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Generative AI Governance Model in Educational Research

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This paper presents a scoping review on the application of generative artificial intelligence (GenAI) in educational research and proposes a living GenAI governance model to ensure a critical, responsible, and ethical usage of GenAI at macro, meso, and micro levels. Employing a quantitative and qualitative integration methodology, this review utilized two software tools: *VOSviewer* provided an initial overview of the field, while *Bibliometrix* revealed its conceptual structure. Through a two-dimensional map, subthemes were categorized into four quadrants: motor themes, basic themes, emerging or disappearing themes, and niche themes. Following the bibliometric analysis, we conducted a more detailed examination through content analysis by reviewing the titles and abstracts of 194 publications, selecting 35 pertinent articles. Based on these findings, we propose a Living GenAI Governance Model that maintains an ethical foundation and a dynamic perspective for using GenAI in educational research. The study's limitations serve as starting points for future research, as this review utilized only one database (*WoS*). Future studies should expand on the use of databases and include updated references, given the rapid theoretical production and practical application in this field. The target audience for this article is diverse and spans multiple levels, including policymakers, academic authorities, university managers, students, teachers, and researchers. The primary contribution of this work lies in its comprehensive and structured vision of the model, which facilitates the study of inter-level relationships and the dynamic mapping of its various components.

KEYWORDS
genAI, education, governance model, bibliometrics, content analysis, conceptual structure mapping, living genAI governance model

1 Introduction

Artificial Intelligence (AI) is a *concept*, that spans any process that involves a machine acting "intelligent." Intelligence is most often defined as 'human-like' in its ability to make decisions, learn from mistakes, generate insights, or understand language (Gordon et al., 2024).

Artificial Intelligence (AI) has significantly evolved since its inception in the 1950s. Kaplan and Haenlein (2019) identified three broad categories of AI based on the complexity and extent of machine intelligence: Artificial Narrow Intelligence (ANI), Artificial General

Intelligence (AGI), and Artificial Super Intelligence (ASI). Figure 1 outlines the three evolutionary stages of AI (Figure 1). First-generation AI applications, which apply AI solely to specific tasks and are commonly known as artificial narrow intelligence (ANI), are widely used. One example is Facebook which recognizes faces in images and tags users. The second generation, Artificial General Intelligence (AGI), is capable of reasoning, planning, and solving problems independently, even for tasks beyond their initial design. The third generation, Artificial Superintelligence (ASI), would have the capability to address complex problems, make decisions, and potentially possess consciousness and emotions when interacting with humans (Alam and Hasan, 2024; Kaplan and Haenlein, 2019).

The evolution of AI reflects a growing trajectory of human control and transparency in machine behavior. In the first generation, often referred to as Artificial Narrow Intelligence (ANI), AI systems were designed to perform specific tasks through tightly constrained algorithms. These applications, such as Facebook's facial recognition system that identifies and tags users in photos, operate within clearly defined boundaries set by human programmers.

The second generation, known as Artificial General Intelligence (AGI), represents a shift toward systems capable of flexible reasoning, autonomous planning, and adaptive problem-solving. While these systems can handle tasks beyond their initial programing, efforts increasingly focus on ensuring that their decision-making processes remain understandable and aligned with human values.

Looking ahead, the third generation—Artificial Superintelligence (ASI) envisions AI systems that could surpass human cognitive capabilities. In this stage, the emphasis is on building frameworks for explainability, ethical alignment, and emotional intelligence to ensure that such powerful systems remain transparent and responsive to human intent, rather than operating as opaque black boxes. Under the AI umbrella, the rise of GenAI. In November 2022, some tools, like ChatGPT, became publicly accessible for society and particularly in Education (Adiguzel et al., 2023). The intense use of GenAI at Higher Education level has several impacts (Lin, 2023; Arowosegbe et al., 2024; Castillo-Martínez et al., 2024). GenAI can be used in Education across a broad spectrum of behaviors, from a means of learning (ElSayary, 2023) to a means of fraud and cheating (Choi et al., 2023).

In research context, there are opportunities (Alli et al., 2024) but also the risk of scientific monocultures, where certain methods and viewpoints dominate. This can reduce innovation and increase vulnerability to errors, leading to a more hegemonic and static science (Messeri and Crockett, 2024).

Some empirical evidence concerning the impact of generative AI in education raises some questions, such as, what are the implications of generative AI for teaching and learning or for student agency, critical thinking, or creativity? A growing body of literature has already explored these dimensions (see, for example Bond et al., 2024; Darvishi et al., 2024; Lo, 2023; Barana et al., 2023; Aditya et al., 2024; Paiva et al., 2025).

This article is structured as follows: introduction, methodology, results, model, conclusions, and future research.

2 Methodology

Literature Review is a critical, analytical view of existing research on a particular topic. There are a variety of review types (Grant and Booth, 2009). Given we aimed to provide a transversal ontological overview of GenAI use in Education, as a solid structure to build a GenAI Governance Model, we adopted a scoping review procedure (Arksey and O'Malley, 2005; Peters et al., 2022). A scoping review is a type of knowledge synthesis that uses an iterative approach to identify and synthesize an existing or emerging body of literature; this kind of review is useful to map the literature on evolving or emerging topics and to identify gaps.

Regardless of the approach and type of literature selected, the fundamental steps and critical decisions involved in conducting a literature review can be categorized into four phases: (1) Planning the review, (2) Conducting the review, (3) Analyzing the findings, and (4) Writing up the review.

The study was conducted within the lens of quantitative and qualitative paradigms, exploring the potentials of their integration (Costa et al., 2023). The main steps followed are research design, data collection, and data analysis (research field overview, conceptual structure mapping, and content analysis).

2.1 Research design

The research design or planning stage is an important time investment. During this stage research team has an interaction to clearly define the scope, the research question and objective(s). In this scope literature review, we agree that scope lies at the intersection of three issues (Figure 2). The topic area is "generative artificial intelligence", the context is education and educational research, and our approach is governance. Governance is the structure of relationships that bring about organizational coherence, authorize policies, plans with decisions, and account for their probity, responsiveness and cost-effectiveness (Gallagher, 2001).

The formulation of questions is one of the main premises of critical and reflective thinking (Stern et al., 2014). Building questions can be supported by standardized structures/acronyms, such as PICO (Population, Intervention, Comparison, and Outcome), that can impact research strategy. The PICO model is the most widely used in the construction of research questions, not only in evidence-based medicine but also in other health science disciplines; variations of the PICO model and specific adaptations have emerged. For the Social Science, the Spider (Sample, Phenomenon of Interest, Design, Evaluation, Research type) model can be used to improve research quality (Methley et al., 2014; Booth, 2001; Cooke et al., 2012; Mohamed et al., 2021).

Given GenAI's multifaceted role in education and research, we outline two main items for the literature review protocol:

1. The literature review question is, how does the interaction with GenAI develop on the various ontological levels in educational research?
2. The main objective is to build a GenAI Governance model in Education Research based on the three levels: macro, meso, and micro.

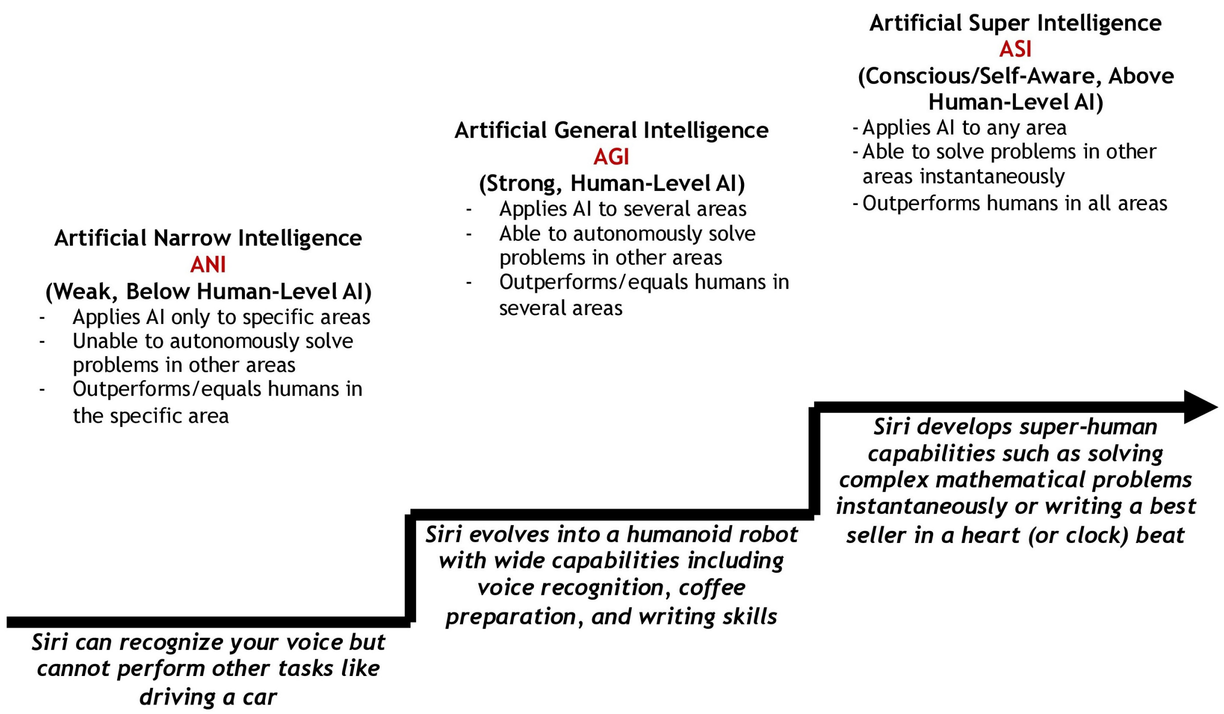

FIGURE 1
Stages of artificial intelligence (Kaplan and Haenlein, 2019).

2.2 Data collection

The bibliographic search was done in the *WoS* database in 2025 (Feb 28). The keywords used to search include "generative artificial intelligence" and its synonyms or acronyms, and "governance" or related issues. We limited to *WoS* categories: Education Educational Research or Education Scientific Disciplines. The result Search string is "generative artificial intelligence" or "GenAI" or "Generative AI" or "ChatGPT" (Topic) and governance or gover* or "AI Governance" or "AI Policy" or "Responsible AI" or "AI Regulation" or ethics (Topic) and Education Educational Research or Education Scientific Disciplines (Web of Science Categories). This search resulted in a total of 195 documents, whose primary information about data is shown in Table 1.

Six review articles were identified that can be considered as starting points for future studies in some subtopics: Use of AI Chatbots among Students (Schei et al., 2024); AI Ethics in Medical Education (Weidener and Fischer, 2023); basic concepts of AI and Gen-AI (Kalota, 2024); Legal and ethical considerations (Cornwall et al., 2025), Teacher Professional Development (Brandao et al., 2024), and AI Chatbot authorship from the perspective of copyright law (Lee, 2023).

The screening process applied inclusion and exclusion criteria to select articles for the sample. Inclusion criteria select relevant articles for analysis; exclusion criteria remove unrelated ones. We decided to include all document types published in peer-reviewed journals; we also considered proceedings papers, because these publications reveal the research front in this emerging theme. After removing one duplicate, 194 articles were selected for bibliometric analysis.

FIGURE 2
Topic area.

2.3 Data analysis

The analysis is done with two techniques: bibliometrics and content analysis. To produce bibliometric maps, it was chosen two open-source software. *VOSviewer* gives an overview of our research field (Generative AI Governance in Educational Research), and *Bibliometrix* reveals the conceptual structure of that field.

VOSviewer is a software tool for creating and visualizing maps based on network data, particularly bibliometric networks (van Eck and Waltman, 2020). Constructing a map involves three

TABLE 1 Main information about the data.

Description	Results
Timespan	2023:2025
Sources (Journals, Books, etc.)	117
Documents	195
Annual growth rate%	−17.28
Document average age	1.06
Average citations per doc	11.15
References	1
Document contents	
Keywords plus (ID)	117
Author's keywords (DE)	637
Author's	
Author's	664
Author's of single-authored docs	35
Author's collaboration	
Single-authored docs	39
Co-author's per doc	3.51
International co-authorships%	27.69
Document types	
Article	131
Article; early access	31
Editorial material	5
Editorial material; early access	1
Proceedings paper	20
Review	6
Review; early access	1

steps: a similarity matrix is calculated based on the co-occurrence matrix, a map is constructed by applying the VOS mapping technique to the similarity matrix, and finally the map is applied three transformations (translated, rotated, and reflected) to ensure consistent results. This process ensures that the distance between two items reflects the strength of the relation between the items (van Eck and Waltman, 2010). By default, *VOSViewer* assigns each term (e.g., author keywords) exactly to one cluster. The cluster technique used is discussed in Waltman et al. (2010).

To analyze the conceptual structure we use *Bibliometrix* which offers functionality to generate a thematic map (Aria and Cuccurullo, 2017; Cobo et al., 2011, Callon et al., 1991) with the following options: Keyword Plus, author keywords, unigrams, bigrams, and trigrams from titles or abstracts. The thematic map is predicated on the assumption that keywords represent concepts, the density and centrality of which can be utilized for categorization and conceptual mapping in a two-dimensional diagram. The thematic map functionality was based on the concepts of strategic diagrams. The steps required to reveal the conceptual structure of a scientific field are succinctly illustrated in Figure 3.

Detected communities can be represented by degrees of relevance (Callon's centrality) and of development (Callon's density) (Callon et al., 1991). Callon's centrality (CC) measures the intensity of links between a given community and others, representable as a measure of a theme's significance across the entire corpus. Callon's density (CD) gauges the internal strength of the community, representable as a measure of the theme's development. Utilizing these two measures, research themes can be mapped onto a two-dimensional strategic diagram with four quadrants: (1) upper right quadrant: motor themes; (2) lower right quadrant: basic themes; (3) lower left quadrant: emerging or disappearing themes; (4) upper left quadrant: niche or highly specialized.

3 Results

The first results came from the utilization of *VOSviewer*, which gives an expansive landscape of artificial intelligence (AI) and generative artificial intelligence (GenAI), limited to education research. Next, we present a conceptual map, using *Bibliometrix*, to capture relevant and deep information (Moresi and Pinho, 2023; Costa et al., 2023).

To perform data cleaning, we made two files to merge terms, for example, synonyms (AI and artificial intelligence) and singular/plural (chatbot, chatbots). For *VOSviewer* it was a Thesaurus file and for *Bibliometrix* a synonyms file.

3.1 Research field overview

The analysis with *VOSViewer* gives an overview of the research field and reveals the most used terms by authors (van Eck and Waltman, 2010). The authors' keywords were restricted to at least two occurrences, which yielded a total of 96 keywords (out of 625 total author keywords). From those 96 keywords, *VOSViewer* calculated the total link strength of the co-occurrence links with other keywords. We present the network with 50 keywords with the highest total links (Figure 4). In the Figure, the size of a bubble is directly proportional to the number of publications that contain the keyword analyzed. Usually, terms co-occurring often tend to be located close to each other.

In this network, the 50 author's keywords are divided into eight clusters. The most frequent keywords are AI (106), ChatGPT (100) and GenAI (58) and they are in the center of the map. It seems that clusters 1, 4, and 7 are more linked to Ethics, clusters 2, 3, 6 to Education, and cluster 5 to both.

In cluster 1 (red) there is the connection between Gen AI (58) and Ethics (43). In cluster 4 (yellow) there are two areas, Medical and Ethics in AI, with terms: academic integrity (18), medical education (13), machine learning (6), and OpenAI (6). In cluster 7 (orange), the focus is on plagiarism (5) and student perceptions (5).

The cluster 2 (green) shows terms like higher education, K-2 (elementary and secondary education), teaching, and learning, thus is related to Levels in Educations. In the cluster 3 (blue) the keywords are related to Education Technology: chatbot (18), education technology (9), and GPT (4). The cluster 6 (light blue) display terms related to practical education: education (26), assessment (4), pedagogy (3). The cluster 5 (purple) the focus is on AI (106)/ChatGPT (100), and its relationship with Ethics (AI ethics—10), and Education (AI education—7).

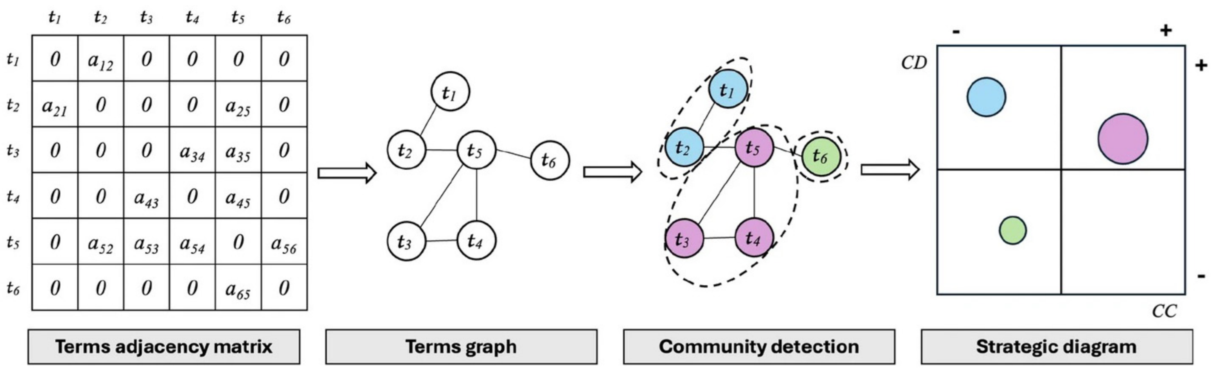

FIGURE 3
Analytical strategy for detecting and mapping the conceptual structure (Aria et al., 2024).

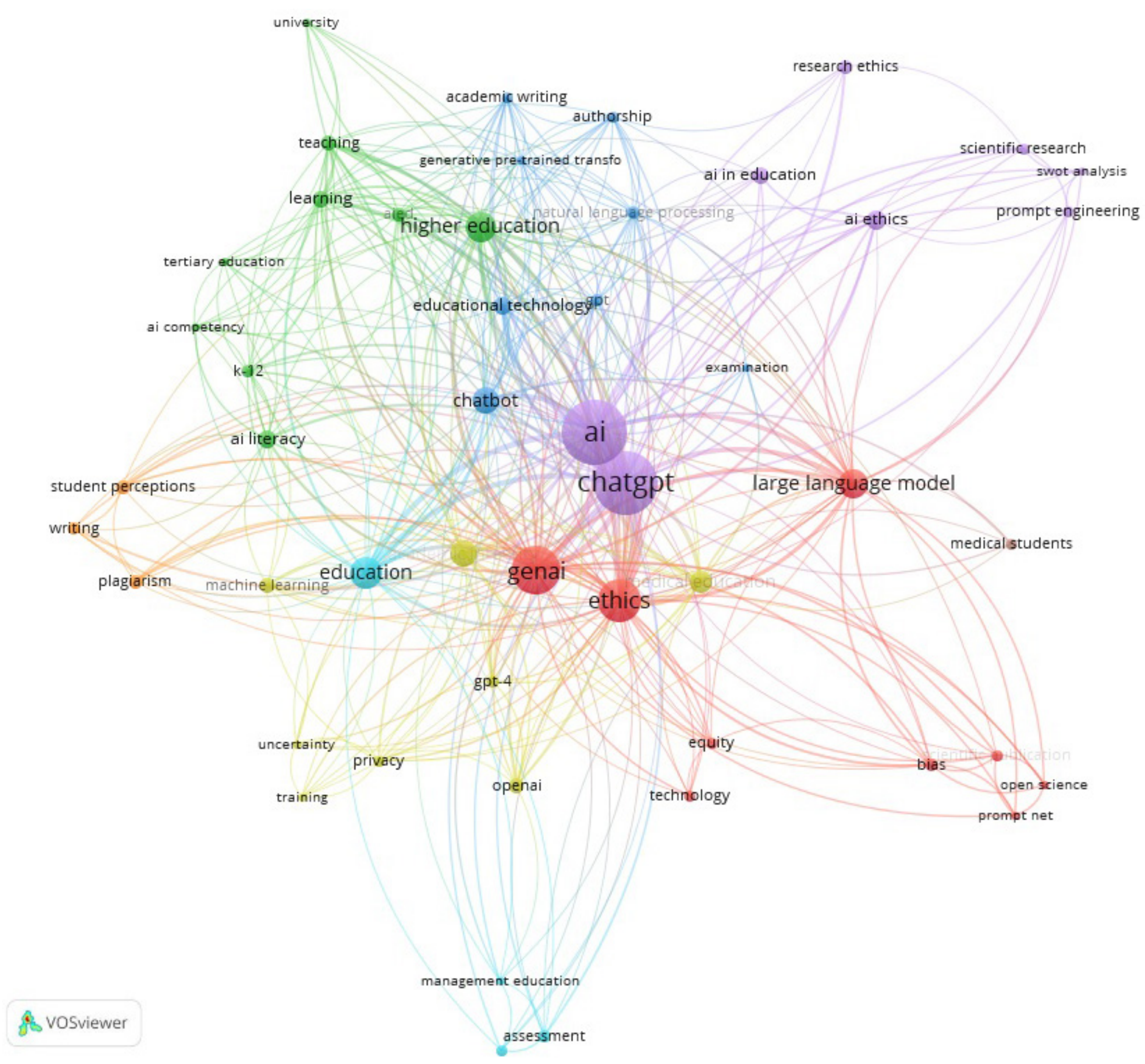

FIGURE 4
Authors' keywords co-occurrence.

This overview shows how this topic is multidisciplinary and complex; next, we use *Bibliometrix* to *deep* understanding how themes are organized and have a thematic big picture.

3.2 Conceptual structure mapping

We use *Bibliometrix* to build a thematic map (Strategic diagram) from 194 documents retrieved in the *WoS* database (min cluster frequency (per thousand docs): 20; clustering algorithm: Leading Eigenvalues). Thematic map is display in Figure 5.

The R-Bibliometrix package allows the co-occurrence network of keywords and their relationship with the thematic map to be obtained. The words can be extracted from the following metadata: indexing keywords, author's keywords, unigrams, bigrams or trigrams of titles or abstracts. In this work, we used the author's keywords. The words represent concepts whose density and centrality can be used in categorization and conceptual mapping in a two-dimensional diagram. The detected communities can be represented by two measures: the degree of relevance (Callon centrality) and the degree of development (Callon density) (Callon et al., 1991). This thematic map define four quadrant; based on Callon et al. (1991) and Aria et al. (2022), a brief description is carried out of each quadrant where we can observe the localization of the themes (see Figure 5).

The clusters/themes in Basic and Motor quadrants have high centrality. These clusters are central to the general network, so they are relevant. The difference between the quadrants is the density. In the Basic quadrant, the internal links density is relatively low, the two clusters/themes (cluster 1—AI; cluster 6—chatbot) are basic and transversal to the research area. In the Motor quadrant the density is high, so the two clusters that belong to this quadrant, Higher education (cluster 7) and Large Language Model (cluster 4), are core themes and well-developed. Notice that GenAI cluster/theme is located on the border between the motor and basic theme quadrants; we can classify them as Basic/Motor frontier.

The clusters in the other quadrants (Emergent or Declining and Niche) are not central to the research area. In the Emergent or Declining quadrant, the clusters have low density, so they have low relevance and development. They are on the margins of the network. We consider that AI ethics (cluster 9) and Education (cluster 8) are in the initial stages of development (emerging issues) because is very recent the field under study. In the Niche quadrant, the clusters Research ethics (5), Medical education (3), and Skills (10) are also peripheral but have high internal density. Those clusters can be classified as specializations because of their weak interaction with other clusters while being well-developed. Cluster 11 (AI literacy) falls within the Basic/Emerging frontier.

3.3 Content analysis

The results of the bibliometric analysis allow us to proceed to a more in-depth analysis. At this stage, we start by presenting one table for each quadrant (Basic, Motor, Emerging, Niche) with the respective clusters, the frequency of author keywords, and examples of publications. Two clusters are on the frontier between one quadrant and another, so we had to present two more tables (Basic/Motor frontier and Basic/Emerging frontier). The choice of these publications results from reading the title and abstract of each of the 194 publications. Following these procedures allowed an organized reading of each of the selected publications, but with interconnection and coherence. Thus, the complexity of the theme acquires an internal organization that facilitates understanding and reflection.

We used computer-aided text analysis (CATA) tools to organize and manage data, code bibliographic categories, and analyze the content of key publications (Costa and Amado, 2018). Defining categories is an essential stage in content analysis (Saldaña, 2021; Krippendorf, 1980; Neuendorf, 2017). Categories can be created by reading the data and/or *a priori* reading (deductive model and the open/inductive model). The method for building the category system, including main categories and subcategories, combines both inductive and deductive approaches. We began by considering Category1: ontological levels, with 3 subcategories: Macro, Meso, and Micro.

Ontological levels refer to different layers of reality or existence, often organized hierarchically based on their complexity, dependence, or fundamentality. The concept is used in philosophy (especially metaphysics), systems theory, and some areas of science to explain how different kinds of things exist or relate to one another (Tahko, 2021).

We can organize publications on an ontological level and classify them in those levels; this close approach is deductive. Classifications allow to assign a "descriptive label" to an entire document, such as an article. But, when we read each article, new categories may emerge that were not foreseen in the theory, such as GenAi Literacy (Annapureddy et al., 2024) or explainable AI (Sharma et al., 2024); in this case we are taking an open or inductive approach.

The quality assessment of these publications is structured according to how they can contribute to answering our review question and how they can structure the construction of the GenAI governance model. We read those publications and present the most relevant content of each. This presentation has two components: six tables and the main ideas captured from selected publications.

3.3.1 Basic quadrant publications

In the Basic quadrant, there are two clusters AI and Chatbot (Table 2). These concepts/topics are common for the scientific field and pertain to general issues transversal to its different research areas or themes (Aria et al., 2024).

The main cluster is Artificial Intelligent (AI) positioned in the basic quadrant. The analysis of some articles from the cluster reveals the various facets of in AI and Education space, ranging from macro (Bai et al., 2024), meso (Spivakovsky et al., 2023), and micro (Kamoun et al., 2024) perspectives.

Bai et al. (2024) look at artificial intelligence in education (AIEd) by considering General Data Protection Regulation (GDPR) and the use of ChatGPT. They notice the need for multi-stakeholder dialogue and collaboration between legal scholars, computer scientists and AI ethicists, educators and students.

At Meso level (institutional level), an article summarizes and systematize the experience of forming institutional policies for the application of artificial intelligence in learning, teaching, and research in higher education institutions (Spivakovsky et al., 2023).

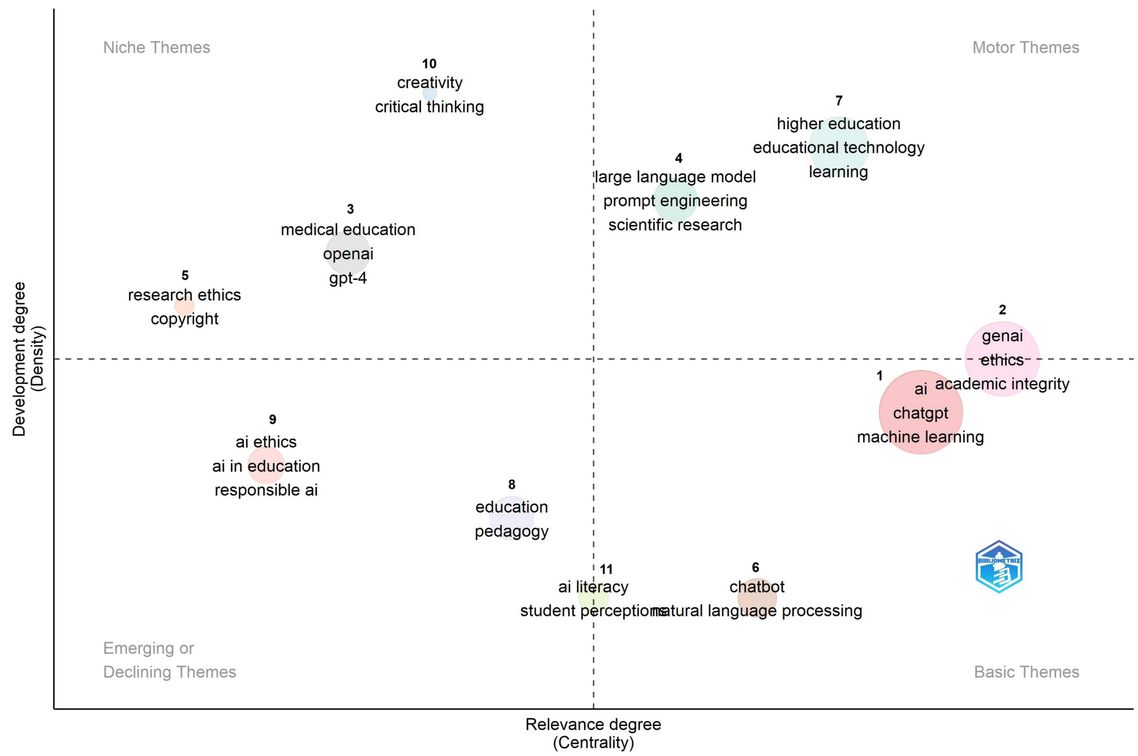

FIGURE 5
Thematic map and four quadrants.

TABLE 2 Basic quadrant.

Quadrant	Cluster	Keywords	Freq.	Examples of publications
BASIC				
	1 - AI	AI	106	
		Chatgpt	100	(Spivakovsky et al., 2023)
		Machine learning	6	(Bai et al., 2024)
		writing	4	(Belda-Medina and Kokosková, 2024)
		Assessment	4	(Chan, 2023)
		Knowledge	3	(Kamoun et al., 2024)
		Medical students	3	
	6- Chatbot	Chatbot	18	(Barambones et al., 2024)
		Natural language processing	4	(Egara and Mosimege, 2024) (Hu, 2024)

They provide some recommendations to empower all participants in the implementation of those tools. An empirical study, proposed AI Ecological Education Policy Framework for university teaching and learning, with three dimensions: Pedagogical, Governance, and Operational AI Policy Framework (Chan, 2023). Focus on the University context.

At Micro level some articles focus on skills (Belda-Medina and Kokosková, 2024), while others in attitudes and perceptions of students and teachers using Technology Acceptance Model (TAM) to evaluate ChatGPT use (Kamoun et al., 2024).

Regarding Cluster Chatbot, we identified several relevant articles. An exploratory study on the Personas technique, addressing the validity and believability of interviews designed by human-computer interaction, gives some useful insights (Barambones et al., 2024). Human-computer interaction trainers can use ChatGPT to help their students master persona creation skills before working with real users in real-world scenarios for the first time. Concerns about repetitive responses and low variability highlight the need for better prompt design research to generate diverse and well-developed replies.

Teachers who use ChatGPT report positive outcomes, such as improved teaching effectiveness, increased student engagement, and better understanding of complex concepts, but the overall perceptions of its impact are moderate. The main challenges related to technical adaptability, curriculum alignment, and the need for customization to accommodate diverse learning styles (Egara and Mosimege, 2024).

Ethical decision-making is challenging for every student. Hu (2024) proposes a human-machine learning framework that helps students to perform values clarification in the context of moral dilemmas and tests it with 70 university students (divided into an experimental group and a control group). The results revealed that the generative-AI-chatbot-assisted VCE (GAIC-VCE) system effectively improved the experimental-group students' ethical self-efficacy and ethical decision-making confidence and reduced their decisional conflicts.

3.3.2 Motor quadrant publications

In this quadrant, we can find some structural clusters: Higher education (cluster 7) and Large language model (cluster 4), with high centrality and density; in some sense they constitute the file's core (Table 3). They are motor themes, well-developed and relevant for structuring the conceptual framework of the domain (Aria et al., 2022) because the research period for these topics is longer compared with themes like GenAI or ChatGPT within the context of our scope, the intersection of three issues; generative artificial intelligence, education and educational research, and governance.

3.3.2.1 C7-Higher education

Within the Motor quadrant, in the cluster Higher Education, there is an article at the Macro level that examines GPT technologies within the academic ecosystem (Cai et al., 2024). Viewing academia as an ecosystem positions governance to integrate GPT technologies, complement educational goals, help students use these tools effectively, and encourage teachers to update evaluation methods and guide AI-assisted learning. Governance must ensure equity and access, as disparities in AI tool availability can create educational inequalities. Policies should ensure fair access to technologies and responsibly scale their use in various educational settings. Note that algorithmic models and data are often controlled by large corporations, while regulations lag technological advancements, challenging corporate ethics and third-party oversight. Additionally, excessive reliance on automated tools may diminish operator skills, which is also a concern.

One study evaluates the impact of ChatGPT, on students' learning in the Social Education degree, focusing on Transversal competencies (Rivera and León, 2024). The researchers used a mixed-methods approach, which incorporated both quantitative and qualitative methodologies. The instruments utilized included the CrossCutting Skills Assessment Questionnaire for Degrees (CECTGRA), a ChatGPT usage scale, an open-ended questionnaire, and an assessment rubric (Rivera and León, 2024).

With a provocative title, "GenAI et al.: Cocreation, Authorship, Ownership, Academic Ethics and Integrity in a Time of Generative AI" (Bozkurt, 2024a); this paper proposes the Academic Integrity and Transparency in AI-assisted Research and Specification (aiTARAS) Framework for acknowledging and disclosing the use of generative AI in scholarly writing. The purpose is to uphold academic integrity, transparency, and ethical standards.

We present three examples of publications for the cluster Large Language Model, related to scientific research: Alfarraj and Wardat (2024), Giray et al. (2024), and März et al. (2024). A SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis was conducted to evaluate the benefits and drawbacks of leveraging ChatGPT in scientific research (Alfarraj and Wardat, 2024). The findings indicate potential advantages such as evaluation and assessment, individualized and continuous learning, linguistic competence, comprehensive knowledge, increased accessibility, and efficient information retrieval. However, notable shortcomings include the absence of contextual knowledge, outcome and information bias, and limited advanced cognitive ability.

The analysis also highlights several threats: plagiarism, academic dishonesty, ethical challenges, as well as cybersecurity and privacy concerns. Furthermore, the data suggests various prospects, such as creating interactive environments, enhancing teaching and learning, contributing to literature, collaborative brainstorming, language translation, and knowledge sharing. It is emphasized that caution is necessary when employing artificial intelligence applications, as the potential of ChatGPT to enhance scientific research depends on how researchers utilise its strengths and opportunities while mitigating its weaknesses and threats (Alfarraj and Wardat, 2024).

With a similar approach, other authors perform SWOT analysis using ChatGPT in Scientific Research (Giray et al., 2024). The analysis examines the model's strengths, which include its extensive knowledge base, language proficiency, information retrieval capabilities, and ability for continuous learning. It also identifies the weaknesses, such as limited contextual understanding, potential reliance on training data, challenges in verifying information, and restricted critical thinking abilities. Opportunities presented by the model involve facilitating literature reviews, encouraging collaborative brainstorming, enabling language translation and interpretation, and enhancing knowledge dissemination. However, there are various threats, including issues related to plagiarism, ethical concerns, the spread of misinformation, and the potential impact on higher-order cognitive thinking. These diverse aspects require thorough consideration. Large language models in examination and theses contexts must be defined where use is legitimate or prohibited (März et al., 2024).

3.3.3 Basic/motor frontier publications

Cluster 2 (GenAI) is located between the Basic/Motor quadrants, which means the GenAI theme is naturally less dense than the two clusters located in the motor quadrant (Higher education and Large language model) since this theme is more recent (Table 4).

At Macro level, some publications remember that the vast amount of information-generative AI and its software is trained on and created by people and inherently reflects the societal biases present in the training material and reflected on outputs such as racial and socioeconomic stereotypes that have an impact on Education (Ramos and Wilson-Kennedy, 2024). Notice that GenAI produces outputs and biases that are embedded in the datasets perpetuate and amplify existing social inequalities. So instead of learning, we have a dissemination of information that is contrary to training based on Human Rights.

At Meso level, in the university context and around ethics of academic integrity, some authors defend rather than make the argument that cheating is morally wrong; the focus must be on the idea that cheating is detrimental to the learning process itself (McIntire et al., 2024).

TABLE 3 Motor quadrant.

Quadrant	Cluster	Keywords	Freq.	Examples of publications
Motor				
	7-Higher Education	Higher education	24	(Cai et al., 2024)
		Educational technology	9	(Rivera and León, 2024)
		Learning	7	(Bozkurt, 2024a)
		Teaching	6	
		aied	5	
		GPT	4	
		K-12	4	
		Academic writing	3	
		Authorship	3	
	4-Large Language Model	Large language model	22	(Alfarraj and Wardat, 2024)
		Prompt engineering	3	(Giray et al., 2024)
		Scientific research	3	(März et al., 2024)

TABLE 4 Basic/motor frontier.

Quadrant	Cluster	Keywords	Freq.	Examples of publications
Basic/Motor				
	2-GenAI	GenAI	58	
		Ethics	46	
		Academic integrity	18	(Ramos and Wilson-Kennedy, 2024)
		Plagiarism	5	(McIntire et al., 2024)
		Bias	4	(Penabad-Camacho et al., 2024)
		Equity	3	
		Scientific publication	3	
		Technology	3	

At Micro level, we choose a publication that provides guiding elements for reporting the use of AI in the activities that make up the scientific publication process (Penabad-Camacho et al., 2024).

3.3.4 Emerging quadrant publications

In emerging quadrant (Table 5) there are two clusters: AI ethics and Education.

For the cluster AI Ethics, we select three publications. At Meso Level, one example of the GenAI impact on national education system is given by an article from Australia (Knight et al., 2023). This article reports on a public inquiry taken by the Federal Government, with a lens on several stakeholder attitudes regarding GenAI. The "how" of developing alignment on many of the identified issues and values that must be at the center are some relevant recommendations.

Perceptions of cheating and learning are crucial for the responsible use of AI (Mah et al., 2024). Teachers and students arrived at similar conclusions about learning with ChatGPT but different conclusions about cheating. This disagreement creates four main tensions: (1) using ChatGPT as a shortcut vs. a scaffold; (2) generating ideas vs. language with ChatGPT; (3) support from ChatGPT vs. other sources; and (4) learning from ChatGPT vs. overall learning. There is also a need to redesign assessments to better align with human creative and critical thinking skills. Administrators should establish consistent policies for responsible AI use, ensuring all stakeholders understand the benefits and risks of developing effective AI literacy.

Educators' beliefs about their alignment with AI ethics were examined through metaphor analysis and probing educators' lived experiences and semi-structured interviews with (Kamali et al., 2024). Findings are relevant and presented through the lens of activity theory (Figure 6). This overview of AI ethics alignment reinforces the need to look at each component from a systemic and governance perspective.

For the cluster Education we found two publications. An empirical study offers valuable insights on ChatGPT among pharmacy students, with implications for responsible AI usage and education (Iwasawa et al., 2023). This student's knowledge and attitudes survey to artificial intelligence (AI) and ChatGPT confirms that educating students on AI fundamentals helps them utilize AI tools like ChatGPT effectively.

A succinct article recommends robust strategies for resolving ethical concerns, such as implementing explicit policies, utilizing sophisticated plagiarism detection technologies, and employing innovative evaluation techniques (Williams, 2024). Authors suggest that educators, AI developers, policymakers, and students can

TABLE 5 Emerging quadrant.

Quadrant	Cluster	Keywords	Freq.	Examples of publications
Emerging				
	9-AI ethics	AI ethics	10	(Knight et al., 2023)
		AI in education	7	(Mah et al., 2024)
		Responsible AI	3	(Kamali et al., 2024)
	8-Education	Education	26	(Iwasawa et al., 2023)
		pedagogy	3	(Williams, 2024)

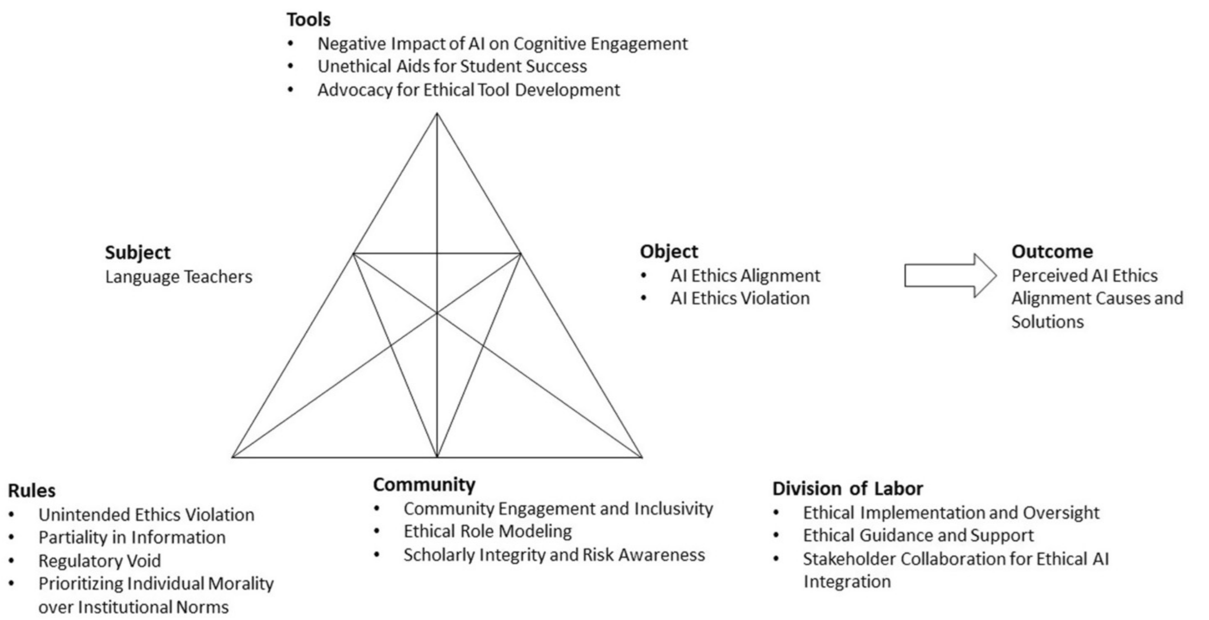

FIGURE 6
Activity theoretic exploration of educators' AI ethics alignment (Kamali et al., 2024).

utilize chatbots to create a more inclusive, empowering, and ethical educational future.

3.3.5 Basic/emerging frontier publications

In the Basic/Emerging frontier (Table 6) there is one important cluster, AI literacy.

AI Literacy Concept is a starting point of a concise article that asks some crucial questions: Why Generative AI Literacy, Why Now and Why it Matters in the Educational Landscape (Bozkurt, 2024b).

An empirical study employed an iterative co-design cycle to discuss and revise the framework for K-12 education throughout four cycles, with the participation of 30 experienced AI teachers from 15 middle schools in Zhang K. et al. (2024). They began by analyzing the definition of AI competency, and the proposed framework comprises five key components: technology, impact, ethics, collaboration, and self-reflection, of a useful review that answers 3 research questions: (1) What is the concept of AI literacy? (2) What are the frameworks and applications of AI literacy? (3) What are future education and content of AI literacy? Those authors also note that the proposed framework has not been empirically tested, and more research is needed to investigate its usefulness in real-world settings.

An empirical article builds a comprehensive framework to support artificial intelligence literacy and competency (Chiu et al., 2024).

3.3.6 Niche quadrant publications

In Niche Quadrant (Table 7) some themes are flagged: Medical education, Research ethics, and Skills.

For Cluster Medical Education we select three articles, examples for micro, meso and macro level. At the meso level, GenAI is a rapidly emerging field, with the integration of GenAI into the education ecosystem. This requires continuous effort to identify the necessary stakeholders, their roles, and responsibilities, and to provide standards and guidelines for the effective integration of GenAI into teaching, learning, and research (Shailendra et al., 2024). In this article, proposal 4E framework delineates various phases of adoption and offers a workflow to assist universities in adopting GenAI, enhancing the scholarship of teaching and learning, and assessing its impact on research methodologies. To measure the impact of these changes, the framework also provides an evaluation matrix.

From a Macro level, Medical Education is an innovative space on intense use of AI. Knopp et al. (2023) defend that several stakeholders in health care and medical education must

TABLE 6 Basic/emerging frontier.

Quadrant	Cluster	Keywords	Freq.	Examples of publications
Basic/emerging				
	11-AI literacy	AI literacy	9	(Bozkurt, 2024b)
		Student perceptions	5	(Zhang K. et al., 2024) (Chiu et al., 2024)

TABLE 7 Niche quadrant.

Quadrant	Cluster	Keywords	Freq.	Examples of publications
Niche				
	3-Medical Education	Medical education	13	
		OpenAI	6	(Shailendra et al., 2024)
		GPT-4	4	(Knopp et al., 2023)
		Digital technology	3	(Songkram et al., 2024)
		Privacy	3	
	5-Research Ethics	Research ethics	5	(Chaaban, 2025).
		Copyright	3	(Cornwall et al., 2025) (Skulmowski, 2025)
	10-Skills	Creativity	3	(Urban et al., 2024)
		Critical thinking	3	(Shahzad et al., 2024)
		Student perceptions	5	(Bouchard, 2024)

work together to develop a robust ethical framework, foster interdisciplinary collaboration, invest in education and training, promote transparency and accountability, and continually monitor and evaluate the impact of AI technologies.

At Micro level, researchers can use ChatGPT as a valuable tool, particularly in the initial

stages of research design, data analysis, and literature synthesis, by taking into account limitations of ChatGPT in academic research (Songkram et al., 2024). In this micro context, some future research should explore several key areas as follows: (1) Longitudinal studies: Investigate the long-term impact of using AI tools like ChatGPT on research quality, innovation, and academic integrity. (2) Cross-disciplinary application: Examine how ChatGPT's potential varies across different academic disciplines and research methodologies. (3) Comparative analysis: Conduct systematic comparisons between AI-assisted and traditional research methods to quantify differences in efficiency, accuracy, and innovation. (4) Ethical frameworks: Develop and test ethical frameworks specifically designed for AI-assisted research in educational contexts. (5) Methodological advancements: Explore ways to enhance ChatGPT's context-specific understanding and its ability to provide more transparent reasoning for its outputs.

For the cluster Research Ethics we found three publications: Chaaban (2025), Cornwall et al. (2025), and Skulmowski (2025). From graduate students' experiences (as novice researchers) with AI ethics in the context of an educational research methodology course, Chaaban (2025) wrote a conceptual paper that outlines research avenues on how to better support graduate students in developing AI ethics through pedagogy and policy.

Copyright infringement and visual plagiarism are important issues in anatomical and health sciences due to their impact on the integrity of scientific publishing and academia (Cornwall et al., 2025).

This article gives some good legal and ethical practice considerations, guiding to maintain and promote legal and ethical standards in the academic and publishing communities.

GenAI is a significant research trend in education and psychology. However, obtaining empirical results involves risks to the cognitive and socio-emotional development of children and adolescents. Biomedical sciences use risk-reduction measures like dose escalation and stopping rules. Additionally, dynamic informed consent can enhance transparency (Skulmowski, 2025).

In this Skills Cluster, some issues take relevance like creativity and critical thinking. One article defends ChatGPT improves creative problem-solving performance in university students (Urban et al., 2024). This study found that student collaboration with ChatGPT improved creative problem-solving and self-efficacy. However, it also highlighted the need for educators and students to use valid monitoring cues and metacognitive skills during tasks. While ChatGPT may enhance divergent thinking, its ease of task resolution does not guarantee more useful or original solutions.

A study examines generative AI-based technologies' impact on learning performance through self-efficacy, fairness & ethics, creativity, and trust in China's higher education context (Shahzad et al., 2024). Additionally, it examines the moderating role of trust among these variables.

An article from Japan discusses ChatGPT's impact on the separation between knowledge and the knower, offering important insights (Bouchard, 2024). Teachers should go beyond understanding technology and deepen their knowledge of educational philosophy. They can discuss the ethical implications of ChatGPT with students, clarifying core educational principles and helping them become more responsible learners. Teachers can ensure students understand specific words and ask them to summarize meanings and intentions in paragraphs. Students should explain how they gathered information, justify citation choices, and broadly explain their learning from extensive reading. It is essential to prioritize face-to-face interactions, focusing on developing dialectical and rhetorical skills.

4 Living genai governance model

We advocate that a Governance approach is essential to understand and develop a comprehensive GenAI governance model for education research, by considering frameworks and components that operate at macro, meso, and micro levels, building to ensure a critical, responsible, and ethical use of GenAI (Pinho, 2021; Batista et al., 2024; Pinho et al., 2019; Moresi et al., 2020).

4.1 Building the model

This GenAI Governance model must align with those levels and have a dynamic and living process (UNESCO, 2023; OECD, 2024). GenAI Governance model must be living because all the components are interconnected and GenAI has a lifecycle nature that evolves in response to users' needs and contextual changes (Mahajan, 2025; Zhang D. et al., 2024). We build a Living GenAI Governance Model as a synthesis and as a product of this scoping review (Figure 7). This is a living model because it requires an adaptive and iterative approach that surpasses traditional static regulatory support in addressing emerging risks and challenges associated with technological development (Taeihagh, 2025).

This model considers multiple stakeholders and actors involved in tasks and processes that need to address ethical, regulatory, and operational challenges. The key factor is the 'scale' or 'granularity' of the analysis, that gives the contextualization where GenAI are used. This is divided into three levels: micro, meso, macro. Micro refers to individual actors or team projects. Macro refers to the system, like Global or Big Regional Geographical scope. Meso occupies the space between, referring to institutional, organizational and communities, like Universities or National Science Funding agencies. This model is a possible representation of a multilevel phenomenon, such as the use of GenAI.

This multi-scalar approach defines social spaces where individual and institutional agents have open possibilities, and causation flows from any of the interacting local, national and global scales. It should be noted that this multi-scalar phenomenon can have a top-down approach, if we consider that there are supranational recommendation documents (macro) that aim to harmonize the responsible use of GenAI, which can be adopted and adapted by national institutions and universities (meso), which in turn will have an impact on individual behavior (micro) where individual and institutional agents have open possibilities and causation flows from any of the interacting local, national and global scales. Another approach can be bottom-up if we consider that the actions of individuals and their interactions are the starting point. Individual attitudes, intentions, motivations, and behaviors are determinants of the results of the use of GenAI, both at the individual level, at the team level, at the network level, and at the institutional level. The various stakeholders are part of this system, but the different spaces or arenas are interconnected. For example, individuals should identify gaps and seek to acquire skills to use GenAI responsibly and effectively, but institutions should publicize their codes of ethics and provide training in the use of GenAI for the various user segments (Gupta et al., 2007; Marginson, 2022; Moresi et al., 2020; Pinho, 2021; Bozkurt, 2024b; Jobin et al., 2019).

The model was created based on the review of existing literature and an organized examination of concepts related to the subject. It is a framework that can be refined in future systematic reviews. Additionally, it will serve as a structured approach for analyzing the articles and documentation. To better clarify the description of this model, in the following section we will apply it to the context of Education Research.

GenAI Governance refers to choosing structures and mechanisms that can influence the processes of build, implement and monitoring GenAI responsible use, looking the interrelation between micro, meso and macro levels, with a Human Centered strategic focus. By taking this holistic approach, we can look at each component but also the integration and alignment of dimensions.

4.2 Applying the model to education research

We choose to apply this governance model to a specific context: Education research. This is a particularly space where knowledge mobilization can ensure that education systems are better equipped to integrate evidence into policy and practice (OECD, 2025).Some authors refer to the need to build a holistic pedagogical framework, from the Human-Centered Artificial Intelligence perspective (Anastasiades et al., 2024).In times of misinformation schizophrenia, where technocracy overthrows politics, the value of research and evidence structured in ethical values and respect for Human Rights becomes even more pressing.

With this background we decide articulate and organize the topic according to the macro, meso and micro levels. At Macro-Level, several international organizations, including the European Union (2024), with Artificial Intelligence Act, the OECD (2023b,c), and UNESCO (2023), make global efforts on responsible development and use of AI or GenAI.

The Harmonized GenAI Framework (H-GenAIGF) identifies four constituents, fifteen processes, and nine principles essential for the global governance of GenAI, emphasizing risk-based approaches for better process coverage (Luna et al., 2025).

In the researcher's specific context, starting with broad international regulations, such as the European Commission's Living guidelines on the responsible use of generative AI in research (Bockting et al., 2023) aligned with the European Code of Conduct (ALLEA, 2023), and then narrowing down to specific national, institutional and local standards to ensure compliant and ethical use.

At Meso-Level we can locate National (Khanal et al., 2024) and Institutional stakeholders (Dai et al., 2024). Institutions must develop flexible and iterative policy frameworks that can adapt

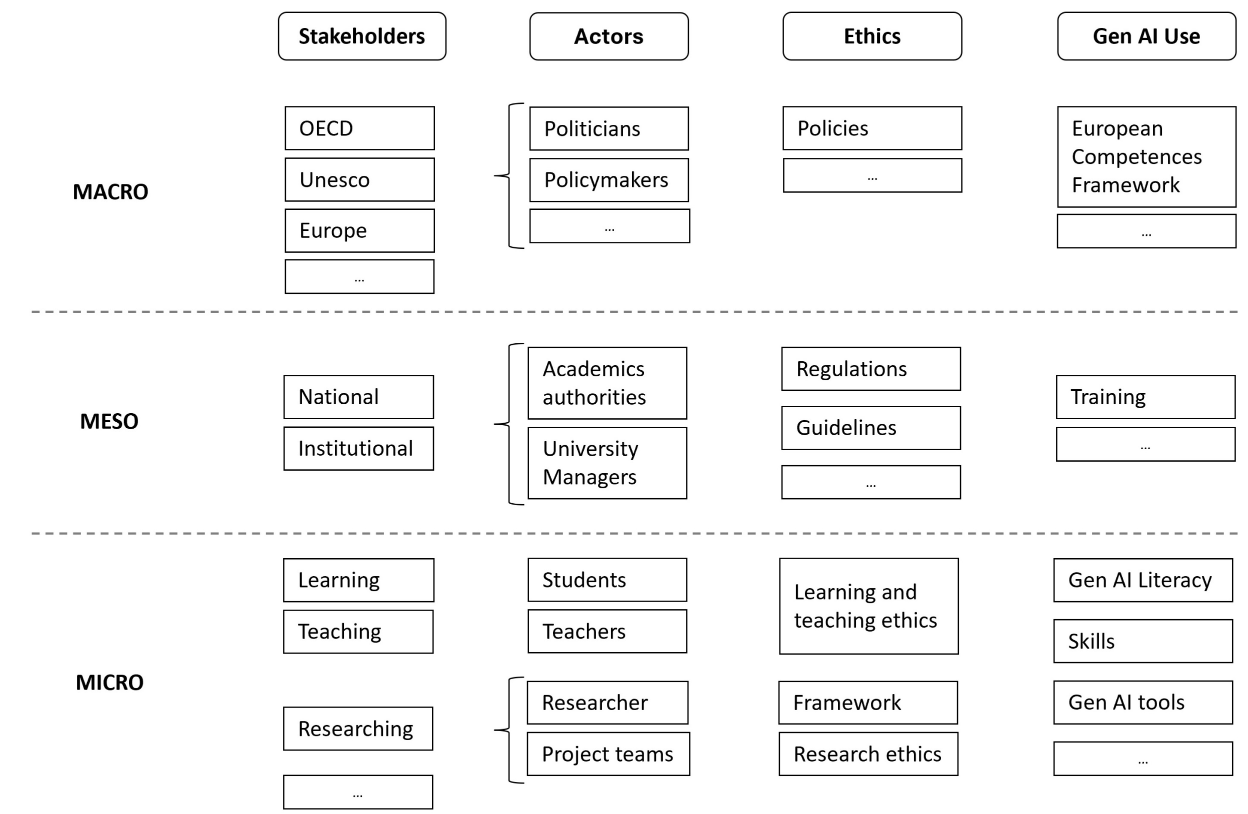

FIGURE 7
Living GenAI governance model.

to the evolving nature of GenAI, ensuring they address ethical concerns such as bias and privacy (Lamberti, 2024). Engagement and continuous training for policymakers and public engagement initiatives are crucial for fostering inclusive AI policymaking. This author advocates for enhanced transparency, accountability mechanisms, public engagement initiatives, and continual adaptive frameworks to address ethical considerations and algorithmic biases in AI applications within policymaking.

Many educational institutions lack specific guidelines for the ethical deployment of AI tools, highlighting the need for overarching policies that address privacy and algorithmic transparency (Ghimire and Edwards, 2024).

A concept introduced and loosely defined as "proficiency in understanding, interacting with, and critically evaluating generative AI technologies", which "entails not only knowing how to use AI-driven tools but also understanding the ethical considerations, biases, and limitations inherent in such systems" (Bozkurt, 2023). GenAI literacy is an important topic (O'Dea et al., 2024; Annapureddy et al., 2025).

The Meso level, institutions includes teachers, students, researchers, and other stakeholders who need to identify the main skills and competencies that they must acquire by formal training or self-training, in university space in the presence of GenAI (OECD, 2023a; Chan, 2023).

Emphasizing interpretability and sustainability in AI applications, at the micro level can help mitigate risks associated with GenAI use in education (Chan and Tsi, 2024; Lamberti, 2024). At Micro-Level, at Research context, the focus is Responsible Use of GenAI (Smith et al., 2024). In the GenAi era, possessing a diverse set of skills is highly advantageous for researchers (European, Directorate-General for, and Innovation et al., 2022). ResearchComp can serve as a starting point to identify and promote research-specific skills, as well as transversal skills that enhance quality research, by offering training and learning opportunities (European Union, 2024). Skills or competencies are strong themes for exploring effectively GenAI (Borneo et al., 2025; Costa et al., 2024).

At the micro level, individual initiatives aimed at developing skills in critical evaluation and responsible use of generative AI technologies are integral to bridging gaps in understanding. Researchers, educators, and students are encouraged to cultivate GenAI literacy, which extends beyond basic operation to encompass ethical considerations, bias recognition, and system limitations. This literacy serves as a foundation for both individual agency and collective innovation, ensuring that these tools are wielded in ways that align with broader educational and ethical goals.

At the micro level, there is literature about perceptions about the use of GenAI. The Dunning-Kruger Effect is a cognitive bias where individuals with limited knowledge or skill overestimate their competence (Figure 8). This overestimation arises because their lack of knowledge prevents them from understanding it. As people improve competence and skill, they

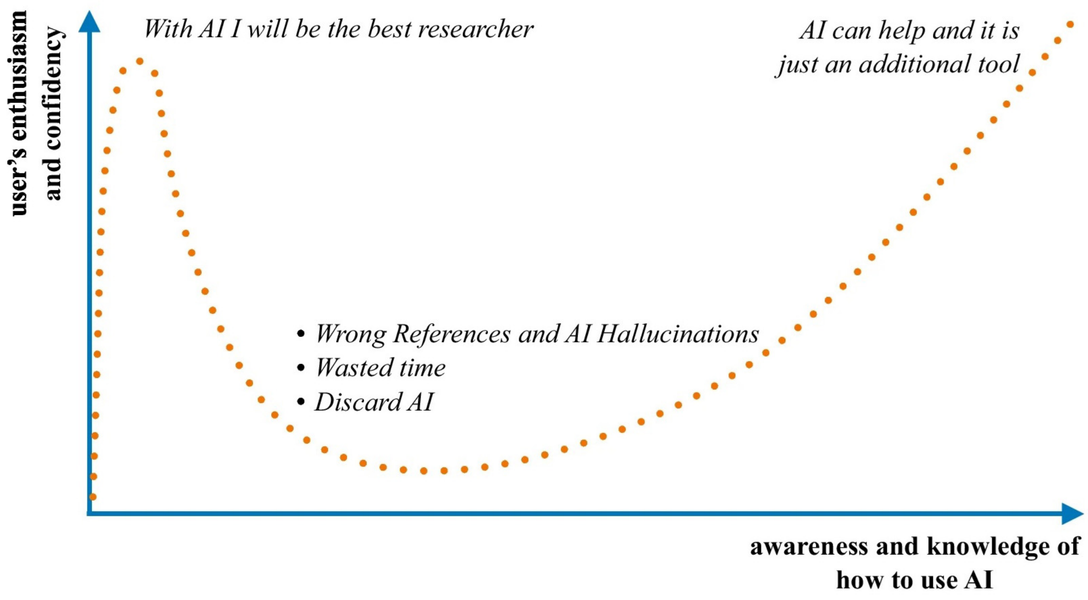

FIGURE 8
Dunning-kruger effect. Source: Salvagno et al. (2023).

develop an understanding of how much they don't know. As such, confidence decreases and then increases as skill and awareness are gained (Kruger and Dunning, 1999). An author focus on negative effects of GenAI on researchers, such as on skill erosion (Giray et al., 2024). A collaborative auto-ethnography explored a non-technology lecturer's first encounter with GenAI, analyzed through the 2023 Gartner Hype Cycle for Emerging Technologies (King and Prasetyo, 2023). A revised Dunning-Kruger effect was applied to using ChatGPT or other Artificial Intelligence (AI) in scientific writing (Salvagno et al., 2023). Initially, excessive confidence and enthusiasm for this tool's potential may lead to the belief that producing papers and publishing can be accomplished quickly and effortlessly. Over time, as the limitations and risks of ChatGPT and other AI technologies are understood, along with the complexity of their operation requiring specific prompts, enthusiasm and confidence may wane. With increased awareness, ChatGPT and other AIs can become effective and supportive tools in scientific writing, akin to computers and internet search engines, ultimately leading to conscious and correct usage (Salvagno et al., 2023).

5 Conclusion and future research

This scoping review has made a substantial contribution to the emerging field of GenAI in educational research by proposing a Living GenAI Governance Model that integrates macro-, meso-, and micro-level considerations. Theoretically, it bridges ontological levels with practical governance, offering a multi-scalar perspective on the ethical, responsible, and context-sensitive use of GenAI. Methodologically, the review demonstrates the value of integrating quantitative and qualitative bibliometric analyses, combining tools such as *VOSviewer* and *Bibliometrix* to map the conceptual landscape and identify key thematic areas. After mapping the research landscape, a content analysis was carried out, with *webQDA* support, that facilitates having a profound understanding of this complex issue.

The proposed governance model is dynamic and adaptable, recognizing that GenAI technologies—and their implications—evolve rapidly. This "living" characteristic is essential for addressing ethical dilemmas, institutional readiness, stakeholder literacy, and systemic integration challenges. The model's capacity to accommodate both top-down policy interventions and bottom-up user agency strengthens its applicability in varied educational contexts.

Importantly, this work underscores the need for GenAI governance to move beyond static compliance toward reflexive, iterative structures that can respond to technological advances, cultural diversity, and pedagogical shifts. This provides a valuable foundation for both theoretical advancement and institutional policy-making in educational research.

Practically, the proposed governance model serves as a dynamic resource for policymakers, academic leaders, educators, and researchers, supporting the responsible and ethical implementation of GenAI to enhance academic and research practices. These contributions collectively advance both theoretical and practical discourse on GenAI in education and establish a foundation for future research and policy development in this rapidly evolving area.

Governance and interdisciplinary AI must be based on responsible development and use of AI (Baum et al., 2023). The authors highlight the potential issue of ownership and power being concentrated in large technology companies without democratic oversight, which could result in a decrease in prosperity and independence for citizens, societies, and public administrations globally.

Mapping the research landscape is essential for gaining a comprehensive understanding of this field. This scoping review

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has some limitations, particularly concerning the number of database sources. The search was primarily limited to English publications, but publications in other languages were included to support the analysis. Expanding the search to other databases, languages, and even considering gray literature could enhance the comprehensiveness of this knowledge. Given the rapid development of this field, an annual update of this review is suggested to maintain current understanding and practical application of this subject only using one referential database. We also limited the search to English publications but included publications in other languages to support the analysis. Expanding to other databases, other languages and even considering gray literature can be expansions that can enrich this knowledge. As this is a field in rapid development, an annual update of this review is also proposed, to keep the understanding and practical application of this theme alive (Pinho et al., 2022).

Future research should empirically validate the Living GenAI Governance Model in diverse educational settings like academic institutions, research organizations, and policy-making bodies. Such empirical engagement would provide critical insights into the model's practical relevance, adaptability, and capacity to guide ethical, responsible, and context-sensitive implementation of GenAI across macro, meso, and micro levels (Pinho and Pinho, 2016). Additionally, there is a growing imperative to operationalize GenAI literacy by developing robust conceptual frameworks and validated assessment tools that encompass not only technical proficiency but also ethical awareness, critical thinking, and reflective judgment. Investigating how GenAI literacy manifests across diverse educational roles and sociocultural settings will contribute to more inclusive and equitable pedagogical strategies. Furthermore, future enquiries should adopt interdisciplinary and participatory methodologies to co-design governance mechanisms in collaboration with key stakeholders—educators, learners, researchers, developers, and policymakers. Such inclusive approaches are essential to ensure that governance frameworks are contextually grounded, socially legitimate, and responsive to the complex challenges posed by the integration of GenAI in educational research and practice.

Discussion can encompass various viewpoints. For instance, some scholars explore how GenAI tools impact academic practices and learner behaviors in education at a micro-level. e Lo et al. (2025) defend that GenAI integration into pedagogical practices offers a promising avenue for advancing educational outcomes on a global scale. This article offers empirical insights into the impact of GenAI tools on students' engagement with writing tasks and their revision behaviors. This perspective can be extended to researchers as continuous learners who must use GenAI tools responsibly and reflectively. GenAi Literacy is needed to capitalize on the potential of using technologies and mitigate their risks.

A governance approach emphasizes the importance of alignment. When we consider, for example, the ethical and responsible use of GenAI by researchers in academia, we are apparently at the micro level, of individual actions and behaviors. However, this requires the responsibility of university institutions to promote the development of ethical codes and guidelines, as well as institutional implementation through practical training and monitoring of the ethical, responsible and effective use of GenAI. However, these codes and guidelines must be developed following the main ethical principles and recommendations of supranational entities such as the United Nations or UNESCO, as well as the national guidelines of each country or each large region, like European Union. The implementation of GenAI in Educational Research requires a holistic approach that integrates teaching, research, and administration. The approach to ethics in all phases and tasks of educational research requires alignment at all levels (macro, meso and micro), linking ethical principles, regulations and practices; thus, the different levels must be aligned and harmonized.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

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