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Generative AI in Developing Critical Reading and Misinformation Detection among Secondary Students: A Systematic Literature Review Avoided

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Abstract

Generative artificial intelligence (GenAI) offers opportunities to develop critical reading while posing challenges related to misinformation and uncritical acceptance of AI-generated content. This systematic literature review examines GenAI's role in critical reading and misinformation detection among secondary students. Following PRISMA 2020, literature searches identified a working evidence set of 25 records, comprising 12 primary studies and 13 supporting studies. Thematic synthesis identified four critical-reading operations: claim, evidence, source, and perspective/bias evaluation, alongside five stages of misinformation evaluation: identification, verification, corroboration, credibility assessment, and calibrated judgment. Findings indicate that GenAI's educational value depends on epistemic engagement, teacher scaffolding, task design, and students' prior knowledge and AI literacy. The study proposes the Generative AI–Mediated Critical Reading and Misinformation Evaluation (GAI-CReME) Framework to explain how epistemic activity connects GenAI interaction with critical reading and misinformation evaluation. Further empirical research is needed to validate the framework, particularly regarding source and bias evaluation.

Keywords: generative artificial intelligence, critical reading, misinformation, secondary education, AI literacy, information evaluation, critical literacy.

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1. Introduction

The development of Generative Artificial Intelligence (GenAI) has fundamentally transformed the landscape of digital literacy. Students now interact with systems that not only recommend information but also

generate texts, arguments, and analytical solutions in real time. In education, this transformation creates substantial opportunities for personalized learning, interactive dialogue, and idea exploration. However, GenAI's ability to produce coherent language does not necessarily correspond to epistemic accuracy. Unconstrained integration of GenAI may foster cognitive dependency and uncritical acceptance of information when it is not accompanied by adequate AI literacy (Zawacki-Richter et al., 2019). Research involving secondary students indicates that AI literacy encompasses knowledge, affective, and evaluative dimensions, while systematic reviews emphasize the importance of pedagogical design and scaffolding when students use such technologies (Liu & Zhong, 2025; Wu & Zhang, 2025; Zhong & Liu, 2025). Therefore, a central challenge for contemporary education is not merely to facilitate GenAI use, but to cultivate students' critical evaluative capacities and epistemic integrity when responding to technological outputs (Dwivedi et al., 2023; Yan et al., 2024).

This issue becomes increasingly critical in the domain of critical reading within digital environments. Contemporary information settings require readers not only to comprehend texts literally but also to evaluate source credibility, argument quality, communicative purpose, and potential bias embedded in the text. Kiili et al. (2022) confirmed that secondary students draw on criteria such as author expertise, intentionality, publication-venue credibility, and evidential weight when justifying the validity of online texts. The development of source-evaluation skills is more effective when integrated into explicit instruction that trains students to compare and contrast trustworthy and untrustworthy information sources (Abel et al., 2024; Mertens, 2023). Moreover, evaluating multimodal media such as videos and scientific webpages requires students to coordinate content, source, evidence, and contextual criteria holistically (Abed & Barzilai, 2023). In AI-based learning contexts, structured epistemic reasoning is therefore essential for helping students critically validate the truthfulness of texts generated by GenAI (Barzilai & Chinn, 2024; Yan et al., 2024). Accordingly, critical reading in digital environments is fundamentally an epistemic activity that connects text comprehension with critical evaluation of the validity of the knowledge it conveys (Barzilai & Chinn, 2024).

The integration of Generative Artificial Intelligence (GenAI) further complicates the challenges of critical reading in the digital era. Texts generated by large language models often display persuasive rhetorical structures and argumentative styles while potentially containing factual hallucinations, oversimplifications, or unsupported claims. This condition places GenAI in a dual role: as a pedagogical instrument and as an object of critical evaluation. Cheung et al. (2024) confirmed that when secondary students interact with ChatGPT to analyze socioscientific issues such as climate change, they are required not only to understand the content but also to engage in epistemic processing and verification of system outputs. Similarly, a study of students' experiences in STEM learning indicates that GenAI use can prompt epistemic safeguarding strategies, namely students' critical awareness of when to limit AI use and verify information accuracy when they encounter limitations or inaccuracies in GenAI outputs (Valeri et al., 2025). Furthermore, evaluating the acceptability of AI-generated drafts requires students to integrate critical thinking with epistemic risk assessment simultaneously

(Dwivedi et al., 2023). Digital literacy must therefore move beyond operational skills such as prompt engineering toward metacognitive capacities to deconstruct, evaluate, and interrogate the validity of AI-generated texts critically (Kong et al., 2024).

Another equally important dimension is the escalating threat of misinformation within the digital information landscape. Secondary students' vulnerability to scientific misinformation is closely related to how they represent and assess the reliability of news sources (Siani et al., 2024; Siani & Gennari, 2026). In this context, sourcing strategies and corroboration across sources have emerged as key mechanisms for building students' cognitive resilience to misinformation (Marten et al., 2025; Marten & Stadtler, 2025). Furthermore, media-literacy interventions and analytical-thinking training indicate that distinguishing fact from falsehood is a complex cognitive process; excessive critical vigilance may even foster epistemic cynicism or destructive doubt toward all information sources (Ghazi et al., 2025; Pennycook & Rand, 2021). Addressing fake news also requires robust counterargumentation scaffolding, through which students are trained to construct evidence-based justifications and consider counterarguments objectively (Garcia-Mila et al., 2026). Thus, resilience to digital misinformation depends not merely on passive skepticism but on students' ability to evaluate argumentative structures and evidentiary networks actively and systematically (Kiili et al., 2022; McGrew, 2024).

In the context of Generative Artificial Intelligence (GenAI), these dynamics take on a new form because the same technology can be used both to produce and to examine the validity of information. Fulsher et al. (2026), through a systematic scoping review, confirmed that GenAI in education has the potential to strengthen information literacy and mitigate misinformation while simultaneously creating risks of amplifying or fabricating inaccurate information. At the secondary-school level, Lao et al. (2025) position fact-checking of GenAI outputs as a core practice for developing media and information literacy. Similarly, Tang et al. (2026) underscore the importance of critical questioning in developing students' AI literacy, while Zhou (2026) identified a cognitive process in which students moved from initial trust toward consistency checking, external verification, idea reconstruction, and ultimately rejection of invalid AI outputs. This transformation underscores that successful GenAI integration depends heavily on pedagogical scaffolding that promotes interactive fact-checking Swiecki et al. (2022). Thus, the pedagogical value of GenAI lies not simply in algorithmic sophistication, but in the quality and depth of the epistemic activity accompanying students' use of the technology (Roy & Jony, 2026).

Recent literature indicates that although research on GenAI in education, critical reading, and misinformation evaluation has developed rapidly, these three domains remain fragmented and are often studied separately. A systematic synthesis of GenAI and critical thinking in language learning confirms substantial variation in empirical evidence with respect to intervention design and application context (Liu et al., 2025), while broader reviews of GenAI integration emphasize the importance of pedagogical scaffolding and teacher competence (Liu & Zhong, 2025). Meanwhile, most misinformation studies involving secondary students continue to focus on conventional source evaluation, credibility assessment, corroboration, and argumentation scaffolding

without explicitly incorporating the dynamics of AI-generated texts (Garcia-Mila et al., 2026; Kiili et al., 2022; Marten & Stadtler, 2025). Consequently, theoretical and methodological limitations remain in understanding how interaction with GenAI influences students' cognitive processing and critical evaluation (Yan et al., 2024). This creates a meaningful conceptual and empirical gap at the intersection of GenAI use, critical-reading competence, and misinformation mitigation among secondary students (Şahan et al., 2026).

The gap is not merely thematic but also conceptual. Much of the literature treats critical thinking or AI literacy as broad umbrella terms, leaving specific cognitive operations involved in critical reading – such as claim deconstruction, evidential weighting, source attribution, perspective identification, and bias detection – insufficiently mapped. Yet ethical and responsible GenAI use depends substantially on students' metacognitive ability to distinguish text that is linguistically coherent from information that is epistemically valid (Mollick & Mollick, 2023). Although research on AI literacy among secondary students emphasizes the importance of AI thinking (Zhong & Liu, 2025), and information-evaluation research highlights the importance of credibility justification and cross-source corroboration (Abed & Barzilai, 2023; Kiili et al., 2022), the two domains remain largely disconnected. Without an integrated conceptual framework, educators may struggle to design precise scaffolding to mitigate the illusion of explanatory depth when students consume GenAI outputs (Chiu, 2024). A holistic theoretical synthesis is therefore needed to connect AI literacy, specific critical-reading operations, and misinformation-evaluation frameworks within a single systemic account.

Against this theoretical and empirical background, this systematic literature review aims to synthesize recent scientific evidence by addressing four main research questions:

a. How is Generative AI (GenAI) designed and integrated into learning practices to facilitate critical reading and misinformation detection among secondary students?
b. How does the use of GenAI contribute to secondary students' critical-reading processes, particularly in evaluating claims, evidential weight, source credibility, and potential bias in texts?
c. How is GenAI used as both a pedagogical instrument and an object of evaluation to support secondary students' ability to identify, verify, and interrogate misinformation in digital texts?
d. What enabling and constraining factors – including cognitive, technological, and pedagogical-scaffolding dimensions – influence the success of GenAI use in developing critical reading and misinformation detection among secondary students?

The main novelty of this study lies in formulating a theoretical synthesis that integrates these three domains through the proposition of AI-mediated epistemic activity. This systematic synthesis is developed into the Generative AI–Mediated Critical Reading and Misinformation Evaluation (GAI-CReME) Framework as an evidence-informed conceptual framework. The framework positions critical questioning, verification, corroboration, evidence evaluation, and source assessment as fundamental epistemic mechanisms linking students' interaction with GenAI to the formation of calibrated judgment. Accordingly, the review does not treat GenAI as a direct determinant of improved critical-reading competence, but rather as an

epistemic environment that may activate two adaptive pathways: a critical-reading pathway or a cognitive-dependency pathway. The direction of these cognitive pathways depends on the dynamic interaction among students' prior knowledge, AI literacy, task design, teacher scaffolding, technological characteristics, and the broader learning ecosystem (Dahlan, 2026; Vendrell & Johnston, 2026).

2. Method

This study employed a systematic literature review (SLR) approach to identify, critically evaluate, and synthesize empirical evidence on the use of generative artificial intelligence (GenAI) to facilitate critical reading and misinformation detection among secondary students. The review procedures and reporting followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework (Page et al., 2021) to ensure transparency and traceability from literature identification and screening through eligibility assessment, quality appraisal, and evidence synthesis. Systematic reviews require explicit and reproducible procedures for identifying, appraising, and synthesizing relevant evidence (Pollock & Berge, 2018; Xiao & Watson, 2019). The four research questions (RQs) provided an integrated framework for developing the search strategy, selection criteria, data extraction, coding, and synthesis.

Literature searches were conducted across four academic databases: Scopus, Web of Science (WoS) Core Collection, Education Resources Information Center (ERIC), and Dimensions. To broaden coverage and reduce the likelihood of missing relevant studies, the search was supplemented by backward and forward citation searching of key articles and by Google Scholar as a supplementary source. The use of multiple bibliographic databases is recommended to improve the comprehensiveness of evidence identification, while citation-based searching can provide an additional means of locating relevant studies that may not be retrieved through database queries alone (Gusenbauer & Haddaway, 2020; Wohlin, 2014). The literature was limited to publications from January 2020 through September 2026 and included articles published in English or Indonesian. The search strategy used Boolean operators across four conceptual blocks: GenAI technology, critical reading or literacy, misinformation and information evaluation, and the secondary-student population. The GenAI block included "generative AI," "generative artificial intelligence," ChatGPT, "large language model," LLM, "AI chatbot," and "generative language model"; the reading and literacy block included "critical reading," "critical literacy," "information literacy," "media literacy," and "digital literacy"; the misinformation block included misinformation, disinformation, "false information," "misleading information," "fake news," "information verification," "fact checking," and "source credibility"; and the population block included "secondary school," "high school," "middle school," "secondary education," "secondary student," adolescent, teenager, and "school student." The search was conducted in two stages: a broad search to identify studies concerning GenAI and literacy among secondary students, followed by a focused search that added concepts related to misinformation and information evaluation. This staged search strategy was intended to balance breadth in initial evidence identification with specificity during the subsequent retrieval of studies directly relevant to the review questions (Xiao & Watson, 2019).

Studies met the inclusion criteria if they (1) involved secondary students, including middle school, junior high school, or high school students; (2) used GenAI or large language models (LLMs) in a learning

scenario; (3) examined critical reading, critical literacy, information literacy, media literacy, digital literacy, information evaluation, or evaluation of claims, evidence, sources, perspectives, and bias; (4) assessed students' identification, verification, evaluation, or resilience toward misinformation; (5) were conducted in formal educational settings; (6) were peer-reviewed journal articles with full text available; and (7) were published between January 2020 and September 2026. Studies were excluded if they focused exclusively on primary-school students or university students without separable secondary-school data, used only non-generative AI, did not address information evaluation or misinformation, were opinions, editorials, book reviews, conference proceedings, or abstracts without full text, focused purely on technical AI algorithm development without a student-learning context, or were duplicate publications. Explicitly defined inclusion and exclusion criteria are essential for maintaining alignment between the review questions, study population, evidence characteristics, and synthesis (Pollock & Berge, 2018; Xiao & Watson, 2019). These criteria were used to maintain alignment among the population, technology, learning context, and outcomes with the review focus.

Study selection proceeded through identification, deduplication, title-and-abstract screening, and full-text assessment in accordance with PRISMA 2020 principles (Page et al., 2021). Identified articles were evaluated according to the target population, involvement of GenAI, learning context, and relevance to critical reading and misinformation evaluation. Systematic review methodology emphasizes transparent documentation of the study-identification, screening, eligibility, and inclusion processes to support reproducibility and reduce ambiguity in study selection (Pollock & Berge, 2018). In the synthesis, empirical studies located directly at the intersection of GenAI, secondary students, and critical or evaluative foci were treated as core primary studies, whereas empirical studies providing relevant evidence on critical reading, source evaluation, information credibility, or misinformation but not directly integrating all of these components were treated as supporting studies. This distinction was used to preserve interpretive precision in the evidence base and to prevent supporting evidence from being treated as though it represented an empirically identical context to the primary studies.

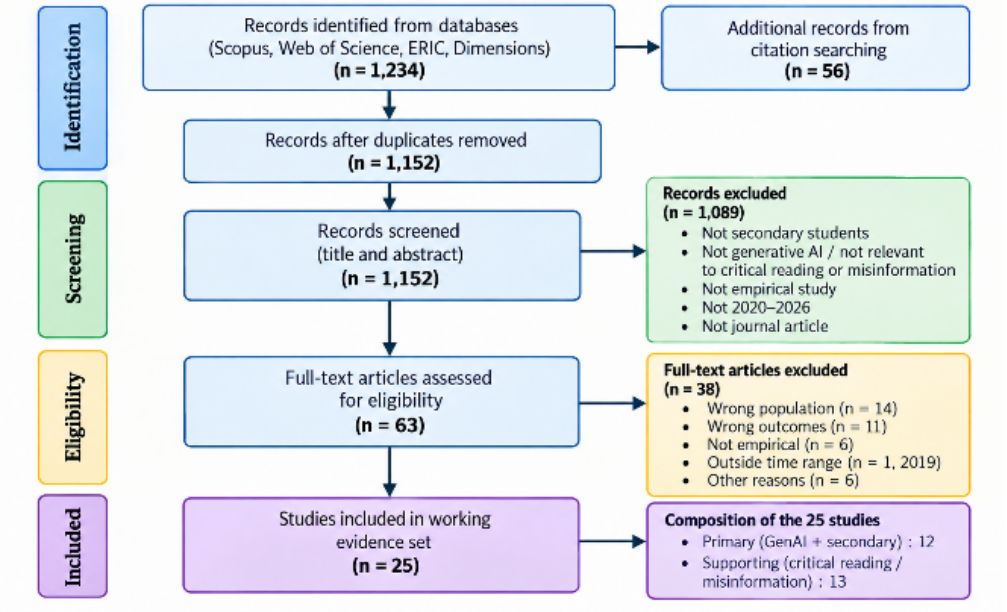


Figure 1. PRISMA 2020 Flow Diagram for Study Selection

Figure 1 shows the selection process of the 25 studies included in the working evidence that produced the final number of studies at each selection stage was to be reported based on the actual search and screening results; therefore, the working evidence set was not treated as a substitute for the final PRISMA inclusion count.

The methodological quality and potential risk of bias of studies meeting the selection criteria were assessed using the Joanna Briggs Institute Critical Appraisal Tools, matched to the study design, including quantitative, qualitative, and mixed-methods studies (Aromataris & Munn, 2020). The use of design-specific critical appraisal tools is consistent with systematic review guidance that recommends assessing methodological quality in relation to the characteristics and design of the included evidence (Pollock & Berge, 2018). Each indicator was rated as Yes, No, or Unclear, with Yes assigned a score of 1 and No or Unclear assigned a score of 0. Scores were converted into percentages to classify study quality as high (≥80%), moderate (60–79%), or low (<60%). Quality appraisal was not used to mechanically exclude studies on the basis of score alone; rather, it informed interpretation of the strength of evidence, identification of potential methodological limitations, and consideration of each study's contribution to the synthesis. This approach is consistent with the broader purpose of critical appraisal in evidence synthesis, namely to inform interpretation of the trustworthiness and limitations of individual studies rather than to reduce methodological quality to a purely mechanical inclusion decision (Aromataris & Munn, 2020).

Data extraction was conducted using a standardized data-extraction matrix to maintain consistency across studies. The extracted data comprised four groups of information: study characteristics and context, technology and pedagogy characteristics, cognitive and evaluative indicators, and findings and methodological quality. Systematic reviews benefit from predefined and consistently applied data-extraction procedures that correspond directly to the review questions and eligibility criteria (Pollock & Berge, 2018; Xiao & Watson, 2019). Study characteristics and context included authors, publication year, country, educational level, participant size and characteristics, and subject or curricular context. Technology and pedagogy characteristics included the GenAI platform, AI pedagogical function, learning activities, intervention design, duration, and teacher and student roles. Cognitive and evaluative indicators included critical-reading outcomes; evaluation of claims, evidence, sources, and bias; misinformation-detection outcomes; identification, verification, and evaluation processes; and measurement instruments. The dataset also included main findings, enabling and constraining factors, cognitive or epistemic risks of AI use, quality-appraisal scores, and limitations reported in each study.

Analysis was conducted through descriptive synthesis and thematic synthesis. The demographic and methodological characteristics of the studies were first mapped descriptively, after which empirical findings were deductively coded according to the four RQs. The use of thematic synthesis enables findings from heterogeneous empirical studies to be organized into descriptive and higher-order analytical themes while retaining links to the underlying evidence (Thomas & Harden, 2008). RQ1 was coded according to GenAI's pedagogical functions in learning, including information provision, explanation, dialogue, perspective comparison, feedback, fact-

checking, simulation, and verification support. RQ2 was coded according to critical-reading operations, including critical questioning, claim evaluation, evidence evaluation, source credibility, perspective, bias, and multimodal reading. RQ3 was coded according to identification, verification, corroboration, evidence checking, credibility assessment, and decision-making regarding potentially misleading information. RQ4 was mapped onto five determinant domains: learner, pedagogical, task-design, technological, and contextual factors. Findings were then compared across studies to identify convergent patterns, differences, recurring mechanisms, and conditions influencing outcomes. Given the heterogeneity of study designs, instruments, intervention durations, learning contexts, and outcomes, synthesis was qualitative and thematic rather than forced into quantitative meta-analysis. A qualitative synthesis is appropriate when substantial heterogeneity across study designs, outcomes, and contexts limits the meaningful aggregation of findings into a statistical effect estimate (Pollock & Berge, 2018; Thomas & Harden, 2008). The cross-study synthesis was subsequently used to formulate the Generative AI–Mediated Critical Reading and Misinformation Evaluation (GAI-CReME) Framework as an evidence-informed conceptual framework explaining the relationship among students' interaction with GenAI, critical-reading processes, information verification, calibrated judgment, and misinformation evaluation.

To strengthen the analytical rigor of the synthesis beyond thematic description, three supplementary analytical procedures were applied. First, an evidence-density mapping was conducted in which each synthesized finding was linked to the specific studies contributing to it, distinguishing direct evidence (studies at the intersection of GenAI, secondary students, and critical or evaluative outcomes) from indirect evidence (supporting studies without GenAI). Second, confidence in each review finding was appraised using an approach adapted from GRADE-CERQual (Lewin et al., 2015), which considers four components: methodological limitations of the contributing studies, coherence of the finding across studies, adequacy of the data, and relevance of the contributing studies to the review question. Each finding was rated as high, moderate, low, or very low confidence; indirectness (i.e., reliance on non-GenAI supporting studies) was treated as a relevance concern that lowered confidence. Third, a cross-case configurational analysis examined how determinants co-occurred and interacted across studies, rather than treating them as independent factors, and the resulting mechanisms were formalized as testable propositions. These procedures do not convert the qualitative synthesis into a quantitative estimate; rather, they make explicit how strongly each conclusion is warranted by the available evidence.

3. Result and Discussion

a. Study Characteristics and General Evidence Pattern

To establish the overall structure of the evidence base, the 25 records were mapped according to publication year, study group, research design, and educational level. This descriptive mapping provides an overview of the temporal development and methodological diversity of the literature, while distinguishing studies directly addressing the intersection of generative AI (GenAI), secondary education, and critical or evaluative literacy from supporting studies examining information evaluation and

misinformation without GenAI. Figure 2 summarizes these characteristics and provides the empirical context for interpreting the subsequent thematic synthesis.

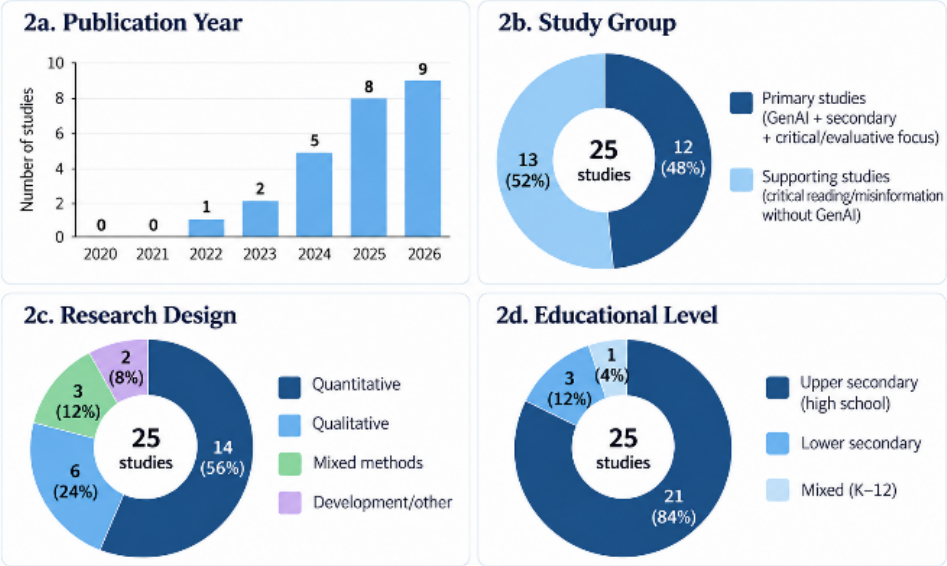


Figure 2. Characteristics of the 25 Studies

Figure 2 shows that the studies on GenAI increased continuously every year with various kinds of research design. These findings indicate that research on GenAI, critical reading, and misinformation evaluation among secondary students is still developing and remains heterogeneous in terms of aims, designs, subject contexts, activities, and outcomes. Studies most closely aligned with the review focus can be grouped into the use of GenAI as a learning partner, the reading and evaluation of GenAI outputs, critical questioning, AI-literacy development, and fact-checking of GenAI outputs. Studies of information and misinformation evaluation without GenAI provide a basis for understanding the epistemic capacities that need to be mediated when GenAI enters the reading ecosystem.

A central pattern is a shift from GenAI as a source of answers toward GenAI as an object of reading and scrutiny. Tang et al. (2026) position critical questioning within AI-literacy development, whereas Zhou (2026) demonstrates a process moving from initial trust to consistency checking, external corroboration, reconstruction, or rejection. Cheung et al. (2024) show that reading ChatGPT-generated texts about climate change involves content interpretation, genre reasoning, and epistemic evaluation. Thus, understanding the content of a GenAI output is distinct from determining whether the information is trustworthy.

In misinformation research, information evaluation among secondary students requires consideration of expertise, intent, venue, evidential quality, and source reliability (Kiili et al., 2022; Siani et al., 2024). This pattern indicates that misinformation detection is a layered epistemic activity rather than a simple act of labeling information as true or false.

A closer examination of the working evidence set reveals an asymmetry in evidential directness that shapes how the findings should be read. Only 12 of the 25 records (48%) are located at the direct intersection of GenAI, secondary education, and critical or evaluative literacy, whereas 13 records (52%) contribute indirect evidence

from information and misinformation evaluation without GenAI. The two groups also differ in the type of knowledge they provide. The primary studies are predominantly qualitative, exploratory, or design-oriented and illuminate *how* students engage with GenAI outputs; for example, Zhou (2026) used a constructivist grounded-theory design with 21 upper secondary students, and Cheung et al. (2024) analyzed students' holistic reading of ChatGPT-generated texts. By contrast, intervention evidence on *whether* trained evaluation strategies improve students' resilience to misinformation comes largely from the supporting, non-GenAI studies (Ghazi et al., 2025; Marten et al., 2025; Marten & Stadtler, 2025; Mellberg et al., 2025).

This asymmetry has an important interpretive consequence. Claims about the process of GenAI-mediated epistemic activity rest mainly on process-oriented evidence collected directly in GenAI settings, whereas claims about the effectiveness of sourcing, corroboration, and analytical-thinking instruction are transferred from conventional digital-text settings. Such transfer is a theoretically reasonable inference, because the epistemic operations involved are similar, but it is not yet an empirically demonstrated effect in GenAI environments. The following sections therefore distinguish between findings that are directly observed in GenAI contexts and findings that are inferred from adjacent evidence, and Section 3.6 reports the confidence attached to each.

b. GenAI Use in Learning

The synthesis identifies at least six functions of GenAI: generating information, explaining information, asking and answering questions, comparing perspectives, serving as an object of scrutiny, and supporting verification. These functions can form a learning cycle when students do not stop at the initial response.

As a text generator, GenAI becomes a new object of reading. Cheung et al. (2024) show that students read ChatGPT-generated socioscientific texts while simultaneously engaging in epistemic evaluation. Fulsher et al. (2026) characterize GenAI as a technology with dual capacity: it can help address misinformation while also generating or reinforcing inaccurate information.

GenAI also functions as a dialogic partner. Tang et al. (2026) demonstrate the importance of critical questioning, while Zhou (2026) shows that students can move from trust toward scrutiny and reconstruction. These interactions indicate that the quality of use is determined not only by system capability but also by the quality of students' questions and checking practices.

Fact-checking is particularly important. Lao et al. (2025) directly use fact-checking of GenAI outputs as a media-information literacy practice. GenAI can therefore become material for reading, questioning, source checking, and revising understanding. This finding reinforces the conclusion that the pedagogical value of GenAI for critical reading lies in epistemic provocation rather than in information generation alone.

Read together, the six functions are not equivalent in the epistemic demand they place on students. As summarized in Table 1, they can be ordered along a continuum of epistemic agency: generating and explaining information position the student mainly as a *recipient*; asking and answering questions and comparing perspectives position the student as an *interlocutor*; and treating GenAI output as an object of scrutiny and as a verification aid position the student as an *evaluator*. The evidence is also uneven along this continuum. The evaluator-oriented functions are the ones most directly documented in the primary

studies (Cheung et al., 2024; Lao et al., 2025; Zhou, 2026), whereas perspective comparison is largely inferred from dialogic interaction rather than measured as a distinct outcome. This pattern suggests that the pedagogical value of GenAI for critical reading rises as the student's role shifts from recipient to evaluator, and that the same tool can be positioned at either end of the continuum depending on how the task is framed (Mollick & Mollick, 2023).

Table 1. GenAI functions ordered by students' epistemic agency

GenAI function	Student role	Epistemic demand	Illustrative evidence
Generating information	Recipient	Low: comprehension of output	Fulsher et al. (2026)
Explaining information	Recipient	Low–moderate: understanding, clarifying	Valeri et al. (2025)
Asking and answering questions	Interlocutor	Moderate: formulating critical questions	Tang et al. (2026); Zhou (2026)
Comparing perspectives	Interlocutor	Moderate: contrasting viewpoints	Inferred; not measured separately
Object of scrutiny	Evaluator	High: judging claims, genre, evidence	Cheung et al. (2024); Zhou (2026)
Supporting verification	Evaluator	High: fact-checking, corroboration	Lao et al. (2025)

c. GenAI Contributions to Critical Reading

GenAI's contribution to critical reading can be understood through four operations: claim evaluation, evidence evaluation, source evaluation, and perspective/bias evaluation. These four operations do not necessarily develop simultaneously.

Claim evaluation begins when students question whether a GenAI statement should be accepted. Zhou (2026) shows that fluent responses can generate initial trust, whereas Tang et al. (2026) demonstrate that critical questioning can create opportunities to test reasons, evidence, and alternative explanations. The ability to question therefore functions as an initial mechanism that transforms answer consumption into evaluation.

Evidence evaluation is more complex than understanding content. Cheung et al. (2024) show that epistemic evaluation is a central demand in reading ChatGPT-generated texts. Findings from Kiili et al. (2022) and Digan et al. (2026) emphasize that students need to connect claims with evidence quality and evidentiary practices. Learning therefore requires more than fact-checking; it also requires students to determine the relevance and sufficiency of evidence.

Source evaluation becomes problematic because GenAI outputs do not always provide an adequate source trail. Kiili et al. (2022) and Mellberg et al. (2025) demonstrate the importance of source credibility, expertise, evidence, and consensus. In GenAI contexts, students need to understand that a system that generates text is not, by itself, a source that validates the content of that text.

Perspective and bias evaluation requires both AI literacy and reading literacy. Kong et al. (2024) show that project-based AI literacy can develop metacognitive strategies and ethical understanding. Thus, GenAI contributes to critical reading through the mediation of epistemic activity rather than as an automatic effect of technology use.

A cross-operation analysis reveals two further patterns that strengthen the interpretation of these findings (Table 2).

First, the four operations appear to be sequentially dependent rather than parallel. Claim evaluation functions as the entry point: unless students first question whether a fluent GenAI statement should be accepted, evidence and source evaluation are not triggered at all (Tang et al., 2026; Zhou, 2026). Evidence and source evaluation are, in turn, mutually dependent, because judging the sufficiency of evidence requires knowing where it comes from (Kiili et al., 2022). Perspective and bias evaluation is the most demanding operation because it requires students to recognize what a text omits, not only to assess what it states.

Second, the evidence density across operations is inversely related to how strongly GenAI disrupts each operation. Source evaluation is the operation most fundamentally altered by GenAI, because generative outputs often lack an identifiable author, publication venue, or stable reference trail; yet the evidence on source evaluation in this review derives almost entirely from non-GenAI supporting studies (Abel et al., 2024; Kiili et al., 2022; Mellberg et al., 2025). This finding implies that conventional source evaluation, which asks "Who wrote this and can they be trusted?", must be reconceptualized in GenAI contexts as *provenance reconstruction*: students need to leave the generated text and locate independent sources that can confirm or disconfirm its claims, a practice closely related to lateral reading (McGrew, 2024). The operation that GenAI most transforms is thus the one least directly studied, which constitutes a clear priority for future research.

Table 2. Critical-reading operations: GenAI-specific challenges and evidence density

Operation	GenAI-specific challenge	Direct evidence (GenAI)	Indirect evidence	Density
Claim evaluation	Fluency triggers initial trust	Tang et al. (2026); Zhou (2026)	–	Moderate
Evidence evaluation	Claims rarely linked to verifiable evidence	Cheung et al. (2024)	Kiili et al. (2022); Digan et al. (2026)	Moderate
Source evaluation	No identifiable author, venue, or reference trail	Limited	Abel et al. (2024); Kiili et al. (2022); Mellberg et al. (2025); McGrew (2024)	Low (indirect)
Perspective/ bias evaluation	Bias embedded in training data; omissions invisible	Kong et al. (2024) (broad AI literacy)	–	Low

d. Identification, Verification, and Evaluation of Misinformation

Misinformation detection is a multistage epistemic process involving claim identification, external verification, cross-source corroboration, credibility assessment, and evidence-based judgment. Rather than simply classifying information as true or false, students need to justify their decisions based on the quality and reliability of available evidence (Ghazi et al., 2025). Research highlights the importance of sourcing, corroboration, and analytical thinking in strengthening students' resilience to misinformation (Marten & Stadtler, 2025).

In GenAI-mediated learning, this process becomes more challenging because AI-generated texts may appear coherent and persuasive despite containing inaccurate or unsupported claims. Students should therefore treat GenAI outputs as claims requiring verification rather than authoritative sources. Cheung et al. (2024) and Lao et al. (2025) emphasize the importance of critically

examining and fact-checking AI-generated information. Furthermore, relying on multiple AI systems without consulting independent sources may create circular corroboration, in which apparent agreement does not constitute genuine factual confirmation (Zhou, 2026).

Table 2. Stages of Misinformation Evaluation in GenAI-Mediated Learning

Stage	Objective	Student Activity	GenAI-Related Challenge	Supporting Evidence
Identification	Recognize questionable claims	Identify inaccuracies and inconsistencies	Fluent text may conceal errors	Cheung et al. (2024)
Verification	Check factual accuracy	Consult credible external sources	Unsupported or fabricated claims	Lao et al. (2025)
Corroboration	Confirm claims independently	Compare evidence across sources	Apparent agreement between AI systems	Marten & Stadtler (2025); Zhou (2026)
Credibility Assessment	Evaluate information reliability	Examine source expertise and evidence quality	Perceived AI authority may replace critical evaluation	Kiili et al. (2022)
Calibrated Judgment	Make evidence-based decisions	Accept, revise, reject, or withhold judgment	Excessive trust or indiscriminate skepticism	Ghazi et al. (2025); Pennycook & Rand (2021)

Note. The table synthesizes direct GenAI-related evidence and supporting studies of conventional information evaluation; these evidence types are not equivalent.

These stages may overlap and recur as students encounter new evidence or conflicting information. Effective instruction should consequently emphasize external verification, independent corroboration, and reasoned judgment. The objective is not to encourage generalized skepticism but to help students distinguish accurate information from misinformation while acknowledging uncertainty when evidence remains insufficient (Ghazi et al., 2025).

Overall, GenAI can support misinformation evaluation when instructional activities require students to question, verify, and justify their judgments. Teacher scaffolding and task design remain important, while further empirical research is needed to establish the effectiveness of these strategies specifically among secondary students (Pennycook & Rand, 2021).

e. Factors Influencing Success and Limitations

Success cannot be explained by technology alone. The evidence matrix indicates five layers: learner, pedagogical, task, technological, and contextual factors.

At the learner level, prior knowledge, reading ability, AI literacy, metacognition, and self-efficacy influence how students scrutinize outputs. Zhou (2026) demonstrates the role of prior knowledge, while Zhong & Liu (2025) emphasize AI Knowledge, AI Affectivity, and AI Thinking in secondary students' AI literacy.

At the pedagogical level, teacher scaffolding is central. Tang et al. (2026) demonstrate the importance of teachers and instructional design for critical questioning, while Marten & Stadtler (2025) show the benefits of sourcing and corroboration training. GenAI should therefore not be released to students with nothing more than instructions to search for answers.

Task design determines the depth of interaction. Tasks that merely request answers create opportunities for cognitive offloading, whereas tasks requiring comparison of responses, evidence seeking, source tracing, and justification promote epistemic activity. Cheung et al. (2024) and Garcia-Mila et al. (2026) demonstrate the importance of activity designs that require evaluation and argumentation.

At the technological level, hallucinations, inaccuracies, bias, prompt sensitivity, and limited source transparency constitute both risks and objects of literacy. Fulsher et al. (2026) demonstrate GenAI's dual capacity within misinformation ecosystems, while Valeri et al. (2025) document students' experiences of the benefits and limitations of ChatGPT in STEM.

School context, teacher competence, curriculum, technological access, and norms governing AI use also shape outcomes. Kong et al. (2024) and Tang et al. (2026) demonstrate the importance of instructional design and classroom norms. Thus, the more consequential variable is not simply whether students have access to GenAI, but what they are asked to do with its outputs.

A configurational reading of the evidence indicates that these five layers operate interactively rather than additively. Three interaction patterns can be identified. The first is *compensatory*: teacher scaffolding appears able to partially offset limited prior knowledge. Zhou (2026) shows that prior knowledge shapes whether students detect inconsistencies in GenAI outputs, while teacher-led sourcing and corroboration training improves the evaluation strategies of lower secondary students who lack such knowledge (Marten & Stadtler, 2025). The second is *conditional*: technological limitations such as hallucinations become learning resources only when the task requires verification, as in fact-checking activities (Lao et al., 2025) or critical reading of generated texts (Cheung et al., 2024); without such task demands, the same limitations function as risks. The third is *threshold-like*: AI literacy without reading literacy tends to produce procedural competence in tool use without epistemic evaluation, whereas AI-literacy frameworks that include evaluative thinking explicitly address this gap (Kong et al., 2024; Zhong & Liu, 2025).

These patterns refine the conclusion of this section. The success of GenAI integration is not determined by the presence of any single favorable factor but by the alignment between learner readiness, task demands, and instructional support. A well-designed verification task may fail when students lack the background knowledge needed to recognize errors and receive no scaffolding, whereas the same task may succeed when scaffolding compensates for that gap. This interaction-based account explains why studies using similar GenAI tools report divergent outcomes.

f. Cross-RQ Synthesis: Contradictions and Mechanism

The cross-RQ synthesis integrates findings from the four research questions to identify converging patterns, apparent contradictions, and underlying mechanisms shaping the relationship between GenAI, critical reading, and misinformation evaluation. Rather than treating GenAI use as a direct determinant of learning outcomes, this synthesis examines how epistemic activity, teacher scaffolding, task design, and learner characteristics interact to influence whether GenAI supports critical evaluation or encourages cognitive dependency.

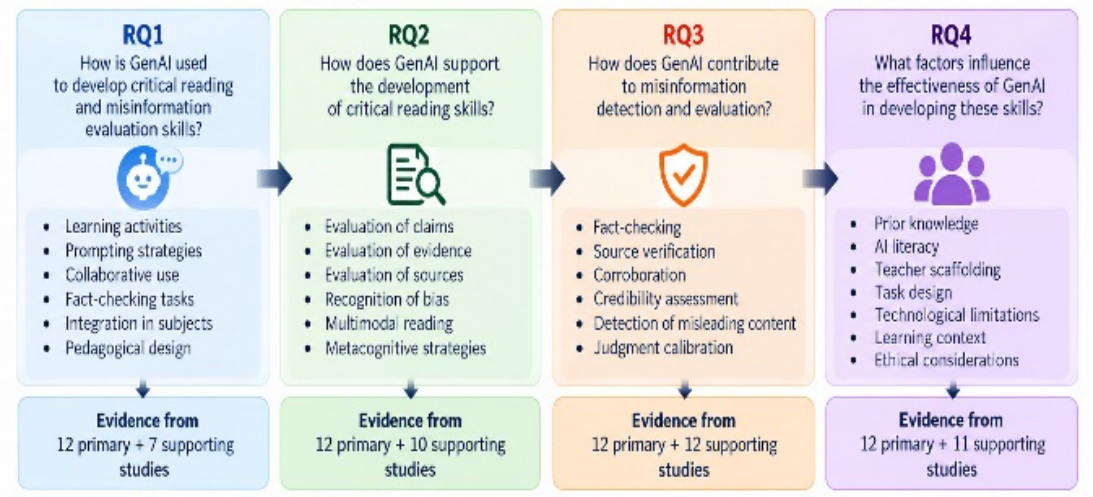


Figure 3. Thematic Mapping Across Four RQs

Figure 3 outlines four core research questions investigating how GenAI is used to develop critical reading and misinformation evaluation skills. It systematically maps out learning activities, mechanisms for evaluating claims, fact-checking contributions, and the various factors that influence GenAI's overall effectiveness. However, synthesizing the evidence across these areas reveals that integrating GenAI into educational practice is highly complex.

Four major contradictions emerge. First, efficiency may conflict with depth of thinking because rapid answers can reduce the incentive to check. Second, trust and skepticism need to be calibrated: excessive trust is risky, but doubting all information is not the goal of critical literacy. Third, AI literacy and reading literacy are mutually supportive but not identical. Fourth, GenAI can function both as a tool and as an object of critique.

This mechanism indicates that GenAI does not directly produce critical-reading ability. Rather, GenAI creates an epistemic situation that can activate critical reading when instruction requires students to scrutinize and verify information (Adhantoro et al., 2026b). Accordingly, a more productive unit of analysis is not AI use but AI-mediated epistemic activity.

To indicate how strongly each conclusion is warranted, the main review findings were assessed for confidence using the adapted GRADE-CERQual approach described in the Method section (Table 3). Three findings are supported with moderate confidence: the central role of epistemic activity, the moderating role of scaffolding and task design, and the general effectiveness of sourcing and corroboration instruction. Their confidence is limited mainly by small samples, the predominance of qualitative designs, and the narrow range of countries and subjects represented. Findings concerning automation bias, fact-checking of GenAI outputs, and calibrated judgment are rated low, largely because they rest on few direct studies or on non-GenAI evidence. The finding concerning perspective and bias evaluation is rated very low because it derives from a single study measuring a broader AI-literacy construct.

Table 3. Summary of confidence in the main review findings (adapted GRADE-CERQual)

Review finding	Contributing studies	Main concerns	Confidence
F1. GenAI supports critical reading through epistemic activity, not through access alone	Cheung et al. (2024); Lao et al. (2025); Tang et al. (2026); Valeri et al. (2025); Zhou (2026)	Small samples; mostly qualitative; limited contexts	Moderate
F2. Teacher scaffolding and task design moderate outcomes	Cheung et al. (2024); Garcia-Mila et al. (2026); Kong et al. (2024); Marten & Stadtler (2025); Tang et al. (2026)	Partly indirect (non-GenAI)	Moderate
F3. Sourcing and corroboration instruction strengthens misinformation resilience	Abel et al. (2024); Marten et al. (2025); Marten & Stadtler (2025); McGrew (2024); Mellberg et al. (2025)	Strong in conventional settings; transfer to GenAI untested	Moderate (general); Low (GenAI)
F4. Students initially trust fluent GenAI outputs (automation bias)	Valeri et al. (2025); Zhou (2026)	Few studies; self-report and interview data	Low
F5. Fact-checking GenAI outputs develops media and information literacy	Fulsher et al. (2026); Lao et al. (2025)	Few direct studies; one review	Low
F6. Calibrated judgment, not skepticism, is the appropriate outcome	Ghazi et al. (2025); Pennycook & Rand (2021)	Non-GenAI evidence; conceptual support	Low
F7. GenAI supports perspective and bias evaluation	Kong et al. (2024)	Single study; broad construct	Very low

This confidence profile clarifies the structure of the evidence base. The core of the GAI-CReME Framework, namely that the effect of GenAI depends on the epistemic activity it is embedded in and on the instructional conditions surrounding it, rests on findings with moderate confidence and convergent support across studies. The more specific links, particularly those involving source and bias evaluation of generative texts, remain at the frontier of the evidence and should be treated as plausible hypotheses rather than established conclusions.

g. Theoretical Contribution: GAI-CReME Framework

Based on the synthesis, this study develops the Generative AI–Mediated Critical Reading and Misinformation Evaluation (GAI-CReME) Framework as an evidence-informed conceptual framework rather than a theory independently validated through empirical testing (Adhantoro et al., 2026a). The framework integrates three domains that have previously developed largely in parallel: GenAI in education, critical reading, and misinformation evaluation.

The first contribution is a shift in the unit of analysis from AI use to AI-mediated epistemic activity. The second is the positioning of critical questioning as an initial mechanism that opens the verification process. The third is the positioning of calibrated judgment as an intermediate outcome rather than a simple trust-versus-distrust distinction. The fourth is the positioning of teacher scaffolding and task design as key moderators.

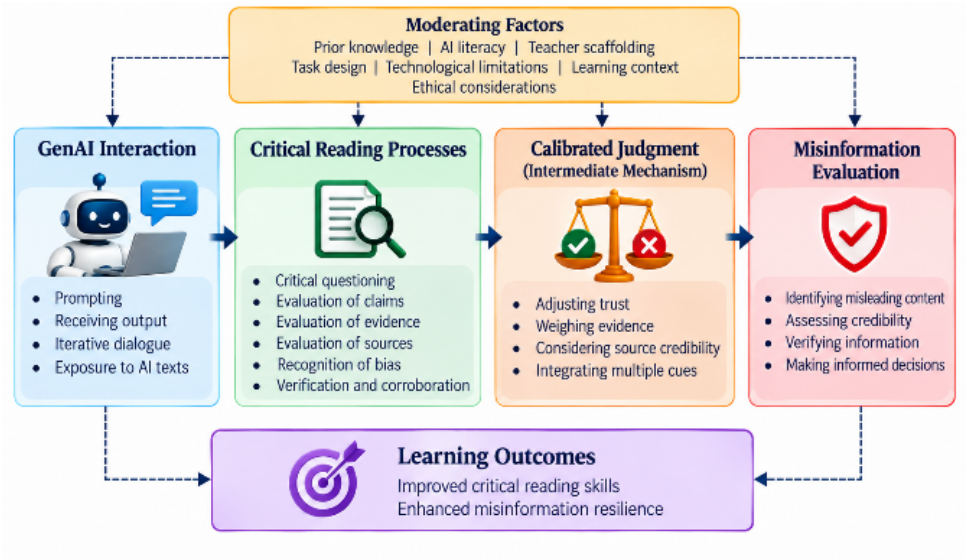


Figure 4. GAI-CReME Framework

The distinctive contribution of GAI-CReME becomes clearer when it is compared with adjacent frameworks. The AIR model of epistemic performance (Barzilai & Chinn, 2024) specifies the aims, ideals, and reliable processes involved in evaluating knowledge claims, but it was not developed for situations in which the text itself is produced by a generative system without a human author. AI-literacy frameworks for secondary students (Kong et al., 2024; Zhong & Liu, 2025) treat evaluation as one dimension of a broader competence in understanding and using AI, but they do not specify the reading operations through which evaluation occurs. Misinformation-resilience research (Marten & Stadtler, 2025; McGrew, 2024) specifies sourcing and corroboration strategies but assumes texts with identifiable origins. GAI-CReME integrates these perspectives by specifying the conditions under which GenAI interaction triggers, or bypasses, the epistemic operations that each framework describes.

To make the framework empirically testable, five propositions are derived from the synthesis. *P1:* Holding access to GenAI constant, tasks that require students to verify GenAI outputs against external sources will produce greater gains in claim and evidence evaluation than tasks that use GenAI as an answer source. *P2:* Critical questioning mediates the relationship between GenAI interaction and calibrated judgment. *P3:* The effect of GenAI-mediated activities on misinformation resilience is moderated by prior domain knowledge, and teacher scaffolding weakens this dependency. *P4:* Instruction that emphasizes skepticism without calibration will reduce acceptance of accurate information as well as inaccurate information, resulting in little or no gain in discernment. *P5:* Source-evaluation skills acquired in conventional digital-text contexts will transfer to GenAI contexts only when instruction explicitly addresses provenance reconstruction. Each proposition corresponds to a specific link in the framework and can be tested through experimental, quasi-experimental, or longitudinal designs.

h. Implications for Secondary Reading Education

Generative artificial intelligence (GenAI) requires secondary reading education to move beyond conventional text comprehension toward the critical evaluation of AI-generated information. Students need to examine claims, assess evidence, verify sources,

identify potential bias, and justify their judgments rather than accept fluent AI responses as inherently reliable. However, the available evidence suggests that these competencies depend on instructional design, teacher scaffolding, and students' prior knowledge and AI literacy rather than technology access alone (Tang et al., 2026; Zhou, 2026).

In classroom practice, teachers can integrate GenAI into structured reading activities that require students to compare AI-generated narratives with credible primary sources, identify unsupported claims, and reconstruct interpretations based on verified evidence. A practical sequence involves four stages: Ask, formulate critical questions; Check, verify claims using independent sources; Compare, examine differences between AI responses and external evidence; and Decide, accept, revise, reject, or withhold judgment with an evidence-based justification (Cheung et al., 2024). This sequence connects reading comprehension with source evaluation, argumentative reasoning, digital literacy, and AI literacy.

Table 4 presents the proposed instructional implications and their corresponding learning objectives. These recommendations are evidence-informed implications of the review, rather than a teaching intervention whose effectiveness has already been experimentally established.

Table 4. Instructional Implications for Secondary Reading Education in GenAI-Mediated Learning

Instructional Focus	Learning Objective	Classroom Activity	Assessment Indicator	Supporting Evidence
Critical questioning	Develop analytical reading	Formulate questions about AI-generated claims	Quality of critical questions	Tang et al. (2026); Zhou (2026)
Evidence verification	Strengthen factual evaluation	Check AI claims against independent sources	Accuracy of verification and evidence use	Lao et al. (2025); Cheung et al. (2024)
Source evaluation	Assess information credibility	Examine source provenance and reliability	Quality of source-based justification	Kiili et al. (2022); McGrew (2024)
Comparison and bias analysis	Recognize conflicting perspectives and potential bias	Compare AI responses with credible texts and alternative viewpoints	Ability to identify inconsistencies and bias	Kong et al. (2024); Cheung et al. (2024)
Calibrated judgment	Make evidence-based decisions	Accept, revise, reject, or withhold judgment on claims	Appropriateness of conclusions relative to evidence	Ghazi et al. (2025); Pennycook and Rand (2021)
Teacher scaffolding	Support responsible and independent evaluation	Provide guided verification tasks and feedback	Quality of reasoning and verification strategies	Tang et al. (2026); Marten and Stadtler (2025)

Note. The table translates the review findings into proposed instructional practices. Supporting evidence includes both direct GenAI studies and research on conventional information evaluation; the transferability of the latter to GenAI-mediated settings requires further empirical testing.

Ultimately, effective secondary reading education should position GenAI as both a learning resource and an object of critical scrutiny. Teachers should prioritize evidence-based reasoning and calibrated judgment rather than unquestioning acceptance or indiscriminate skepticism. Nevertheless, the limited direct evidence on source and bias

evaluation in GenAI contexts highlights the need for longitudinal and experimental studies to test these instructional approaches and determine their effects on students' critical-reading and misinformation-detection competencies.

4. Conclusion

This systematic literature review shows that the relationship among generative artificial intelligence (GenAI), critical reading, and misinformation detection among secondary students cannot be understood as a linear relationship between technology use and improved literacy ability. The pedagogical value of GenAI emerges primarily when the technology is embedded in activities that require students to question, verify, compare, and take responsibility for the information generated. The central issue is therefore no longer whether students use GenAI, but how such use shapes epistemic practices in reading and evaluating information.

The main theoretical contribution of this study is the Generative AI–Mediated Critical Reading and Misinformation Evaluation (GAI-CReME) Framework, which conceptualizes critical reading in GenAI environments as a process of epistemic mediation. The framework connects exposure to GenAI-generated texts or responses, students' initial responses, critical questioning, verification, corroboration, evidence and source evaluation, and calibrated judgment. Calibrated judgment is important because the goal of literacy is neither to make students always trust nor always distrust AI, but to enable them to adjust the level of trust to the quality of evidence and the credibility of sources. The framework thus extends the conception of critical reading from the evaluation of digital texts to the evaluation of generative texts.

The confidence assessment further shows that the evidence base is strongest for the claim that the effect of GenAI depends on the epistemic activity in which it is embedded and on teacher scaffolding and task design, and weakest for claims concerning source and perspective/bias evaluation of generative texts. The interaction analysis indicates that determinants operate in compensatory, conditional, and threshold-like ways rather than independently. These analyses strengthen the framework by distinguishing its well-supported core from the links that still require empirical confirmation.

Practically, schools and curriculum developers should avoid approaches that position GenAI merely as a tool for finding answers. GenAI integration should be accompanied by task designs that require students to trace sources, check claims, compare AI outputs with external sources, identify weaknesses in arguments, and provide evidence-based justifications. Teacher competence development is also important so that AI-literacy and critical-reading scaffolding become integral components of instruction. At the policy level, guidelines for GenAI use in schools should not focus only on safety, academic integrity, or restrictions; they should also incorporate information-evaluation and verification competencies as components of students' AI literacy.

Several limitations should be acknowledged. The available literature remains heterogeneous in research design, participant characteristics, subject areas, types of GenAI, intervention duration, and indicators of critical-reading ability and misinformation detection. Evidence directly integrating all four components – GenAI, secondary students, critical reading, and misinformation – also remains relatively limited. In addition, some studies focus

broadly on AI literacy or critical thinking and therefore do not always measure specific critical-reading operations. This heterogeneity limits the feasibility of quantitative meta-analysis and requires cautious interpretation of the findings. Moreover, the confidence ratings reported in this review are provisional because they are based on the working evidence set; they should be re-examined once the final PRISMA inclusion count and the complete full-text screening log are available.

Future research should empirically test the GAI-CReME Framework through longitudinal and experimental studies that measure changes in claim, evidence, source, and bias evaluation separately. Research should also compare instructional designs with and without critical questioning, examine the influence of teacher scaffolding, and explore how prior knowledge, AI literacy, and reading ability moderate students' responses to GenAI. Cross-linguistic and cross-cultural research, particularly in Indonesian language education, is also needed to determine whether the mechanisms identified in the international literature remain applicable when students encounter generative texts, local misinformation, and the characteristics of Indonesia's information ecosystem. The five propositions (P1–P5) formulated in Section 3.7 offer a concrete agenda for such testing, with priority given to the least-evidenced links: provenance reconstruction in source evaluation, perspective and bias evaluation of generative texts, and the transfer of conventional sourcing skills to GenAI environments.

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