https://doi.org/10.1016/j.scs.2020.102072

47. Blokus A, Dziula P. Relations of Imperfect Repairs to Critical Infrastructure Maintenance Costs. Sustainability. 2021;13:4917. https://doi.org/10.3390/SU13094917

48. Wee X, Herrera M, Hadjidemetriou G, Parlikad K. Simulation and Criticality Assessment of Urban Rail and Interdependent Infrastructure Networks. Transportation Research Record. 2022;2677:1181-1196. https://doi.org/10.1177/03611981221103594

49. Rangrazjeddi A, González A, Barker K. Adaptive algorithm for dependent infrastructure network restoration in an imperfect information sharing environment. PLoS ONE. 2022;17(8): e0270407. https://doi.org/10.1371/journal.pone.0270407

50. Bracho Fuenmayor PL. Teoría de la justicia de John Rawls, desde una perspectiva de la filosofía política. Revista Chilena de Derecho y Ciencia Política. 2021;12(2):109-132. https://doi.org/10.7770/rchdcp-V12N2-art2650

51. You D, Xiao J, Wang Y, Yan H, Wu D, Chen Z, et al. Online Learning From Incomplete and Imbalanced Data Streams. IEEE Transactions on Knowledge and Data Engineering. 2023;35:10650-10665. https://doi.org/10.1109/TKDE.2023.3250472

52. Wang M, Yang C, Zhao F, Min F, Wang X. Cost-Sensitive Active Learning for Incomplete Data. IEEE Transactions on Systems, Man, and Cybernetics: Systems. 2023;53:405-416. https://doi.org/10.1109/TSMC.2022.3182122

53. Pleszczyński M. Implementation of the computer tomography parallel algorithms with the incomplete set of data. PeerJ Computer Science. 2021;7:e339. https://doi.org/10.7717/peerj-cs.339

54. Zhu C, Chen C, Zhou R, Wei L, Zhang X. A new multi-view learning machine with incomplete data. Pattern Analysis and Applications. 2020;23:1085-1116. https://doi.org/10.1007/s10044-020-00863-y

55. He J, Han X. Efficient Skyline Computation on Massive Incomplete Data. Data Science and Engineering. 2022;7:102-119. https://doi.org/10.1007/s41019-022-00183-7

56. Gong Y, Li Z, Liu W, Lu X, Liu X, Tsang I, et al. Missingness-Pattern-Adaptive Learning With Incomplete Data. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2023;45:11053-11066. https://doi.org/10.1109/TPAMI.2023.3262784

57. Wen J, Zhang Z, Zhang Z, Fei L, Wang M. Generalized Incomplete Multiview Clustering With Flexible Locality Structure Diffusion. IEEE Transactions on Cybernetics. 2020;51:101-114. https://doi.org/10.1109/TCYB.2020.2987164

58. Bhagat H, Singh M. A novel algorithm for imputing the missing values in incomplete datasets. Iran Journal of Computer Science. 2023; 7:13-23. https://doi.org/10.1007/s42044-023-00154-9

59. Miao X, Wu Y, Chen L, Gao Y, Yin J. An Experimental Survey of Missing Data Imputation Algorithms. IEEE Transactions on Knowledge and Data Engineering. 2023;35:6630-6650. https://doi.org/10.1109/TKDE.2022.3186498

60. Slota S, Fleischmann K, Greenberg S, Verma N, Cummings B, Li L, et al. Good systems, bad data?: Interpretations of AI hype and failures. Proceedings of the Association for Information Science and Technology. 2020;57(1):e275. https://doi.org/10.1002/pra2.275

61. Al-Taezi M, Wang Y, Zhu P, Hu Q, Al-Badwi A. Improved generative adversarial network with deep metric learning for missing data imputation. Neurocomputing. 2023;570:127062. https://doi.org/10.1016/j.neucom.2023.127062

62. Jäger S, Allhorn A, Biessmann F. A Benchmark for Data Imputation Methods. Frontiers in Big Data. 2021;4:693674. https://doi.org/10.3389/fdata.2021.693674

FINANCING
None.

CONFLICT OF INTEREST
None.

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