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From Evaluation to Verification: Reconceptualizing Information Literacy Frameworks in the Age of Generative AI

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ABSTRACT

The digital information ecosystem has undergone significant changes as a result of the rapid development of generative artificial intelligence (generative AI), especially in the process of information creation, dissemination and use. This development has challenged the conventional information literacy paradigm that has emphasized the evaluation of sources based on accuracy, authority and reliability. In an increasingly complex digital environment, the information literacy approach is now seen to shift from mere evaluation to information verification to ensure the validity and accuracy of the information used. Therefore, this study aims to examine how the information literacy framework is re-evaluated in the era of generative AI and identify new skills needed by users to navigate information generated by AI. This study uses a Systematic Literature Review (SLR) approach guided by the PRISMA framework to ensure that the process of identifying, screening, assessing eligibility and selecting studies is carried out transparently and systematically. A total of 673 articles published between 2022 and 2026 were identified through a systematic search using keywords related to information literacy, AI literacy, generative AI and information verification. After removing duplicate records and excluding studies that did not meet the inclusion criteria and articles that did not have accessible full text, a total of 53 studies were selected for the final analysis. The data obtained were analyzed using thematic analysis methods to identify key themes, research trends and existing research gaps. The study findings show that generative AI has challenged traditional source evaluation practices by producing content that appears convincing but potentially contains inaccuracies, algorithmic bias and AI hallucinations. This study also emphasizes the importance of information verification practices, the use of cross-referencing sources, and the integration of AI literacy into the information literacy framework as an essential competency in the digital age. This study concludes that information literacy needs to be redefined with greater emphasis on information verification to enable users to evaluate information more critically and accurately in the face of the challenges of the information environment driven by generative AI.

Keywords: Information Literacy, Generative AI, Verification, Digital Information Verification, AI Literacy

INTRODUCTION

Many parties who practice information literacy have all seen significant changes because of the quick growth of artificial intelligence, particularly generative AI. It is a system built on machine learning models, such as large language models (LLMs), that can autonomously produce new text, images, and material based on vast amounts of training data (Vivas-Urias et al., 2026). This technique is increasingly popular due to its ability to produce content quickly and convincingly which provides significant learning support to users. At the same time, its confusing nature raises new problems for how information is produced, evaluated, and verified in digital environments.

Although various studies have discussed the impact of generative AI in various fields, the existing literature is still fragmented across various disciplines such as education, technology, and information science (Murni, 2026). In addition, most studies focus more on technological performance or the use of AI in general, but less emphasis is placed on the changing aspects of information literacy, in particular the shift from evaluation to verification. There is also a gap in terms of deeper analysis of dimensions such as AI literacy as a mediating competency, differences in context of use, and teaching approaches that support the development of critical thinking skills among students.

This study conducted a Systematic Literature Review guided by the PRISMA guidelines to ensure that the process of selecting, screening, and reporting literature was carried out systematically, transparently, and replicable. It also aims to provide a more comprehensive synthesis of how information literacy frameworks are being reconceptualized in the era of generative artificial intelligence. This study specifically examines methods that aid users in developing pre-verification, the transition from assessment-based to verification-based approaches, and the role of AI literacy as a mediating factor in enhancing user skills.

Therefore, this study is guided by the following research questions:

- **RQ1:** How must established information literacy frameworks be restructured to prioritize "verification" over "evaluation" in the context of algorithmically generated content?
- **RQ2:** What specific role does AI literacy play as a mediating factor in empowering students to verify information autonomously?
- **RQ3:** What instructional strategies, such as "Think First, ChatGPT Later," are most effective in fostering a "verification-first" mindset among higher education students?

Overall, this study is expected to contribute by providing a structured synthesis of the changing paradigm of information literacy in the generative AI era, while offering a clearer understanding for the development of future information literacy frameworks that are more adaptive, critical, and relevant to the current digital ecosystem.

METHODOLOGY

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was adopted to ensure transparency, thoroughness, and reproducibility throughout the study selection and reporting phases. This systematic protocol provides a structured pipeline to identify, screen, and critically evaluate the literature, thereby enhancing the methodological consistency and internal validity of the review.

By aligning the search mechanics with the core research objectives, this methodology systematically isolates studies exploring the intersection of Generative AI (GenAI) and the impacts towards information literacy. Furthermore, the method guides the selection of target databases and the execution of targeted Boolean search strategies. By applying explicit inclusion and exclusion criteria, this process filters out extraneous data to compile a high-quality, specialized output that directly addresses the research questions.

Collection of Past Works

To ensure a structured and comprehensive gathering of relevant literature, this study adopted the systematic review protocol outlined by Hemingway and Brereton (2009). The initial search was executed across three primary academic databases: ACM Digital Library, SCOPUS, and Web of Science. These specific platforms were selected to ensure a robust, multidisciplinary provide spanning computer science, information systems, and educational technology, directly aligning with the study's focus on the intersection of Generative AI and information literacy frameworks.

Selection of Article Databases

The selection of ACM Digital Library, SCOPUS, and Web of Science was deliberately balanced to maximize bibliographic coverage while maintaining strict quality control. These databases are globally recognized for their rigorous indexing standards, peer-review mandates, and high institutional reputation. Utilizing this specific cluster of databases provided a reliable foundation of authoritative academic literature. Furthermore, their advanced search indexing allowed for precise query execution, ensuring that the retrieved corpus remained strictly relevant to the core research objectives without introducing extraneous or low-quality data.

Search terms

To ensure a comprehensive and systematic retrieval process, a careful search strategy was implemented across all selected databases. Specific search strings were constructed by pairing targeted keywords with Boolean operators (AND, OR) to maximize the conceptual relevance of the retrieved literature while filtering out irrelevant technical data.

The search terminology was derived from the core theoretical pillars of this study: generative artificial intelligence, information literacy and AI, and higher education. The basic search string combinations used included:

- "Generative AI" OR "ChatGPT"
- "Information Literacy" OR "AI Literacy"
- "Information literacy" AND "Generative AI"

This search string was calibrated to balance bibliographic breadth with thematic specificity, effectively isolating relevant educational research while minimizing out-of-scope computer science or purely technical machine learning literature. Using these search queries consistently across the selected repositories produced a robust data set and documented the epistemic shift from information evaluation to algorithmic validation.

Selection of papers (Inclusion and Exclusion Criteria)

In addition, the method used is to set explicit inclusion and exclusion criteria before the screening process to address the core research questions and maintain a tight theoretical alignment and organize the desired studies. This process is carefully carried out to preserve methodological stability, bibliographic reliability and academic validity of the systematic review.

Not only that, among the majority of articles that are limited and selected are the results of publications from the years 2022-2026. This is because, the selection and setting of limits this year is to ensure that the data set taken and reviewed is appropriate for the current situation and recent developments involving the use of Generative AI and its impact on user information literacy. The selection process involves a multi-stage evaluation of the papers taken, systematically eliminating documents that are not peer-reviewed, institutional reports out of scope and purely technical computer science architectures that have no relevance to the educational or information literacy framework.

Table 1 Inclusion and Exclusion Criteria for Studies on From Evaluation to Verification; Reconceptualizing Information Literacy Frameworks in the Age of Generative AI

Inclusion Criteria	**Exclusion Criteria**
Studies on the reformation of the information literacy framework in higher education	Studies that focus only on corporate or early educational training environments
Studies on learner autonomy, AI literacy, or user verification practices	Studies investigating user interface (UI) design, natural language processing (NLP) chat preferences, or general user satisfaction/engagement scores with AI platforms.
Studies on how academic librarians' and information professionals' skills are changing	Studies that focus strictly on academic integrity, how to catch students cheating with ChatGPT, or institutional bans on AI.
Peer-reviewed journal articles and conference papers	Non-scholarly sources (e.g., blogs, reports, magazines)
Publications in English	Non-English language publications

Studies published between 2020 and 2026	Published before 2020
Full-text articles accessible	Articles without full text

Data Analysis

This subsection outlines the analytical framework used to systematically analyze and synthesize the selected literature. Content and thematic analysis served as the primary methodology for filtering, coding, and extracting data from the finalized corpus. This qualitative approach was chosen because it is uniquely suited to unravel the complex conceptual disruptions introduced by Generative AI (GenAI) to existing information literacy frameworks.

Through this iterative coding process, salient qualitative themes and patterns were identified and systematically mapped directly onto four core research questions. Furthermore, this analytical lens facilitated the identification of emerging pedagogical trends, ongoing research gaps, and practical teaching implications regarding the integration of GenAI in higher education. The step-by-step filtering mechanism, which depicts the systematic reduction of records from the initial search results to the final specialized corpus, is visually structured according to the PRISMA guidelines in Figure 1.

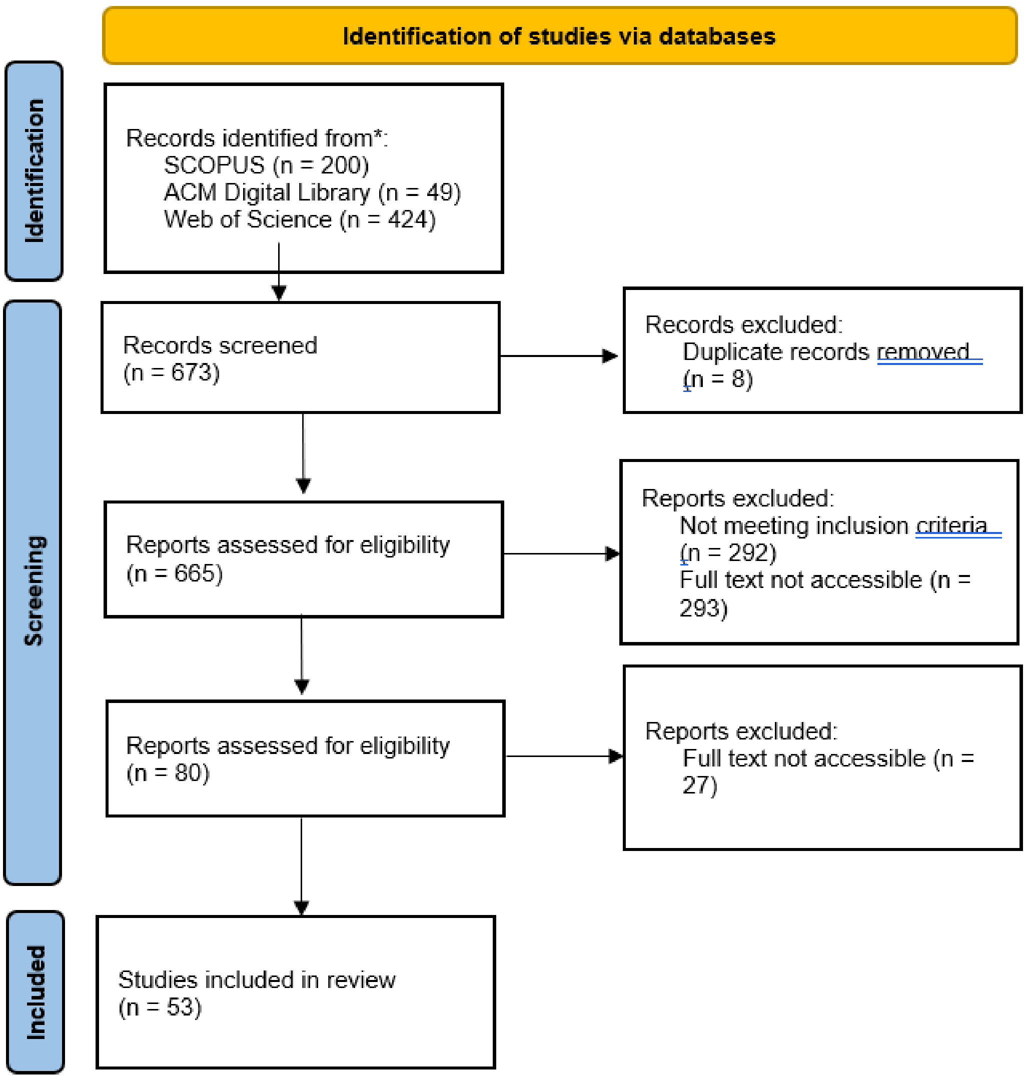

Figure 1: PRISMA flow diagram result of the systematic literature review

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RESULTS

Initially, there were 673 initial records retrieved through a systematic search protocol. After going through several record filtering procedures, the final record was only 53 studies that were selected because out of these 53 studies met the eligibility criteria and were ultimately selected for a more in-depth synthesis. The synthesized data set revealed a diverse spectrum of methodologies, pedagogical trends and structural challenges that characterize the use of Generative AI (GenAI) and its disruptive impact on information literacy.

Table 2: Summary of the systematic literature review search results.

Database	Search String	No. Research Paper
SCOPUS	"Information Literacy" OR "AI Literacy"	200
ACM Digital Library	"Generative AI" OR "ChatGPT"	49
Web of Science	"Information literacy" AND "Generative AI"	424

Research Design

Analysis of the 53 studies reviewed showed that empirical or quantitative designs comprised 16 sources (30.2%), followed by theoretical, conceptual and qualitative studies with 8 sources (15.1%), and mixed methods studies with 12 sources (22.6%). This distribution can be clearly illustrated in a bar chart comparing the proportions of studies using each methodological approach, highlighting the dominance of quantitative designs while still showing significant, albeit smaller, contributions from qualitative and mixed methods research. As illustrated in Figure 2, quantitative studies clearly outperform qualitative and mixed methods designs.

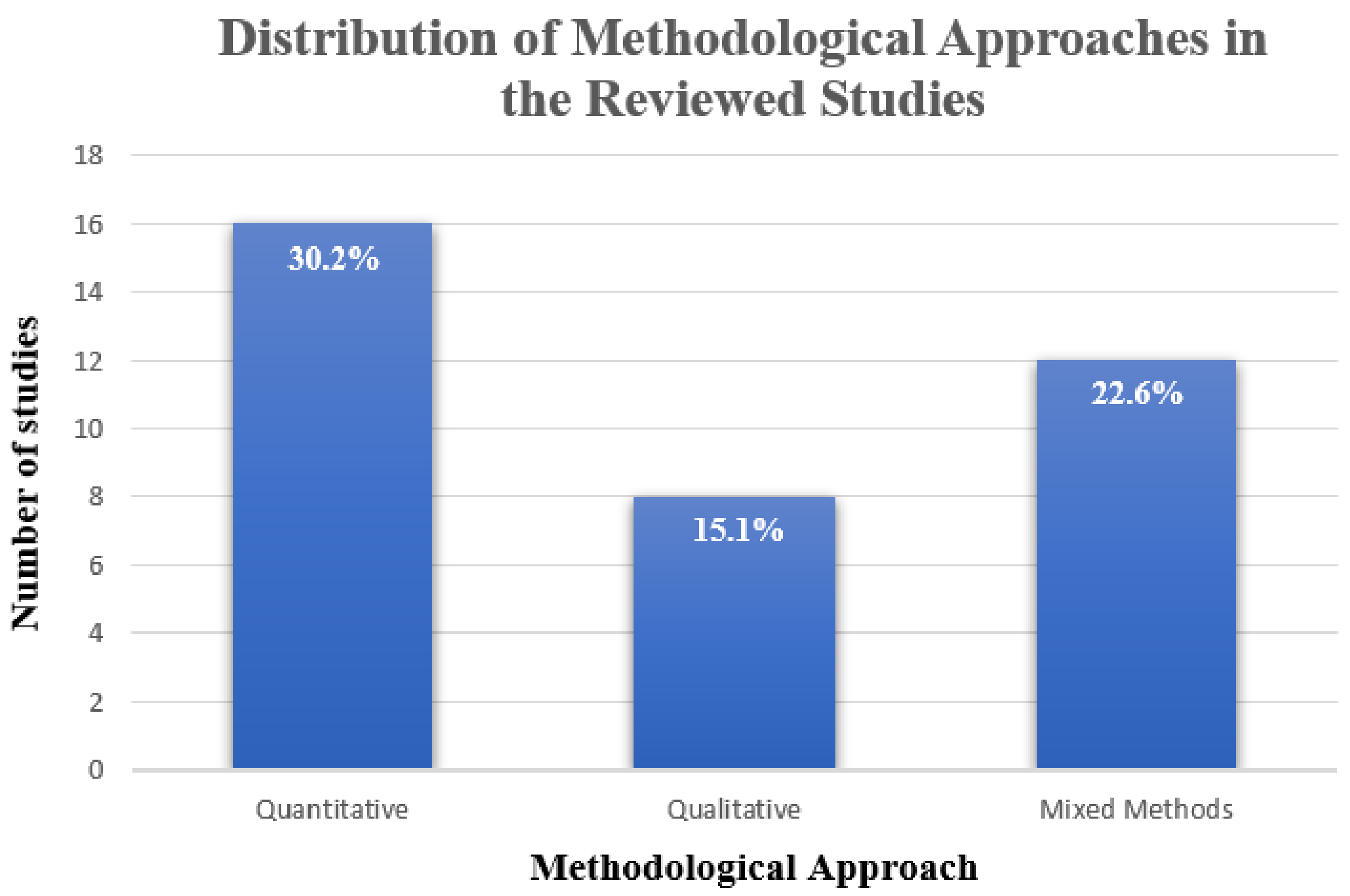

Figure 2: Distribution of methodological approaches across the 53 reviewed studies, showing the predominance of quantitative designs compared to qualitative and mixed-methods approaches.

Quantitative Methodology: Statistical Modeling and Hypothesis Testing

Comprising nearly one-third of the literature reviewed 16 sources (30.2%), quantitative research designs were mostly used to test predictive hypotheses, establish behavioral correlates, and evaluate systemic interventions. Like this study, many of these studies involved generative AI systems and their impact on user information literacy. The primary justification for adopting a quantitative approach across these studies was the need for scalable, generalizable, and statistically robust insights into user behavior and content accuracy.

Psychological and Behavioral Intentions

Survey-based designs are frequently used to map psychological mechanisms and user dynamics. (Liu. et al., 2026) utilized the I-PACE model via an online survey where there were 622 participants involved to examine the structural pathways linking academic stress to generative AI dependency among Chinese university students. Similarly, (Begum. et al., 2025) explained that most of the 496 participants that take part and (Kong. et al.,2024) 367 participants used structured questionnaires to test linear relationships on behavioral intentions, assessing how variable metrics such as self-efficacy and subjective norms determine technology use.

Evaluative Control and Experimentation

In addition to behavioral tracking, quantitative metrics are used to isolate experimental interventions or assess the quality of performance. Garcia and Palares, 2026 implemented a randomized experiment with a difference-in-differences (DiD) model, and involves as many participants as 169 to isolate the net effect of a didactic AI intervention on student digital competence. Meanwhile, Farrokhnia. et al., 2026 used a three-group randomized experimental design which consists of 70 participants to objectively differentiate the quality of human instructor feedback from different AI prompting strategies via a learning management system.

Comparative Artifact Analysis

Quantitative techniques are also applied directly to AI outputs rather than human users. Ibrahim and Mahmoud, 2026 in their study performed a linguistic corpus analysis comparing 300 human-written journal titles with 300 parallel variants generated by ChatGPT to reveal structural and rhetorical differences. In clinical and educational contexts, Hamamra et al., 2026 involving as many as 117 participants and Karamüftüoğlu et al., 2026 used standard benchmark metrics such as EQIP, DISCERN, and GQS. In addition to analysis of variance (ANOVA) to assess the structural reliability and accuracy of pediatric and medical information generated by different AI systems.

Data collection in this paradigm relies almost entirely on digital instruments (e.g., Google Forms, Qualtrics, Microsoft Forms) and targeted sampling strategies, processing large sample sizes through advanced statistical methods such as Partial Least Squares Structural Equation Modeling (PLS-SEM) to ensure empirical validity.

Qualitative Methodology: Contextual Meaning and Lived Experiences

Representing 8 sources (15.1%) of the literature reviewed, qualitative methodologies were used when the research question required depth of exploration, contextual nuance, or interpretation of shifting professional boundaries—insights that numerical acceptance rates naturally cannot capture. The rationale underlying this design is rooted in interpretive constructionism, which focuses on the “making of meaning” and experiences experienced during periods of institutional ambiguity.

The data collection strategy in this category prioritizes depth over breadth, using semi-structured interviews, focus groups, and ethnographic observation.

Institutional and Professional Perceptions

Kalim et al., 2026 in their study conducted targeted face-to-face interviews with university instructors involving 12 participants to uncover specific cognitive and pedagogical challenges in assessing student performance alongside AI. On a global scale, Wolfe and Mitra, 2024 captured institutional perspectives by conducting 30 semi-structured interviews with 38 employees across 29 fact-checking organizations spanning five continents, successfully mapping structural risks and workflow transformations.

Classroom Action Research and Co-Design

To capture authentic real-time dynamics, researchers often use collaborative or participatory designs. In the study (Tang et al, 2026) this study used classroom action research to produce highly nuanced ethnographic data that combined observation notes, video logs, student chat logs, and interviews. The purpose of the method used was to track how critical questioning developed during human-AI interactions. Similarly, Yoo et al., 2026 spent 22.5 hours recording participatory co-design sessions with children, translating those interactions into 262 pages of analytical memos to define the boundaries of GenAI collaboration.

User Engagement and Clinical Risk Assessment

Qualitative frameworks are also used in sensitive populations or new software evaluations. (Yoo et al., 2026) conducted Zoom-based clinical interviews with 20 participants for the interview session, including the involvement of pediatricians to explore the use of technology probes to map safety concerns before introducing AI to a youth population. For interactive systems, Lin and Hu, 2026, paired self-interaction logs with expert interviews to isolate emerging patterns of user engagement.

Through analytical practices such as inductive qualitative coding and thematic framework analysis, this study contextualizes the socio-technical realities of AI use, revealing the ethical dilemmas, concerns, and hidden negotiations that accompany the technology.

A Mixed Methods Approach: Data Triangulation and Configural Pathways

Bridging the empirical and interpretive paradigms, the mixed method design consists of 12 studies (22.6%) that offer a comprehensive view of human-AI collaboration. The core rationale for choosing mixed methods across this literature is data triangulation: matching the statistical power of large-scale surveys with the contextual depth of qualitative narratives or advanced computational clustering to uncover heterogeneous user profiles.

The literature describes several sophisticated configurations of this approach.

Dual-Analytical Configuration (SEM and fsQCA)

A notable methodological trend involves matching linear modeling with asymmetric configuration analysis. Based on a study conducted by Yu et al., 2026, this study has involved a total of 517 postgraduate students together with the results of the study from Li et al., 2026, has combined a traditional quantitative survey with fuzzy set Qualitative Comparative Analysis (fsQCA) and in-depth interviews. This dual logic allows researchers to calculate both the "net effect" of individual variables and the complex and intersecting "configurational pathways" (using Boolean logic) that lead to a high profile of system continuity or digital literacy.

Integration of Algorithms and Machine Learning

Some studies improve survey data through advanced computational clustering. The results of a study by Bahçekapili and Boztas, 2025 involving a total of 362 participants and also a study by a Bencsik et al., 2026 involving a total of 11,910 participants across 58 countries have paired the traditional PLS-SEM structural equation with a non-parametric k-means clustering algorithm. This approach allows researchers to assess macro-level systemic patterns alongside micro-level consumer segments.

Experimental and Protocol Triangulation

A mixed design was also used to validate user experience testing. This study can be proven as a result of (Li, 2026) where in this study a macro-level factorial experiment (N = 234) was carried out through Prolific, then

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triangulation of the findings with a face-to-face micro study (N = 16) that recorded the screen and captured the verbal protocol thinking retrospectively. Not so, (Ma et al, 2025) also evaluated educational games by tracking quantitative task time metrics along with scripts from semi-structured discussion groups.

By combining quantitative metrics such as automated assessment tools such as COMET (Wittkowsky & Krüger, 2025) with manual qualitative reviews such as software-assisted coding through ATLAS.ti (Havelka et al, 2025), this mixed methods study offers a balanced framework that preserves statistical accuracy and human context.

RQ1: How must established information literacy frameworks be restructured to prioritize "verification" over "evaluation" in the context of algorithmically generated content?

Research questions investigating how often GenAI tools are used, which platforms dominate, and background factors influencing adoption are almost exclusively answered by Quantitative Design. The statistical power of large-scale surveys allows researchers to capture clear directional trends and demographic differences across populations. For example, inquiries into usage differences across educational levels or professional cohorts rely on the broad reach of platforms such as Microsoft Forms or Google Forms (Simsek et al., 2026, Józsa et al., 2026) to provide generalizable baseline data.

Sources:

Author	Title name	Significant findings
Araujo & Schneider, 2025	Critical Information Literacy as a Compass: Using Generative AI in Academic Research and Writing	This research proposes a framework based on seven levels of Critical Information Literacy (CIL)—Concentration, Instrumental, Taste, Relevance, Credibility, Ethics, and Critique—to navigate the complex GAI landscape. The findings emphasize that technology does not intrinsically determine authority; instead, researchers must use CIL to evaluate the "black box" algorithms and the veracity of synthetic content
Walczak & Cellary, 2023	Challenges for higher education in the era of widespread access to Generative AI	This study identifies that student often fail to verify content in practice even when they claim to be alert. A major finding is the blurring of boundaries between factual information and hallucinations, necessitating that student possess a strong factual knowledge base to detect inconsistencies and perform human-led verification
Lee et al., 2025	Examining Generation Z's Use of Generative AI from an Affordance-Based Approach	This article highlights the need for students to understand "checkworthiness"—identifying which AI-generated claims require verification before being accepted as true. It finds that the lack of transparency in how models arrive at outputs makes traditional source evaluation difficult, shifting the burden to content verification

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García & Pallarés, 2026	Impact of Generative AI on University Students' Digital Competences	This research uses the DigComp framework to show that the abundance of automated content requires critical skills to filter and cross-check information. A significant finding is that structured AI interventions significantly improve "information and data literacy" by teaching students to verify AI output against reliable complementary sources

RQ2: What specific role does AI literacy play as a mediating factor in empowering students to verify information autonomously?

Inquiries that examine the nuances of human concerns, pedagogical challenges, and institutional ambiguities are driven primarily by Qualitative Design. When research questions try to understand how instructors experience changing assessment boundaries (Kalim et al., 2026) or how organizations navigate information verification risks (Wolfe and Mitra, 2024), the literature relies on interpretive meaning making. These exploratory questions are answered through thick descriptions generated by semi-structured interviews and ethnographic observations rather than numerical usage tracking.

Sources:

Author	**Title name**	**Significant findings**
Hamamra et al., 2026	AI Literacy and Mediated Learner Autonomy in ChatGPT-supported EFL Writing	This qualitative study finds that AI literacy is a prerequisite for learner autonomy; without it, students experience a "paradox of autonomy" where they feel independent but are actually surrendering cognitive regulation to an algorithm. The research highlights that digital confidence (the "digital native" myth) does not translate into the evaluative competence needed to verify output.
Yu et al., 2026	Explore the Impact of Postgraduate Students' AI Literacy on Research Efficacy	This article finds that AI literacy significantly enhances research efficacy, with academic anxiety and campus atmosphere acting as critical mediators. It demonstrates that AI literacy involves not just technical use but the integration of information literacy and moral development to ensure the ethical and standardized use of AI.
Lim & Teh, 2026	IT Mindfulness and AI Literacy Shape Lifelong Learning Orientation	The findings show that AI literacy and IT mindfulness are upstream enablers of student learning agency, which allows students to take ownership of their learning. The study reveals that AI literacy has a stronger influence on engagement than general mindfulness because it provides the domain-specific know-how needed to interact productively with generative systems.

RQ3: What instructional strategies, such as "Think First, ChatGPT Later," are most effective in fostering a "verification-first" mindset among higher education students?

Complex questions that assess how different types of content affect information reception, or the combination of user characteristics that determine digital literacy, are best addressed through a Mixed Methods Approach. The synergy of qualitative coding and the use of quantitative tools allows researchers to capture multidimensional patterns. For example, questions about the configuration path to digital fluency or the evaluation of interactive instant manufacturing workshops are addressed by pairing linear metrics with manual thematic review (Archambault et al., 2025, Havelka et al., 2025), ensuring that individual structural and contextual results are synthesized simultaneously.

Sources:

Author	Title name	Significant findings
Wong & Qiu, 2026	Think First, ChatGPT Later: Guiding Human–AI Collaboration for Learning Gains.	This study provides the primary evidence for the "Think First, ChatGPT Later" approach, proving that students who generate their own ideas before using AI sustain their creativity even after the AI tool is removed. The findings show that spontaneously using AI often leads learners to assume the role of a passive editor rather than an active co-creator.
Tang et al., 2026	Critical Questioning with Generative AI: Developing AI Literacy.	This research outlines a scaffolded four-step questioning process: (1) pose a question, (2) double-check accuracy via external search (e.g., Google), (3) refine the prompt based on research, and (4) summarize in the student's own words. The significant finding is that critical engagement depends on these specific pedagogical conditions rather than the technology itself.
Farrokhnia et al., 2026	Generative AI Offers More, but Students Revise Less.	This study finds that while sophisticated prompting (Chain-of-Thought) produces higher-quality AI feedback, it does not always lead to better revisions. A key finding is that feedback quality alone is insufficient; teachers must provide hybrid support to help students interpret and actively verify AI feedback to avoid "metacognitive laziness".
Archambault et al., 2025	Fostering AI Literacy in	This case study demonstrates the

	Undergraduates: A ChatGPT Workshop Case Study.	effectiveness of the CREATE framework for prompt engineering combined with a "post phenomenological" lens that encourages students to reflect on how AI shapes their perception of knowledge. It identifies a critical gap where students' self-reported confidence in using AI often exceeds their actual knowledge of its limitations.
Kalim et al., 2026	Teachers’ Challenges in Assessing Student Performance.	As a strategic response to AI, this research highlights a significant shift toward process-based and oral assessments. The findings suggest that verifying student learning now requires "traceable learning" (e.g., activity logs or viva voce exams) rather than evaluating only the final written product.

DISCUSSION

The synthesis of the reviewed literature highlights a profound transformation in how stakeholders perceive and navigate the intersection of generative AI (GenAI) and information literacy. Much like traditional digital marketing shifts library communication from static broadcasting to active community cultivation, the explosion of GenAI demands a fundamental pivot from treating information literacy as a set of mechanical search skills to managing it as a dynamic, critical-thinking framework. However, the findings indicate that institutions must first recognize and resolve deep-seated behavioral and operational friction points if they hope to foster an inclusive, secure, and highly effective digital information environment. Advancing this domain requires deep cooperation between educators, information professionals, university administrators, and technological literacy experts to ensure users do not become passive consumers of automated output.

A central insight from the literature indicates that a significant shift in student behavior is underway, moving rapidly from voluntary tool adoption to an acute dependency that threatens foundational information-seeking behaviors. Rather than exploring GenAI out of pure academic interest, a vast portion of the student cohort relies on platforms like ChatGPT or DeepSeek as functional and emotional crutches to mitigate systemic academic stress and workload anxiety. This reliance fundamentally disrupts traditional information literacy pipelines; instead of evaluating primary sources, navigating databases, or synthesizing diverse viewpoints, students increasingly accept centralized, AI-generated summaries at face value. To lower the barriers to entry and ease institutional tension, the literature suggests humanizing the information literacy interface. Moving away from rigid, intimidating policy prohibitions toward collaborative engagement and guided prompt-engineering initiatives allows institutions to appear more approachable, capturing student interest and reshaping their digital intelligence where they already operate.

Nevertheless, critical institutional challenges remain, particularly regarding operational bottlenecks and an apparent behavior-theory alignment crisis among educators tasked with teaching information literacy. Just as inconsistent digital strategies result in poor user engagement, a lack of clear AI guidelines and pedagogical training among faculty frequently leads to structural confusion and fragmented assessment practices. When applied to human-AI collaboration, traditional information literacy frameworks reveal severe bottlenecks. For example, while generative platforms excel at capturing student attention and providing rapid, synthesized answers, their algorithmic outputs often stall at the level of deeper comprehension, occasionally presenting hallucinations as factual truth. When students rely too heavily on AI-generated text early in the research process without independent validation or source-checking, the quality of critical analysis declines, rendering the ultimate educational strategy ineffective.

To overcome these obstacles and maintain institutional relevance, viable future research must investigate cutting-edge pedagogical techniques and emerging technological trends that redefine information literacy for an algorithmic age. One critical strategy is the intentional integration of structured human-AI collaboration models, such as "think first, prompt later" protocols, which ensure that independent human inquiry and problem-solving precede machine execution. Additionally, institutions must actively adapt to changing demographics, such as Generation Z's unique information verification habits, by following current professional and digital literacy trends that treat AI as a conversational partner rather than a final authority. Academic institutions must also design forward-thinking support structures, specifically by deploying targeted AI-literacy workshops and specialized consulting resources for advanced research tiers. Building versatile, AI-literate educators and clear institutional policies ensures that academic environments can guarantee their continued relevance in an increasingly automated landscape.

CONCLUSION

Based on this systematic literature review, the integration of generative artificial intelligence in higher education has resulted in a fundamental shift in the paradigm of learning and knowledge production. There are many important advantages offered by this technology, including reduced workload for students, faster access to information, and learning assistance. However, when there is an overreliance on the use of AI, it results in a reduction of the cognitive effort required in learning and thus poses serious dangers to academic integrity and the growth of critical thinking.

The results of the study also show that the ability to evaluate the accuracy of information does not always correlate with technological proficiency. Even though students appear comfortable using AI systems, they are still prone to making errors when evaluating the generated data because the AI model that produces the responses may sound reasonable but may not be accurate. This suggests that there is a literacy gap where people are more comfortable using technology than they are able to critically evaluate information. In addition, contextual and demographic factors such as variations in user background and education level have an impact on how AI is used to obtain information, and these variations indicate that institutional and social variables influence how AI is used.

Furthermore, this study found that the use of generative AI can easily influence existing assessment methods in education, making them less meaningful and valuable. As a result, there has been a shift towards more process-focused assessment techniques, such as activities that emphasize analytical and reflective thinking, verbal explanations, and critical evaluation of AI outputs. These results have major implications for the development of contemporary information literacy frameworks and they need to be adapted to the digital ecosystem powered by artificial intelligence. This suggests that information literacy frameworks must evolve from static models to more dynamic and responsive models.

Overall, while the literature answers the three research questions, it also points to the need for a “human-in-the-loop” approach to the use of AI, where it is a learning model that balances human and AI skills. This method places a strong emphasis on the approach of “Think First, ChatGPT Later” that encourages students to generate their own ideas before using AI as a tool for review and improvement. In the era of generative AI, this is essential to maintaining cognitive autonomy, fostering responsible AI literacy, and strengthening academic integrity.

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