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REVIEW

GenAI and misinformation in education: a systematic scoping review of opportunities and challenges

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Abstract
Generative Artificial Intelligence (GenAI) has emerged as a transformative and disruptive force in education and society, with the potential to both create and correct misinformation. In education, misinformation manifests at three levels: the individual (when students hold misconceptions or inaccurate beliefs); the community (when groups of individuals share the same misconceptions or inaccurate beliefs); and the system (when educational policies and practices are not based on scientific evidence). We conducted a systematic scoping review to identify existing challenges and opportunities for misinformation generation, sharing, and correction across these levels in education, as well as inform future research in this area of work. Our results indicate three approaches to GenAI and misinformation in education: *identifying misconceptions, prebunking*, and *(re)producing misinformation,* with most research conducted at the individual level. We conclude with suggestions for future research and practice.

Keywords Education · AI literacy · Generative artificial intelligence · GenAI · Large language models (LLMs) · Misinformation

1 Introduction

From the COVID-19 "infodemic" to political conspiracy theories, misinformation threatens the health and well-being of individuals, communities, and democracies (Borges do Nascimento et al. 2022; Colomina et al. 2021; Council of Canadian Academies [CCA] 2023). Information technology advancements have played a prominent role in misinformation propagation, with Generative Artificial Intelligence (GenAI) now at a critical inflection point—capable of exponentially amplifying misinformation and offering innovative solutions to combat it (Costello et al. 2024).

Since OpenAI released ChatGPT in November 2022, the GenAI ecosystem has proliferated, drawing over 3 billion visits to various tools by March 2024 (Liu and Wang 2024). This proliferation has transformed how information is created, consumed, and evaluated across sectors, with education at the forefront of both opportunity and vulnerability (Yan et al. 2024). In this systematic scoping review, we examine the complex relation between GenAI and misinformation in education. We aim to identify the challenges and opportunities GenAI presents for misinformation generation, detection, and correction at individual, community, and system levels (Kendeou and Johnson 2024). By synthesizing research across educational domains, age groups, and specific GenAI applications, we aim to provide a comprehensive understanding of when, how, and why GenAI may contribute to or protect against misinformation in education, informing future research in this area of work.

1.1 The critical intersection of education and misinformation

Education represents the ultimate frontier in addressing misinformation for three main reasons. First, education systems worldwide are responsible for developing critical thinking and information literacy skills that serve as society's primary defense against misinformation (Lewandowsky et al.

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2023). Second, educational contexts are inherently vulnerable to students' naive beliefs and misconceptions that can interfere with learning (Ecker et al. 2022). Third, education is society's fundamental prebunking mechanism; teaching accurate information before exposure to misinformation creates cognitive resilience that extends beyond the classroom.

In this review, we adopt Vraga and Bode's (2020) comprehensive conceptualization of misinformation and define it as information that contradicts the best available evidence at the time. This encompasses traditional misinformation (shared without intent to deceive), disinformation (shared with deceptive intent), and misconceptions (inaccurate beliefs held by individuals). We further build on Kendeou and Johnson's (2024) framework that identifies misinformation at three levels in education:

1. *Individual level* When students believe incorrect information (misconceptions, naive beliefs).
2. *Community level* When educators or learning communities share flawed views or unsubstantiated beliefs.
3. *System level* When educational policies and practices lack scientific evidence.

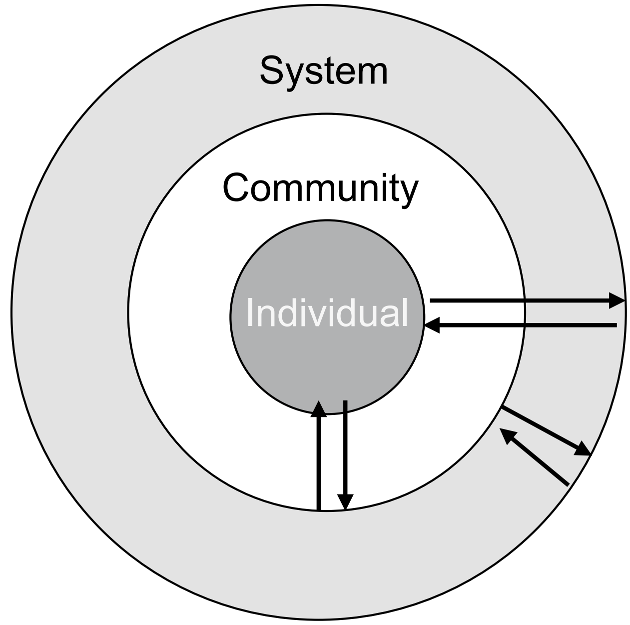

Fig. 1 Misinformation in education levels of analysis and interactions

This multi-level framework provides a comprehensive lens through which to examine the challenges and opportunities GenAI presents for misinformation generation and correction across educational contexts.

Individual, community, and system levels are interdependent with bidirectional influences (Fig. 1). Individuals are embedded within communities and systems, so that decisions made at the community and system levels have downstream effects on individuals. For example, curricula and district policies influence the instructional practices of teachers, which in turn impact individual students. Likewise, individuals comprise communities and systems; the decisions made at community and system levels are ultimately a collection and coordination of individual decisions.

To support effective learning and build long-term misinformation resilience, corrective efforts are needed across all three levels. Prebunking and debunking are two commonly used strategies that have shown efficacy (Ecker et al. 2022). *Prebunking*, or inoculation, exposes individuals to weakened forms of misinformation and provides counterarguments to build resistance against future exposure (Roozenbeek and van der Linden 2019). *Debunking* corrects false information after it has been presented (Lewandowsky et al. 2020) and often employs refutation texts, which explicitly state the misconception, refute it, and provide a plausible, causal explanation supporting the correct information (Kendeou 2024). When used in student feedback and incorporated into debate and media literacy training, prebunking and debunking are particularly helpful for addressing misinformation at the individual level (Ashley et al. 2023; Wineburg et al. 2022). When used in teacher education programs, prebunking and debunking can combat community-level misinformation (Peltier et al. 2020). And when implemented via science communication efforts on social media (Vraga and Bode 2021) and podcasts (Handford 2018) or through state and national legislature (Neuman et al. 2023), prebunking and debunking can help address system-level misinformation.

1.2 The paradox: GenAI as both a misinformation problem and a solution

Emerging research reveals a fundamental paradox in GenAI's relationship with misinformation. On one hand, GenAI represents an unprecedented threat, capable of creating persuasive propaganda and realistic misinformation at scale, with minimal cost or expertise (Ferrara 2024; Goldstein et al. 2024; Lundberg and Mozelius 2024; Menz et al. 2024). Furthermore, GenAI's statistical rather than conceptual approach to information means that misinformation present in training data can manifest in outputs that appear authoritative (Garry et al. 2024). In classrooms worldwide, educators now face GenAI-created essays containing historically inaccurate claims, science projects built on hallucinated research citations, and math homework completed using tools that confidently provide incorrect solutions (Chan and Hu 2023).

On the other hand, GenAI offers promising avenues for combating misinformation through prebunking and debunking. GenAI chatbots can deliver personalized, timely corrections to misconceptions (Costello et al. 2024; Huang et al.

2023). GenAI can also generate debunking texts of climate change misinformation (Zanartu et al. 2024) and Russian propaganda (Makhortykh et al. 2024) quickly and at scale. Furthermore, by analyzing large datasets of misinformation and its spread, GenAI models can identify common tactics used to propagate misinformation (Choi and Ferrara 2024; Ernst 2024; Gutiérrez et al. 2024), informing media literacy and prebunking efforts.

1.3 The need: a systematic understanding of GenAI and misinformation in education

While initial studies on GenAI in education highlight benefits for engagement, personalization, and assessment (Albadarin et al. 2024; Bahroun et al. 2023; Baidoo-Anu and Owusu 2023; Halaweh 2023; Kikalishvili 2023; Lo 2023; Zhang et al. 2024), there remains a gap in critically assessing risks as well as benefits specific to misinformation. Given education's role in mitigating misinformation and GenAI's potential as both a problem and solution in this space, a deeper understanding of these risks and benefits can better inform research and practice.

Also absent from existing reviews is a comprehensive analysis of how GenAI operates at the individual, community, and system levels of education. This multi-level understanding is essential, because practices and interventions successful at one level may fail at another. For example, GenAI tools that correct individual student misconceptions may simultaneously undermine community-level teacher expertise or contradict system-level curricula. Without this integrated perspective, educational interventions may solve problems at one level while creating new vulnerabilities at others, resulting in fragmented and ineffective approaches to misinformation correction.

We also have a relatively limited understanding of how different GenAI tools and models present unique challenges and opportunities. This differentiation matters, because GenAI is not monolithic—each model has distinct capabilities, limitations, and biases that shape its potential impact on misinformation (Barman et al. 2024). Without this nuanced understanding, educational stakeholders risk either overestimating GenAI's potential or missing valuable opportunities for effective implementation.

Finally, a pressing question is how education—at all levels—can effectively balance the benefits and risks of GenAI implementation to address misinformation. Educators are already making implementation decisions without comprehensive evidence, often driven by technological enthusiasm or fear of falling behind (Gunawardena et al. 2024). Without evidence-based frameworks for responsible integration, educational institutions risk either uncritical adoption that amplifies misinformation or wholesale rejection that leaves students unprepared for a GenAI-driven information landscape.

1.4 Objectives and research questions

We aim to address these critical gaps by synthesizing empirical evidence on GenAI's role in misinformation in education. Specifically, we ask:

> *RQ* How do the challenges and opportunities of GenAI for misinformation in education manifest across *levels of misinformation* (individual, community, system), *educational contexts* (learning topic, grade level), and *GenAI tools*?

In answering this question, we contribute a nuanced understanding of GenAI's dual potential—as both a misinformation problem and solution—to support learning and develop long-term misinformation resilience. These findings can also inform AI literacy efforts, as comprehensive AI literacy should foster critical and responsible AI users who can leverage these powerful tools while maintaining robust defenses against their potential to spread misinformation (Allen and Kendeou 2024).

2 Method

We used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines for scoping reviews (PRISMA-ScR; Tricco et al. 2018) to guide our methodology and reporting, which consisted of four phases: establishing eligibility criteria, conducting a systematic literature search, screening and selecting relevant studies, and extracting and analyzing data. Datasets and analyses are available in the Open Science Framework repository at https://osf.io/nfwqh/files/osfstorage

2.1 Eligibility criteria

To align with our focus on GenAI as both a problem and solution for misinformation in education, included articles had to reflect the intersection of education (K-12 and higher education), misinformation, and GenAI. While academic research can be considered a part of higher education, it is a distinct component that does not necessarily generalize to other educational contexts. For that reason, we excluded articles that reported only on GenAI and misinformation in research.

Following Zhang et al. (2024), we also included only peer-reviewed, primary research articles. Systematic reviews were checked for sources to include but were excluded to avoid double-counting results. Theoretical and conceptual reviews, opinions, and commentaries that did not report empirical evidence were likewise excluded. This was done, because many of these perspectives were already captured in earlier reviews, before there was a substantive body of empirical research on GenAI in education (Zhang et al. 2024). Furthermore, we focused on peer-reviewed articles to ensure that empirical evidence was synthesized from rigorously assessed research. While this criterion excluded preprints, it included peer-reviewed conference proceedings—the gold standard in several AI-adjacent fields (e.g., learning analytics and machine learning). Finally, articles had to be available as full texts, in English, for data extraction (Table 1).

2.2 Search protocol

Our literature search was conducted on November 21, 2024 and consisted of a Title, Abstract, and Keywords search in the electronic databases *Web of Science*, *PsychINFO, Scopus, ERIC, Association for Computing Machinery (ACM), and Medline* using the following search string: ("generative artificial intelligence" OR "generative ai" OR "genai" OR "large language model*") AND (edu* OR teach* OR student* OR "media literacy" OR prebunk* OR debunk*) AND ("misinformation" OR "disinformation" OR "misconception"). This search resulted in 249 articles across all databases.

2.3 Article screening and selection

We used RAYYAN (https://www.rayyan.ai/) to conduct the title and abstract screening. Rayyan detected $N = 100$ duplicates. One author reviewed and merged duplicates, leaving $N = 149$ articles to screen for eligibility. Two authors screened 8% of article titles and abstracts together (Cohen's kappa = 0.86), resolving discrepancies via discussion, after which one author screened the remaining titles and abstracts. At the full-text screening stage, two authors screened 10% of articles, reaching 100% agreement. The remaining articles were screened independently. This process resulted in 20 articles for inclusion in the systematic scoping review (Fig. 2).

2.4 Data extraction

Two authors coded a 10% subset of articles, reaching 96% agreement, and coded the remaining articles independently. Discrepancies and ambiguities were resolved via discussion. The data extracted from each study are provided in Table 2.

3 Results

To answer our research question—how do the challenges and opportunities of GenAI for misinformation in education manifest across *levels of misinformation* (individual, community, system), *educational contexts* (learning topic, grade level), and *GenAI tools*?—we first categorized each study according to whether misinformation manifested at the individual, community, or system level in education. We then reviewed the misinformation characterizations, challenges, and opportunities identified in each study to inductively derive misinformation themes. Finally, we contextualized thematic results in terms of content learning area, grade level, and GenAI tool.

3.1 Individual level

At the individual level, misinformation manifests as naive beliefs or misconceptions learners hold (Kendeou and Johnson 2024) and can be addressed using prebunking and debunking strategies (Ecker et al. 2022; Lewandowsky et al. 2020). We identified 16 articles related to misinformation in education at the individual level (Table 3). Of these, 6 used GenAI for *identifying misconceptions* (Ahmed et al.

Table 1 Eligibility criteria for papers in the systematic scoping review

Inclusion criteria	Exclusion criteria
Peer-reviewed journal articles and conference proceedings	Not peer-reviewed, e.g., dissertations, preprints, policy documents
Novel empirical research conducted; includes qualitative and quantitative data collections	Not an empirical research article or conference proceeding, e.g., conceptual reviews, opinion pieces, books, ebooks, comments/letters/replies
Research is relevant to misinformation, disinformation, and/or misconceptions; i.e., GenAI output is assessed for misconceptions/inaccurate information/hallucinations, or has been developed/employed to address misinformation, disinformation, and/or misconceptions	Not related to misinformation in education
Research applies to education (i.e., students or teachers in K-12 or higher education)	Not situated in education OR is specific to academia/academic research, which is a specialized subset of education deserving of its own focus in a review
Full-text available in English	No full text available, e.g., abstract-only conference proceedings. Not in English

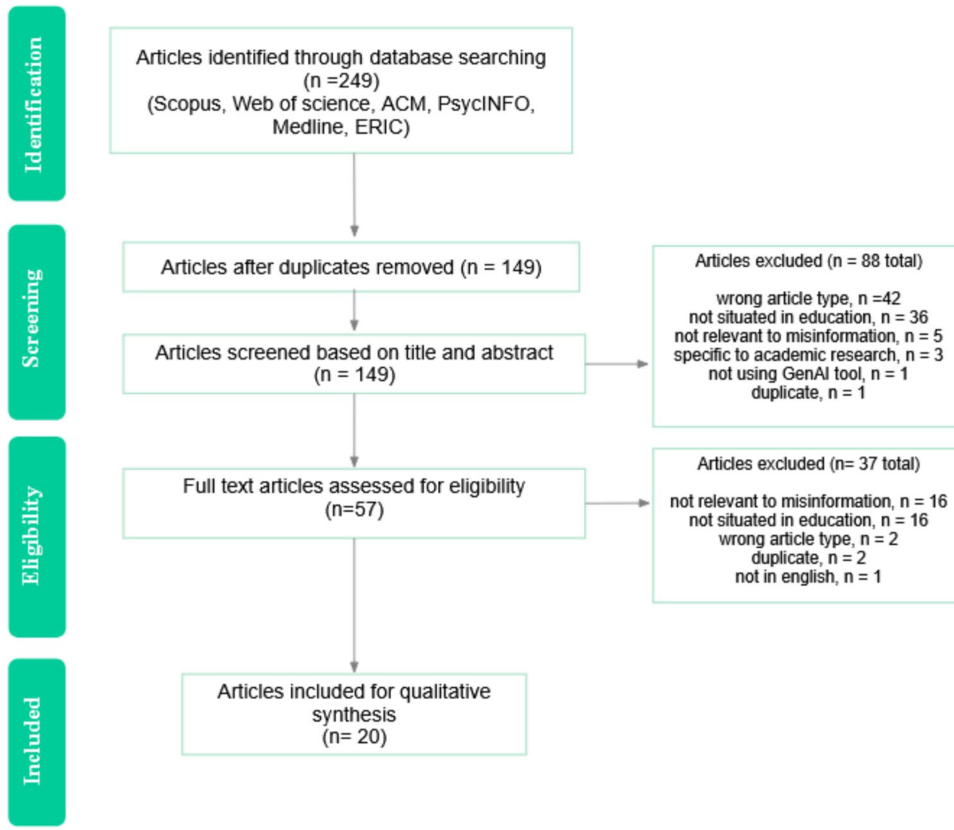

Fig. 2 Flow diagram of the systematic scoping review search and inclusion protocol

Table 2 Data extraction codebook

Code	Description
Participants	We documented whether human participants were included, and if so, who they were (e.g., students, teachers)
Age of participants	We documented the age or grade level of the participants
Misinformation characterization	We created an open-ended code to characterize how misinformation manifested in the given context (e.g., as student misconceptions, as inaccurate or incomplete information, or as improper or hallucinated references)
Misinformation level	Based on the misinformation characterization and research design information, we categorized the studies as individual, community, or system level
Opportunities	We used an open-ended code to document the benefits, advancements, and other opportunities of GenAI reported in the study
Challenges	We used an open-ended code to document the risks, harms, and other challenges of GenAI reported in the study
GenAI tool	We documented the GenAI tool(s) that were used in the study
Education topic	We coded the topic of study according to main content areas (e.g., computer science, mathematics, digital media literacy, and writing studies)
Research design	We used an open-ended code to summarize (~ 1 sentence) the aim and method of the study. This information contributed to misinformation level categorizations

2024; Feng et al. 2024; Kuo et al. 2023; Ross and Andreas 2024; Scarlatos et al. 2024; Smart et al. 2024), 5 used GenAI for *prebunking* (Ali et al. 2021; Jin et al. 2024; Qi et al. 2024; Tang and Singha 2024; Vieira Sousa et al. 2024), and 5 examined its potential to *(re)produce misinformation* (Belghith et al. 2024; Church 2024; Ding et al. 2023; Han et al. 2024; Smith et al. 2023).

Identifying misconceptions using GenAI presents both challenges and opportunities, largely depending on the learning domain. ChatGPT performed poorly when asked to identify and correct common math misconceptions at the 5th grade level (Kuo et al. 2023), and an unspecified GenAI tool could not create distractor items representing different misconceptions for multiple choice math tests

Table 3 Misinformation in education research across individual, community, and system levels

Misinformation theme	Misinformation level	Article	Education level(s)	Education topic(s)	GenAI tool(s)
Identifying misconceptions	Individual	Ahmed et al. 2024	College	Computer Science	ChatGPT 3.5
		Feng et al. 2024	Unspecified	Math	Unspecified
		Kuo et al. 2023	5th grade	Math	ChatGPT 3.5
		Ross and Andreas 2024	Middle school	Math	ATOM*, ChatGPT 4
		Scarlatos et al. 2024	Middle school	Math and English	code-davini-002*, GPT-3.5 Turbo, Llama-2 7b, GPT-4
		Smart et al. 2024	4th, 8th, and 12th grade	Math and Science	Llama-2 7b/13b/70b, GPT 3.5/4, Gemini-pro
Prebunking	Individual	Ali et al. 2021	Middle school	Digital media	Unspecified
		Jin et al. 2024	College	Computer Science	Algebo*
		Qi et al. 2024	Unspecified	Digital media	SNIFFER*
		Tang and Singha 2024	Unspecified	Digital media	ChatGPT 3.5*
		Vieira Sousa et al. 2024	College	Mental Health	ChatGPT 3.5
	Community	Farinetti & Canale 2024	College	Digital media	Student choice
	System	Kumar et al. 2023	College	Digital media	Student choice
(Re)producing misinformation	Individual	Belghith et al. 2024	Middle school	Topic of choice	ChatGPT 3.5
		Church 2024	College	Essay writing	ChatGPT 3.5
		Ding et al. 2023	College	Physics	ChatGPT 3.5
		Han et al. 2024	Elementary	Literacy	ChatGPT 3.5
		Smith et al. 2023	College	Psychiatry	ChatGPT 3.5
	Community	Dilling and Herrmann 2024	College	Math	ChatGPT 3.5, ChatGPT 4.0
	System	Kaufenberg-Lashua et al. 2024	College	Chemistry	Adobe Firefly, DALL·E2, Craiyon, DreamStudio

*indicates researcher-fine-tuned or developed LLM

(Feng et al. 2024). Scarlatos et al. (2024) and Smart et al. (2024) compared multiple GenAI tools, finding that none were able to accurately identify math misconceptions nor consistently provide appropriate, corrective feedback—even after fine-tuning and prompt engineering. Conversely, these GenAI tools identified and corrected English and science misconceptions with greater ease and accuracy (Scarlatos et al. 2024; Smart et al. 2024). Only when using a more advanced model with highly curated fine-tuning did GenAI successfully identify and correct students' math misconceptions (Ross and Andreas 2024). Findings in computer science were more mixed: while students reported their conversations with ChatGPT to be overall accurate and helpful, faculty rated its ability to resolve confusion and correct misconceptions as mediocre (Ahmed et al. 2024).

Prebunking with GenAI showed more promise—though challenges remain. Ali et al. (2021) observed and surveyed middle school students during a digital media literacy workshop on deepfakes. Though students showed no improvement in their ability to identify deepfakes at post-test, their support for policy regulations to reduce misinformation online increased, and they were more inspired to pursue careers in technology, media, and policy-making. Furthermore, the researcher-developed GenAI tool, SNIFFER, was deployed fairly successfully as a digital media literacy tool, debunking misinformation by identifying out-of-context images and inoculating against this disinformation tactic (Qi et al. 2024). GenAI has also been used to gamify prebunking (Tang and Singha 2024; Vieira Sousa et al. 2024). A Mystery for You (Tang and Singha 2024) used GPT-3 to simulate role playing and generate content in a fake news game, where users generate fake news and propaganda articles to familiarize themselves with common misinformation tactics (Roozenbeek and van der Linden 2019). Another game in development focused on mental health literacy (Vieira Sousa et al. 2024). It used ChatGPT-generated narratives of college students experiencing depression, which users read and responded to like a choose-your-own-adventure. However, mental health professionals piloting the game flagged several misconceptions about depression. Nevertheless, they noted the game's potential to promote mental health literacy and suggested fine-tuning with mental health-specific information to improve the accuracy of generated narratives.

(Re)producing misinformation posed the most challenges for misinformation in education. When asked to use ChatGPT to help write their essays, Church's (2024) college students accepted its output uncritically; many of their essays contained false information and made-up sources. Smith et al. (2023) provide additional evidence of ChatGPT generating plausible yet incorrect information in a psychiatry classroom. The potential exposure to misinformation and lack of fact-checking is a particular concern for parents and teachers of elementary school students, who are more vulnerable to GenAI-produced misinformation (Ali et al. 2021; Han et al. 2024).

Students can also have misconceptions about GenAI itself (Amaratunga 2023), which may be introduced or reinforced using GenAI tools (Belghith et al. 2024; Ding et al. 2023). In their focus group with middle school students visiting a science museum, Belghith et al. (2024) noted that ChatGPT's human-sounding text and ability to answer questions on diverse topics led some students to believe it could understand and reason like a human—or even *better* than a human. Ding et al. (2023) reported similar misconceptions in their undergrad physics students: students believed that ChatGPT had superhuman intelligence and was practically infallible, even when it answered their physics questions incorrectly.

3.2 Community level

At the *community* level, misinformation manifests as flawed views or misconceptions shared by members of a community (Kendeou and Johnson 2024). Prebunking and debunking remain effective strategies for addressing misinformation at this level, and are most effective when delivered by a trusted source or member of the community (van Boekel et al. 2017). We identified two articles at the community level (Dilling and Herrmann 2024; Farinetti and Canale 2024), highlighting a significant gap in the literature (Table 3). Dilling and Herrmann (2024) assessed pre-service elementary teachers for AI misconceptions, while they used ChatGPT to develop geometry proofs. Most pre-service teachers displayed some AI misconceptions, which precluded them from engaging with ChatGPT effectively. On the other hand, Farinetti and Canale (2024) offer a positive example of leveraging GenAI and individual expertise to promote community-level misinformation resilience. Sixty third-year media engineering college students developed their own GenAI chatbots, trained on, and connected to a credible database of their choice. They then prompted the chatbot with questions they knew the answers to, evaluating its response for accuracy. Despite having access to accurate information, the GenAI chatbots hallucinated content and sources, demonstrating their inherent potential for misinformation.

3.3 System level

At the *system* level, misinformation manifests as state or district educational policies and practices that are not supported with scientific evidence (Kendeou and Johnson 2024). With humans in the loop, GenAI brings opportunities for improving evidence-based curricula at scale (Abd-Alrazaq et al. 2023; Dwivedi et al. 2023; Wong 2024). Without careful oversight, however, GenAI may perpetuate systemic biases and inequities (Capraro et al. 2024; Chiu 2023; Dwivedi et al 2023; Sison et al 2023; Varsik and Vosberg 2024). We identified two articles at the system level (Kaufenberg-Lashua et al. 2024; Kumar et al. 2023), highlighting another critical gap in the literature (Table 3).

To evaluate the presence of gender bias in GenAI outputs, Kaufenberg-Lashua et al. (2024) compared four GenAI image generators (Adobe Firefly, DALL·E2, Craiyon, and DreamStudio) as they produced images of chemists across a variety of occupations. Fifty images were collected for each model and coded for gender presentation by researchers and students, with over 95% agreement (Kaufenberg-Lashua et al. 2024). Image results were compared to 2021 NSF survey data to assess (mis)representativeness (as of 2021, men make up 70% of chemistry professions and higher education students). DreamStudio showed the greatest systemic gender bias in its output, generating exclusively images of men. DALL-E2 and Craiyon were more accurate, producing images of men about 75% of the time, while AdobeFirefly produced images of men 54% of the time. Across all models, however, women were more likely to be represented as teaching assistants whereas men were more likely to be represented as chemists.

Kumar et al. (2023) showed more promise for system-level prebunking via AI literacy. After watching an AI bias and reliability video, approximately 100 Computer Science undergraduates interacted with various GenAI-based chatbots, documenting and annotating the different forms of misinformation present (e.g., inaccuracies, biases, misrepresentations). Their data were synthesized into an AI Reliability framework (AIR) that identified eight key components of AI reliability and mapped them to specific strategies students and stakeholders could use. To our knowledge, this data-driven framework has not yet been translated into AI literacy standards, but it has the potential to inform AI literacy curricula at scale.

4 Discussion

Education is critically positioned to support long-term misinformation resilience for society, yet it is also vulnerable to the challenges of misinformation and rapid technological changes such as GenAI. In this systematic scoping review, we aimed to expand our understanding of when, how, and why GenAI might serve as a problem or solution to misinformation in education. We organized existing empirical evidence according to individual, community, and system levels of misinformation in education (Kendeou and Johnson 2024) and described how GenAI contributed to or helped correct misinformation across content areas, grade levels, and GenAI tools. Our findings revealed three approaches to GenAI and misinformation in education: *identifying misconceptions, prebunking,* and *(re)producing misinformation.*

Unsurprisingly, *(re)producing misinformation* presented the most risks to education and was evident at all three levels. ChatGPT version 3.5 was used across these studies, suggesting that more advanced models or additional fine-tuning may improve reliability—though these solutions can create new problems around equitable access to GenAI (Capraro et al. 2024; Han et al. 2024). Less expected were the failures of GenAI to reliably *identify misconceptions*. These findings can be partly explained by the focus on math misconceptions in our reviewed studies. Large *language* models are less adept at interpreting non-linguistic input, such as mathematical symbols, figures, and charts (Smart et al. 2024). Furthermore, math misconceptions often involve conceptual errors rather than factual mistakes (Rittle-Johnson and Alibali 1999) that are harder for GenAI to diagnose. Finally, all studies aimed at identifying misconceptions were conducted at the individual level—GenAI may show more promise with community- and system-level debunking.

Across all levels, GenAI showed the most promise when leveraged for *prebunking*. However, model fine-tuning, prompt engineering, and thoughtful classroom integration were needed to mitigate—and in some cases intentionally leverage—the inaccuracies and bias in GenAI output. These caveats highlight the importance of technical knowledge, ethical considerations, and evaluation skills—all core competencies of AI literacy (OECD 2025)—to facilitate human–AI collaborations that ultimately foster misinformation resilience (Allen and Kendeou 2024).

Across misinformation levels and themes, studies predominantly examined the GenAI output itself and did not collect additional data on student learning outcomes or teacher pedagogical practices. This was in part because much of the research was not conducted with any human participants. Researchers are wise to scrutinize GenAI output before widespread deployment in the classroom, which should be a cornerstone of ethical and responsible GenAI-use in education. When accurate information is not present or cannot be routinely generated, teacher scaffolding of student use should be used. With college students, such scaffolding could be problem-based learning activities in which students are told about the limitations of GenAI before being asked to use it (e.g., Kumar et al. 2023), or have the requisite expertise to evaluate its output for accuracy themselves (e.g., Farinetti and Canale 2024). With younger students, early exposure to the limits of GenAI will be important to preempt the misconception that GenAI is infallible (Belghith et al. 2024).

4.1 Future research directions

Assessing GenAI output for accuracy is paramount, but measuring its effects on learning and instruction is equally critical to ensure that these tools are being leveraged effectively. As one example, computer science faculty evaluated the pedagogical practices of GenAI, rating how well ChatGPT provided relevant examples, encouraged problem-solving skills, and used appropriate language and tone when conversing with undergraduate students in a programming course (Ahmed et al. 2024). Future research can build on this by evaluating and comparing additional GenAI models, content areas, and grade levels for flexible, adaptive use of appropriate teaching strategies. Future research can also assess student learning processes and outcomes with learning analytics tools, mixed-methods designs, and longitudinal measures.

To address the gap in community- and system-level research, we propose a multi-level research agenda that simultaneously studies GenAI implementation across individual, community, and system levels within the same educational contexts, revealing how it can affect student learning while impacting teacher communities and institutional systems. Cascading implementation studies that intentionally introduce GenAI tools at one level (such as system-wide GenAI tool access and integration) while tracking ripple effects at others (like changes in teacher communities' misconceptions and individual student outcomes) can complement this approach. These efforts must be supported by assessment that simultaneously measures misinformation resilience at all three levels, identifying when successful interventions at one level might facilitate or undermine efforts at another. Equally important is investigating power dynamics across educational levels (Fig. 1, p. 4), examining how GenAI might redistribute authority and expertise (i.e., credibility judgements) by potentially empowering individual learners while challenging community expertise or institutional authority over content knowledge.

Our review also revealed significant variability in how different GenAI models perform in educational contexts, yet current research lacks systematic comparison of these differences, making implementation decisions very challenging. To address this issue, we propose conducting comparative performance benchmarking (Ali et al. 2024) that systematically evaluates different GenAI tools against standardized misinformation tasks and rates models on their accuracy, misconception detection, and refutation/

correction capabilities across subject areas (Ahmed et al. 2025). Related, since our findings indicated that "prompt engineering" was crucial for successful implementation (Federiakin et al. 2024), researchers should investigate prompt sensitivity variations across models and develop model-specific prompting guidelines for educational stakeholders that account for unique sensitivities and limitations of each model. And, given the rapid pace of model development, we recommend establishing longitudinal tracking of how model updates affect performance, with protocols for educators to test new model versions before classroom implementation to avoid unintended consequences.

Finally, given that the findings reveal both promising applications and concerning limitations of GenAI in educational contexts for misinformation generation and correction, we propose a "risk–benefit" approach to guide decision-making for implementation (Fig. 3). For example, we encourage implementation for "low-risk, high-benefit" applications, such as using GenAI for prebunking and digital literacy training with explicit discussion of model limitations and GenAI-supported content creation with human expert review. "Moderate-risk, moderate-benefit" applications need more careful implementation and can include student-led GenAI exploration using structured evaluation protocols and peer-reviewed GenAI outputs within collaborative learning environments. Our findings also clearly identify "high-risk, low-benefit" applications that should be avoided, including unsupervised student reliance on GenAI for factual learning, unreviewed GenAI-generated learning materials (especially in mathematics), and reliance on GenAI tools in areas prone to misconceptions. This risk–benefit profile approach provides educational stakeholders with the initial evidence-based guidance to realize benefits while minimizing risks of GenAI in amplifying misinformation.

4.2 Limitations

Because GenAI technology became widely accessible only a few years ago, research on misinformation specifically in the context of education is so far rather limited: we identified 20 papers in total, 80% of which examined misinformation generation and correction at the individual level. The paucity of studies at the community ($n = 2$) and system ($n = 2$) levels is a critical gap and limits our ability to synthesize and generalize findings about GenAI for misinformation generation and correction at these levels.

It is also important to note methodological limitations in our systematic scoping review. First, our review examined only peer-reviewed research, which excluded preprints. Preprints can be advantageous when dealing with rapidly emerging literature, such as GenAI research, but they may also mislead systematic review results when such research fails to pass quality checks or undergoes substantial revision for publication (Brietzke et al. 2023). We therefore tried to

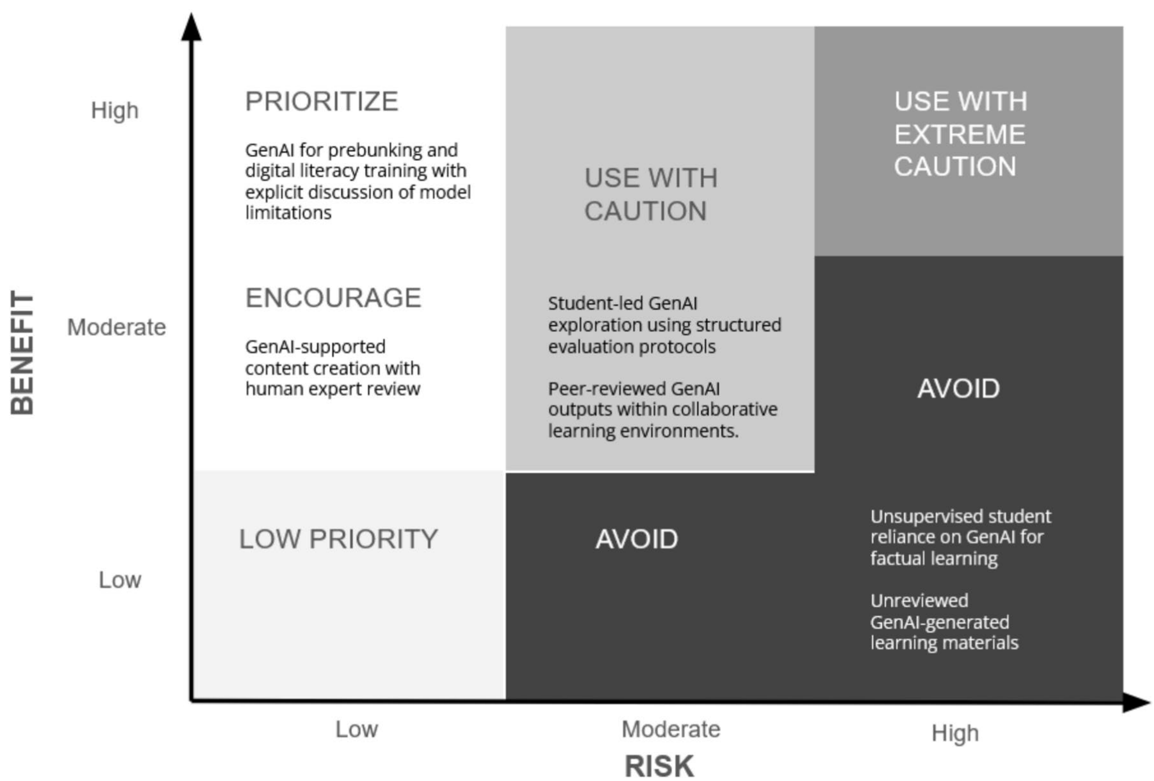

Fig. 3 Risk–benefit analysis

balance research rigor with early access by including peer-reviewed conference proceedings in addition to journal articles, but not preprints. Second, clearly defining the intersection of GenAI, misinformation, and education for eligibility requirements was not a straightforward process; it involved much deliberation and discussion around what constitutes education and misinformation. Though we ultimately came to a consensus on our definitions (establishing IRR at or above 85% agreement), others may conceive of these terms differently.

5 Conclusion

Generative AI is revolutionizing how information is created, consumed, and evaluated, and education must respond and adapt. To do so ethically and equitably, it is imperative that GenAI implementation decisions across individual, community, and system levels are carefully made using the best available evidence. Understanding when, how, and why GenAI contributes to or helps combat misinformation in education is a critical part of this evidence base. In this systematic scoping review, we examined the current evidence for GenAI as both a misinformation problem and a solution at the individual, community, and system levels of education. Our findings describe key challenges and opportunities researchers and practitioners should be aware of and contribute a nuanced understanding of how GenAI can be leveraged within educational contexts to support learning and long-term misinformation resilience. We believe that all education stakeholders—students, teachers, administrators, and policymakers—must be prepared to thoughtfully navigate GenAI's dual potential as both a source of and solution to misinformation. Even though a comprehensive understanding of these challenges and opportunities is a critical first step and could be achieved with AI literacy efforts (OECD 2025), it is equally important for education stakeholders to actively shape ethical and responsible GenAI implementation via innovative pedagogy, curriculum development, and evidence-based advocacy.

Author contributions All authors collaborated on conceptualization and development of methodology. A.F. developed the search protocol and conducted the database search, with feedback from M. P. and P.K. A.F. screened titles and abstracts for eligibility and P.K. provided inter-rater-reliability. A. F. screened and coded full-text articles for inclusion and M. P. provided inter-rater-reliability. A. F. & P.K. drafted and edited the manuscript. All authors reviewed the manuscript.

Data availability Datasets and analyses are available in the Open Science Framework repository at https://osf.io/nfwqh/files/osfstorage

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