Effects of Generative AI-Assisted Media Literacy Instruction on Learning Achievement and Cognitive Load among Elementary School Students

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***Abstract*—The increasing use of social media by young people, combined with their limited ability to critically evaluate the credibility of media content, highlights the growing need for effective media literacy education. In Taiwan, teachers often rely on tools such as the Taiwan FactCheck Center to help students identify fake news. However, because of elementary school students' limited reading and search skills, their cognitive load may increase and hinder their learning. Generative AI chatbots, with their intuitive interactions and accessible outputs, offer the potential to support learning and reduce cognitive demands. This study examined how integrating a generative AI chatbot into media literacy instruction for upper elementary students affects their learning achievement, cognitive load, and technology acceptance. A total of 56 upper elementary students participated in this quasi-experimental study, which focused on fake news detection as the core instructional theme. The experimental group used a generative AI chatbot as a learning tool, while the control group used the Taiwan FactCheck Center website alongside conventional online search strategies. This study also evaluated differences between two instructional approaches regarding fake news identification and cognitive load. The findings revealed that using a generative AI chatbot significantly enhanced students' ability to identify fake news. Although the difference in cognitive load between groups was not statistically significant, students in the experimental group reported relatively lower levels of cognitive load. Additionally, students showed high technology acceptance for the AI chatbot, suggesting its potential as an effective tool in elementary media literacy instruction.**

***Keywords*—generative artificial intelligence, media literacy, learning achievement, cognitive load, technology acceptance**

I. Introduction

In the digital era, students are increasingly exposed to diverse online media content, that shapes their knowledge and perspectives [1]. However, compared with traditional media, the rapid spread of information and weaker regulations make it challenging for young learners to judge whether the information they encounter is accurate or trustworthy [2]. Studies have shown that many elementary and secondary students lack the skills needed to assess the reliability of online information or identify false or misleading content [3]. Recognizing this issue, Taiwan's Ministry of Education issued the "Digital Media Literacy White Paper" in 2023, which emphasizes the development of responsible, informed, and critical digital citizens through four core strategies: effective media use, responsible technology application, civic engagement, and systematic learning [4].

Among the challenges of media literacy education, the ability to identify misinformation and fake news has become increasingly urgent. Effective detection requires analytical skills to assess the authenticity and credibility of information, along with the ability to verify sources through multiple channels. However, elementary students often lack these abilities because of limited reading and search skills [5], including difficulties in framing effective queries, selecting appropriate keywords, and evaluating source reliability [6].

Generative AI-based conversational tools provide new opportunities for supporting students in the detection of fake news. These tools allow students to express queries in everyday language and receive clearer, simplified responses, reducing the cognitive demands of searching through extensive results. By minimizing information overload, AI chatbots enable learners to focus on the critical task of evaluating information rather than on struggling with search mechanics.

To address these challenges, this study integrates a generative AI chatbot into media literacy instruction and examines its effects on elementary students' learning achievement, cognitive load, and technology acceptance.

Accordingly, this study addresses the following research questions:

RQ1: Does the integration of a generative AI chatbot into media literacy instruction improve elementary students' learning achievement more so than does traditional instruction?

RQ2: Does the use of a generative AI chatbot reduce students' perceived cognitive load during media literacy learning?

RQ3: How do elementary students perceive the use of a generative AI chatbot as a supportive learning tool within the media literacy curriculum?

II. Literature Review

A. Media Literacy

Media literacy has been recognized by numerous scholars as a critical topic in contemporary education and research. According to Buckingham, media literacy comprises two core components: media competency and media text analysis. The former emphasizes the individual's ability to use and produce media content, whereas the latter focuses on interpreting and critically evaluating media messages, particularly in identifying misinformation or problematic content [7, 8]. Potter [9] defines media literacy as the capacity to understand and evaluate information, suggesting that media-literate individuals think independently and can judge the credibility of media content. Expanding on this perspective, Goodson and Norton-Meier [10] argue that media literacy should not be limited to decoding media texts; rather, it should cultivate critical thinking and active engagement, encouraging audiences to explore the deeper meanings embedded in media messages. Taken together, these perspectives highlight that media literacy involves not only understanding and receiving information but also the ongoing processes of evaluation, reflection, and critical analysis of media content [10, 11].

As the speed and volume of media information continue to grow, the role of the media in shaping public communication and democratic participation becomes increasingly more influential. The ways in which information is managed and disseminated have evolved significantly, and the significance of media content has greatly expanded, influencing communication practices and access to information in various areas of daily life. In this context, the need to foster elementary school students' ability to understand and critically evaluate media messages has become a significant educational issue. Experts from the United Nations Educational, Scientific and Cultural Organization (UNESCO) emphasize that as media education constitutes a fundamental right for all citizens, it is closely linked to the freedom of expression and the right to access information. Accordingly, media education should be incorporated into all forms of learning, including formal curricula, supplementary programs, informal education, and lifelong learning systems [12]. In the face of an increasingly complex and pervasive digital information environment, the urgency and relevance of media education have become increasingly more evident.

Traditional media education has often focused on the critical analysis of media content. However, in today's digital environment, students face an overwhelming volume of complex and rapidly changing media messages. Accordingly, analytical skills alone may not be enough to address these challenges. Recent research emphasizes the need to enhance students' ability to comprehend and evaluate media content, particularly in recognizing misinformation and biased information [13, 14]. For elementary school students, implementing media literacy instruction presents several challenges, including limited reading comprehension, insufficient online search skills, and a lack of systematic strategies for evaluating information [6]. These limitations can impede their ability to assess the credibility of media content and may increase their cognitive load during learning. Therefore, identifying appropriate instructional support tools that can reduce students' learning burden while improving their ability to evaluate information has become a critical issue in media literacy education.

In recent years, with the rapid development of media and digital information environments, media literacy has been increasingly emphasized in international education as a critical component of civic competency. Educators and policymakers increasingly advocate cultivating students' critical understanding and evaluative skills at the elementary level [15]. These trends suggest that integrating innovative technologies, such as generative artificial intelligence, could create new opportunities to support students' ability to comprehend and assess information credibility [16]. However, further research is necessary to explore how these tools can be effectively applied in media literacy education, especially in elementary settings.

Taken together, although various frameworks and strategies for media literacy have been proposed, few empirical studies have explored how to effectively support elementary students in overcoming practical barriers, such as limited reading skills and information-seeking strategies. This underscores the need to examine alternative approaches, including the integration of AI tools, to better address these challenges.

B. Cognitive Load

Cognitive load refers to the total amount of mental effort required for learners to process and understand information while performing a learning task [17]. Sweller [18] emphasizes the importance of managing cognitive load in educational settings, particularly when learners are faced with complex or unfamiliar content. In a widely accepted framework, Sweller, van Merriënboer, and Paas [17] further differentiate cognitive load into two distinct but related components: mental load and mental effort.

Mental load is associated with the objective complexity of the task itself and the surrounding environmental conditions. It is determined by external factors such as the amount of information presented, the number of elements that must be processed simultaneously, and the overall structure of the learning material. Mental effort, however, reflects the learner's internal investment of cognitive resources while engaging with the task and indicates the degree to which the learner is attempting to understand or solve the problem, regardless of the task's intrinsic difficulty. This conceptual distinction is crucial when evaluating learning outcomes and interpreting cognitive load data. Whereas mental load captures the inherent challenge imposed by the instructional task, mental effort reflects the learner's voluntary engagement and cognitive processing strategies in response to that challenge. A proper understanding of both dimensions provide deeper insights into how instructional interventions, such as the use of generative AI tools, affect learners' cognitive processes during learning activities.

Several factors affect cognitive load, including content presentation, task complexity, and learners' prior knowledge and strategies. For upper elementary students—whose language comprehension and information-seeking abilities are still developing—excessive task demands or insufficient instructional support can increase their cognitive load, potentially impeding their engagement and learning effectiveness.

Effectively managing cognitive load is thus an important consideration in instructional design. Well-designed strategies and tools can guide students toward essential information, reduce unnecessary processing, and enhance comprehension and efficiency. Research indicates that excessive cognitive load can impair attention and information integration, thereby negatively impacting learning outcomes [19–22]. However, innovative tools, such as generative AI, may offer support by simplifying media evaluation tasks and reducing task-related cognitive demands. These tools warrant further investigation because of their potential to enhance learning experiences.

Nonetheless, few studies have explored how generative AI can support cognitive load management during complex information verification tasks, particularly at the elementary level. This gap highlights the need for further research into how such tools might reduce unnecessary effort and more effectively support the cognitive processes of young learners.

C. Generative AI Chatbots

Generative Artificial Intelligence (GAI) refers to technologies capable of autonomously producing content such as text, images, and audio. Common applications include Natural Language Processing (NLP), language generation, and interactive dialog systems. In recent years, GAI has attracted increasing attention in education due to its potential to transform instructional design. Compared with traditional tools, generative AI chatbots offer real-time feedback, conversational guidance, and personalized interaction. These features make them promising digital learning companions capable of helping students grasp complex concepts and solve problems more effectively [23, 24].

Lim [25] highlights the dual nature of generative AI in education, viewing it as both an opportunity and a challenge, and suggests that educators should embrace its potential and integrate it meaningfully into teaching. A growing number of empirical studies support the benefits of generative AI tools such as ChatGPT for student learning. For instance, Alneyadi and Wardat [26] report that compared with control students, high school students using ChatGPT to study electromagnetism achieved significantly better learning outcomes. Furthermore, Bitzenbauer [27] reports improvements in critical thinking and AI acceptance among students using ChatGPT, while Phung *et al*. [28] reports that GPT-4 outperforms GPT-3.5-based ChatGPT in several programming education tasks and, in some cases, performs on par with human teachers.

Despite these encouraging results, most research to date has focused on secondary or higher education, while empirical evidence on the use of generative AI in elementary school settings remains limited. For upper elementary students—whose reading and information-seeking skills are still developing—interactive tools offering language-based guidance and immediate feedback may, to some degree, reduce their cognitive load and improve their learning outcomes [29, 30]. Investigating the use of generative AI chatbots in elementary media literacy instruction thus addresses a key research gap and points to new directions for enhancing digital-age pedagogy.

III. METHODOLOGY

A. Experimental Design

This study aimed to investigate the effects of integrating a Generative Artificial Intelligence (GAI) chatbot into a media literacy curriculum for upper elementary school students on their learning achievement and cognitive load. In addition, the study evaluated students' acceptance of the GAI chatbot as an educational tool. The participants were 56 fifth- and sixth-grade students from an elementary school in Pingtung County, Taiwan. To ensure consistency in instructional content and minimize external confounding variables, both the experimental and control groups were taught by the same instructor, who had five years of teaching experience.

Each group consisted of one fifth-grade class and one sixth-grade class, with 28 students per group. In the experimental group, there were 14 fifth-grade students (7 boys and 7 girls) and 14 sixth-grade students (9 boys and 5 girls), totaling 16 boys and 12 girls. The control group included 15 fifth-grade students (7 boys and 8 girls) and 13 sixth-grade students (8 boys and 5 girls), totaling 15 boys and 13 girls.

B. Experimental Procedure

This study adopted a quasi-experimental pretest–posttest design. The instructional process comprised three phases—pretest, instructional intervention, and posttest—with a total duration of 120 minutes. One week prior to the intervention, both the experimental and control groups completed a pretest assessing their prior knowledge of fake news detection. Following this, both groups received identical introductory instructions on media literacy. After the initial instruction, the students engaged in hands-on fake news verification activities under different instructional settings.

The experimental group used the generative AI chatbot Microsoft Copilot as a learning support tool, allowing them to verify fake news through natural language interaction. During this phase, students were provided with examples of how to formulate questions and prompts, such as asking whether a piece of news had official sources or requesting help in locating reliable reports. The teacher demonstrated sample prompts and guided students on how to modify and refine their queries on the basis of the chatbot's responses. Basic operational assistance was also provided to ensure that all students could interact effectively with AI and apply the information to complete the verification task. In contrast, the control group completed the same verification task using a traditional web browser by accessing the Taiwan FactCheck Center website and using Google search.

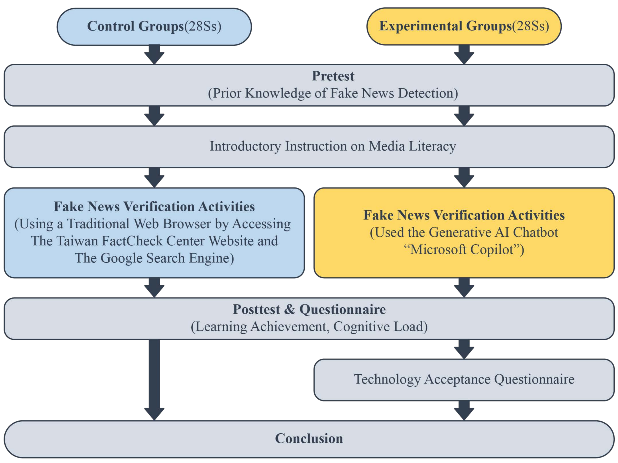

Fig. 1. Experimental procedure of the quasi-experimental design incorporating a generative AI chatbot in media literacy instruction.

After the instructional activities, both groups completed a posttest measuring learning achievement and a cognitive load questionnaire. Additionally, the students in the experimental group completed a technology acceptance questionnaire to assess their perceptions of using the generative AI chatbot during the learning process. An overview of the experimental procedure and timeline is presented in Fig. 1.

C. Research Instruments

This study employed three research instruments: a fake news recognition test to assess prior knowledge and learning achievement, a cognitive load questionnaire, and a technology acceptance questionnaire.

A fake news recognition test was developed using news items that had been circulated on actual online platforms. It consisted of 10 items, including 7 fake news stories and 3 real stories, and students were required to judge the authenticity of each. The test demonstrated acceptable internal consistency, with a Cronbach's α of 0.723. The overall item discrimination index was 0.461, indicating good discriminatory power. This instrument was used to evaluate both students' prior knowledge and their learning outcomes.

To measure students' perceived cognitive load under different instructional strategies, this study adopted a revised version of the scale developed by Hwang, Yang, and Wan [31] based on the original frameworks of Paas [32] and Sweller, van Merriënboer, and Paas [17]. The questionnaire included two dimensions, i.e., mental load and mental effort, that measured the perceived task difficulty and the cognitive resources learners invested. The instrument was comprised of 8 items: 5 items for mental load and 3 items for mental effort. All responses were recorded on a seven-point Likert scale. Cronbach's values were 0.975 for mental load and 0.949 for mental effort, indicating high internal consistency [33].

To assess students' acceptance of the generative AI chatbot, this study used a questionnaire developed by Chu, Hwang, Tsai, and Tseng [34]. The instrument covered two dimensions, i.e., perceived usefulness and perceived ease of use. The first dimension assessed students' views on the practical benefits of the chatbot, whereas the second focused on their ease of interaction with the system. The questionnaire included 13 items in total, with 7 items assessing perceived usefulness and 6 items assessing perceived ease of use, all of which were rated on a five-point Likert scale. The Cronbach's α values were 0.969 and 0.972, respectively, demonstrating strong reliability.

IV. RESULTS

A. Learning Achievement Analysis

To examine whether the experimental group showed significant improvement after the instructional intervention, a paired-sample t test was conducted to compare scores from the prior knowledge test and the learning achievement posttest. As presented in Table 1, the mean score increased by 32.5 points, $t(27) = 6.53$, $p < 0.05$, indicating statistically significant improvement. These results suggest that the integration of a generative AI chatbot as a learning support tool effectively enhanced students' ability to detect fake news.

With respect to the control group, a paired-sample t test was also conducted to assess learning gains after the participants received traditional media literacy instruction. As shown in Table 2, the mean score increased by only 3.93 points, with $t(27) = 0.983$ and $p = 0.334$. Since the p value exceeded the 0.05 threshold, the result did not reach statistical significance, indicating that the use of search engines and fact-checking websites did not yield a measurable improvement in students' learning achievement.

Table 1. Paired sample t test results comparing prior knowledge and learning achievement in the experimental group

Test	N	M	SD	t	df	p
Prior knowledge test	28	55.00	21.170	6.530^{*}	27	< 0.001
Learning achievement posttest	28	87.50	12.656			

$^{*}p < 0.05$

Table 2. Paired sample t test results comparing prior knowledge and learning achievement in the control group

Test	N	M	SD	t	df	p
Prior knowledge test	28	61.43	17.788	0.983	27	0.334
Learning achievement posttest	28	65.36	17.101			

$^{*}p < 0.05$

To further compare posttest performance between the experimental and control groups while controlling for prior knowledge, a one-way analysis of covariance (ANCOVA) was performed with a significance level set at $\alpha = 0.05$. Before conducting the ANCOVA, the assumption of homogeneity of regression slopes was tested. As presented in Table 3, all p values were greater than .05, indicating that there was no significant interaction between the covariate and the independent variable, thereby meeting the assumption required for ANCOVA.

Table 3. Homogeneity of regression slopes between experimental and control groups (pretest scores)

Test	df	MS	F	p
Group * Pretest	1	616.554	2.775	0.102

$^{*}p < 0.05$

The ANCOVA results are summarized in Table 4. After adjusting for prior knowledge, the experimental group achieved an adjusted mean score of 87.66, whereas the adjusted mean score for the control group was 65.20, with a standard error of 2.884 for both groups. The results of the analysis revealed a statistically significant difference, $F(1, 53) = 29.933$, $p < 0.001$, indicating that the students in the experimental group significantly outperformed those in the control group in terms of learning achievement after using the generative AI chatbot.

Table 4. Analysis of covariance (ANCOVA) for posttest scores between the experimental and control groups

Groups	N	M	SD	Adj. M	Adj. SD	F	p
Experimental group	28	87.50	12.656	87.661	2.884	29.933^{*}	<0.001
Control group	28	65.36	17.101	65.196	2.884		

$^{*}p < 0.05$

B. Cognitive Load Analysis

To compare the cognitive load experienced by students in the experimental and control groups, independent samples t

tests were conducted for two dimensions, i.e., mental load and mental effort. The detailed statistical results are presented in Table 5.

With respect to mental load, the experimental group reported a mean score of 2.76, while the control group had a slightly higher mean score of 3.00. *Levene's* test for the equality of variances revealed no significant difference between the groups, $F(1, 54) = 0.003$, $p = 0.958$. Similarly, the t test revealed no statistically significant difference, $t(54) = -0.523$, $p = 0.603$, suggesting that both groups perceived comparable levels of mental load.

Regarding mental effort, the mean score for the experimental group was 2.80, whereas the control group reported a higher mean score of 3.40. Again, *Levene's* test confirmed equal variances ($F = 0.607$, $p = 0.439$), and the t test revealed no significant difference, $t(54) = -1.263$, $p = 0.212$. Thus, no statistically significant difference in mental effort was observed between the groups.

Table 5. Comparison of cognitive load between the experimental and control groups

Dimensions	Groups	N	M	SD	*Levene*'s test		*t* test	
					F	*p*	*t*	*p*
Mental load	Experimental group	28	2.76	1.726	0.003	0.958	−0.523	0.603
	Control group	28	3.00	1.850				
Mental effort	Experimental group	28	2.80	1.824	0.607	0.439	−0.1263	0.212
	Control group	28	3.40	1.772				

C. Technology Acceptance Analysis

With respect to the technology acceptance questionnaire, the descriptive statistics for the perceived usefulness dimension revealed a mean score of 4.16, which is close to the "agree" level on a five-point Likert scale. These findings suggest that the students in the experimental group generally viewed the generative AI chatbot as beneficial to their media literacy learning, reflecting a positive perception of its practical value. For the perceived ease of use dimension, the mean score was 4.23, which was also near the "agree" level. This finding indicates that the students found the chatbot intuitive and easy to interact with, indicating a favorable attitude toward its usability.

Taken together, these findings indicate that the students in the experimental group demonstrated a positive overall attitude toward the integration of the generative AI chatbot into media literacy instruction. The results support the notion that such tools are both acceptable and feasible for use in elementary school classrooms. The detailed statistical results are presented in Table 6.

Table 6. Descriptive statistics of perceived usefulness and perceived ease of use in the experimental group

Dimension	*N*	*M*	SD
Usefulness	28	4.16	0.885
Ease of use	28	4.23	0.894

V. Discussion and Conclusion

This study investigated the effects of integrating a Generative Artificial Intelligence (GAI) chatbot into media literacy instruction for upper elementary students, with a focus on learning achievement, cognitive load, and technology acceptance. The results revealed that students who used the chatbot achieved significantly higher posttest scores for fake news recognition than did those in the control group. These findings suggest that chatbot-supported instruction effectively enhanced students' media literacy. Additionally, students reported generally positive perceptions of the chatbot's usefulness and ease of use.

Although the experimental group reported lower average scores for both mental load and mental effort than did the control group, the differences were not statistically significant. According to cognitive load theory, mental load refers to the complexity and structure of the learning task itself, which is shaped by the instructional design and the intrinsic difficulty of the material. In contrast, mental effort reflects the amount of cognitive capacity that learners actively invest while engaging in a task and is influenced by their motivation, familiarity with the content, and perceived task difficulty [35]. In this study, the fake news verification task likely presented a high intrinsic load to both groups because critical thinking, fact-checking, and evaluative judgment were required. While the chatbot may have supported students by offering structure or clarifying steps, the fundamental cognitive demands of the task remained substantial. Moreover, the novelty of using a generative AI tool may have temporarily increased student motivation, leading to elevated perceived engagement in both groups. This heightened engagement may have equalized self-reported measures of mental effort, thus obscuring any potential cognitive benefits afforded by the chatbot. As a result, the absence of significant differences should be interpreted cautiously, as they may reflect motivational artifacts rather than genuine reductions in cognitive processing demands.

These interpretations are consistent with prior studies showing the benefits of AI-assisted instruction in enhancing conceptual understanding and engagement [26, 27]. The real-time feedback and natural language interaction provided by the chatbot likely supported students' identification with fake news. However, the lack of a significant difference in the cognitive load indicates that effective instructional design must extend beyond technological novelty. As suggested by cognitive load theory [36], instructional tools should aim to reduce extraneous load and optimize learners' allocation of effort to essential processing. Although this study offered basic guidance and examples, it may not have provided sufficiently structured scaffolds to break down task steps or manage learners' cognitive resources. Accordingly, future research should consider refining prompt design, increasing clarity in interaction protocols, and providing step-by-step guidance tailored to students' cognitive readiness. Furthermore, future instructional designs should explicitly target not only a reduction in extraneous load but also the increase in germane load, which supports the construction of schemata and deeper learning [37]. By leveraging AI chatbots to guide students through structured questioning and self-explanation strategies, educators can promote meaningful cognitive engagement beyond task completion.

This study has several limitations that constrain the generalizability and long-term interpretability of the findings. First, the study was conducted in a single elementary school in southern Taiwan with a small sample size and a short intervention duration (120 minutes), which limits the external validity of the results. Second, the observed improvements in learning achievement and positive perceptions may be partially influenced by the novelty effect, wherein students' motivation and performance temporarily increased due to exposure to unfamiliar or innovative tools [38]. This effect is particularly salient among younger learners, whose enthusiasm may mask the true instructional value of the intervention [39]. Related studies on various educational technologies have consistently demonstrated the presence of novelty effects. For instance, research in mobile learning has shown that, compared with traditional instructional materials, mobile devices are often perceived as more novel. This perception of novelty can enhance the fulfillment of basic psychological needs and contribute to short-term achievement. However, further path analyses indicate that lasting learning outcomes emerge only when the tools are designed to support intrinsic needs, such as autonomy and competence. These findings suggest that effective instructional design plays a more critical role than novelty alone in sustaining learning outcomes [40]. Similarly, studies on immersive virtual reality have determined that early-stage improvements in learning performance and user satisfaction are often amplified by novelty. Researchers have noted that the inclusion of operational guidance or instructional tutorials can effectively reduce the disruptive influence of the novelty effect on learning performance [41]. Moreover, research focusing on the temporal aspects of the novelty effect, such as the work of Rodrigues *et al*. [42], has revealed a distinct pattern. In long-term tracking studies, the benefits observed in the initial stage of new technology use often decline within two to six weeks. In some cases, however, a familiarization phase between the sixth and twelfth weeks leads to a partial recovery of learning gains. This pattern forms a U-shaped trajectory in which the initial effect decreases and then increases again over time. These insights emphasize that short-term studies are prone to misinterpreting novelty-induced gains as stable improvements. In reality, the true instructional value of technological tools can be accurately assessed only through extended observation periods. Third, the lack of significant differences in cognitive load may similarly reflect temporary motivational increases rather than genuine reductions in cognitive effort [43]. These factors highlight the importance of interpreting short-term improvements with caution and recognizing the potential for confounding variables. Therefore, future studies should account for novelty effects by incorporating longitudinal designs or repeated exposure over time. This may involve tracking learning outcomes across multiple instructional units or semesters to assess retention, transfer, and evolving student attitudes. The inclusion of teacher-facilitated reflections, usage logs, and measures of students' independent AI tool use over time would also support a more comprehensive evaluation of sustained instructional impact.

From a pedagogical perspective, the integration of generative AI tools in elementary settings requires intentional scaffolding by teachers [44–47]. This includes guiding students to design effective prompts by using specific verbs, narrowing the scope of questions, and providing relevant context. Teachers can apply strategies such as prompt templates, sentence starters, or whole-class demonstrations before allowing students to generate prompts independently. Iterative refinement of prompts based on chatbot responses can also help students develop a deeper understanding of how to communicate effectively with AI tools. In addition, several key conditions must be met to ensure successful AI integration in classrooms. First, teacher guidance is essential, especially for younger students who struggle to interpret AI-generated responses without support [48]. Second, a reliable technological infrastructure, including stable internet access, sufficient devices, and user-friendly interfaces, is necessary to provide all students with equitable learning opportunities [49]. Third, professional development opportunities should be provided to help teachers develop both the technical skills and pedagogical strategies for incorporating AI into their instruction [50]. When these foundational conditions are in place, generative AI tools can support personalized learning, foster inquiry-based exploration, and enhance digital literacy development in age-appropriate ways.

Overall, generative AI chatbots show promise in supporting media literacy instruction. Future research could expand their application to various subject areas and age groups, explore interdisciplinary contexts, and assess their long-term impact on learning achievement, strategy use, and perceived cognitive load. Additionally, examining how teachers adopt and integrate AI tools can offer valuable insights for designing sustainable, scalable models that improve both instruction and learning outcomes.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Y.-T.L. and C.-C.C. conducted the research; Y.-T.L. and C.-C.C. analyzed the data; Y.-T.L., C.-C.C. and Y.-C.L. wrote the paper; Y.-T.L. and Y.-C.L. revised and edited the paper; All authors have read and approved the final manuscript.

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