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NUMERACY LITERACY AND LEARNING STYLES: A SYSTEMATIC REVIEW OF ARTIFICIAL INTELLIGENCE TUTOR USE

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ABSTRACT
Despite the growing integration of Artificial Intelligence (AI) in education, there remains a critical gap in research that specifically synthesizes how AI tutors interact with diverse learning styles to influence students' numeracy literacy. Previous studies tend to address AI in education or learning styles in isolation, without examining their intersecting effects on numeracy outcomes. This study aims to map the profile of students' numeracy literacy across learning styles when using an AI tutor, analyze student interaction patterns with AI tutor features, and identify factors influencing numeracy literacy outcomes. A Systematic Literature Review (SLR) was conducted following PRISMA guidelines, analyzing 14 peer-reviewed articles published between 2018 and 2025 from Scopus and ScienceDirect databases. Bibliometric analysis using VOSViewer identified four conceptual clusters with "numeracy literacy," "learning style," "artificial intelligence," and "ChatGPT" as central nodes. Findings reveal that AI tutors demonstrate significant potential to improve numeracy literacy with gains of 28.7%–32% across studies by adapting to Visual, Auditory, Read/Write, and Kinesthetic (VARK) learning preferences, with visual learners showing the highest gains. This review provides a novel synthesis by integrating AI tutor effectiveness with learning style perspectives in numeracy literacy, offering theoretical and practical implications for educators in developing differentiated AI-integrated learning strategies.
Keywords: *artificial intelligence tutor; learning styles; numeracy literacy; systematic literature review*

ABSTRAK
Meskipun integrasi kecerdasan buatan (AI) dalam pendidikan semakin meluas, masih terdapat kesenjangan penelitian mensintesis bagaimana AI tutor berinteraksi dengan berbagai gaya belajar untuk memengaruhi literasi numerasi siswa. Studi-studi sebelumnya cenderung mengkaji AI dalam pendidikan atau gaya belajar secara terpisah, tanpa meneliti efek persilangannya terhadap hasil numerasi. Penelitian ini bertujuan untuk memetakan profil literasi numerasi siswa ditinjau dari gaya belajar dalam penggunaan AI tutor, menganalisis pola interaksi siswa dengan fitur AI tutor, serta mengidentifikasi faktor-faktor yang memengaruhi hasil literasi numerasi. Systematic Literature Review (SLR) dilakukan mengacu pada panduan PRISMA , dengan menganalisis 14 artikel jurnal ilmiah yang diterbitkan antara tahun 2018- 2025 dari database Scopus dan ScienceDirect. Analisis bibliometrik menggunakan VOSViewer mengidentifikasi empat klaster konseptual dengan "literasi numerasi," "gaya belajar," "kecerdasan buatan," dan "ChatGPT" sebagai simpul sentral. Temuan menunjukkan bahwa AI tutor memiliki potensi signifikan dalam meningkatkan literasi numerasi dengan peningkatan 28,7%–32% lintas studi melalui adaptasi terhadap preferensi belajar Visual, Auditori, Read/Write, dan Kinestetik (VAK), dengan siswa visual menunjukkan peningkatan tertinggi. Tinjauan ini memberikan sintesis baru dengan mengintegrasikan efektivitas AI tutor dan perspektif gaya belajar terhadap literasi numerasi, sekaligus menawarkan implikasi teoritis dan praktis dalam mengembangkan strategi pembelajaran berdiferensiasi yang terintegrasi AI.
Kata kunci: *gaya belajar; kecerdasan buatan tutor; literasi numerasi; systematic literature review*

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Introduction

The global advancement of the digital age demands that individuals possess 21st-century competencies encompassing critical thinking, problem-solving, creativity, collaboration, and numeracy (World Economic Forum, 2020). According to the OECD (2025) in its Education at a Glance report, numeracy skills remain a pivotal indicator for addressing contemporary economic and social challenges, including data-driven decision-making and information literacy. UNESCO (2021) reinforces this by asserting that numeracy is not merely an academic skill but an essential life competency required for meaningful participation in modern society.

Empirical evidence highlights persistent numeracy literacy deficits among Indonesian students. The OECD's Education at a Glance 2025 report documents significant numeracy gaps among youth that may impede their capacity to meet 21st-century demands (OECD, 2025). National assessment data further reveals widespread difficulties among students in understanding contextual problems, interpreting data, and selecting appropriate problem-solving strategies (Kemdikbudristek, 2023). This gap between curriculum aspirations and actual student performance signals an urgent need for innovative instructional interventions.

One variable known to significantly influence learning outcomes is learning style. The VARK model (Fleming & Mills, 1992) posits that students possess distinct preferences for receiving and processing information Visual, Aural, Read/Write, and Kinesthetic which affect their engagement with and retention of content. Simultaneously, AI tutors have emerged as promising technological solutions capable of providing adaptive explanations, immediate feedback, and personalized learning pathways tailored to individual learner needs (Holmes et al., 2022). The proliferation of AI tutors across formal schooling and self-directed learning contexts underscores their growing pedagogical relevance.

However, prior research tends to examine AI in education or learning styles in isolation, without specifically synthesizing how AI tutors interact with different learning styles to influence numeracy literacy. While studies confirm AI's general efficacy in improving academic outcomes (Kestin et al., 2025; Chang & Owen, 2023) and others map learning-style-based interventions (Bajaj & Sharma, 2018; Sari et al., 2025), a comprehensive synthesis integrating these two domains within the context of numeracy literacy remains absent. This gap motivates the present Systematic Literature Review (SLR).

This study was guided by three research questions: RQ1: What is the profile of students' numeracy literacy across various learning styles after using an AI tutor? RQ2: How do students with different learning styles respond to and interact with AI tutor features? RQ3: What factors influence the numeracy literacy of students with different learning styles in the use of an AI tutor? This SLR aims to provide a theoretical foundation for understanding and advancing numeracy literacy development through the lens of learning styles and AI-assisted instruction.

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Research Methods

This study employed a Systematic Literature Review (SLR) methodology to identify, evaluate, and synthesize existing research on students' numeracy literacy based on learning styles in the context of AI tutor use. SLR is defined as a research method designed to identify, synthesize, and evaluate scientific literature in a structured, transparent, and replicable manner (Kitchenham & Charters, 2007). The review was conducted across three stages: (1) review planning, (2) conducting the review, and (3) reporting findings, as outlined in Figure 1.

As illustrated in Figure 1, the SLR process followed a systematic sequence from protocol development through literature retrieval, screening, quality assessment, data extraction, coding, and analysis. Each stage was documented to ensure transparency and replicability in Figure 1.

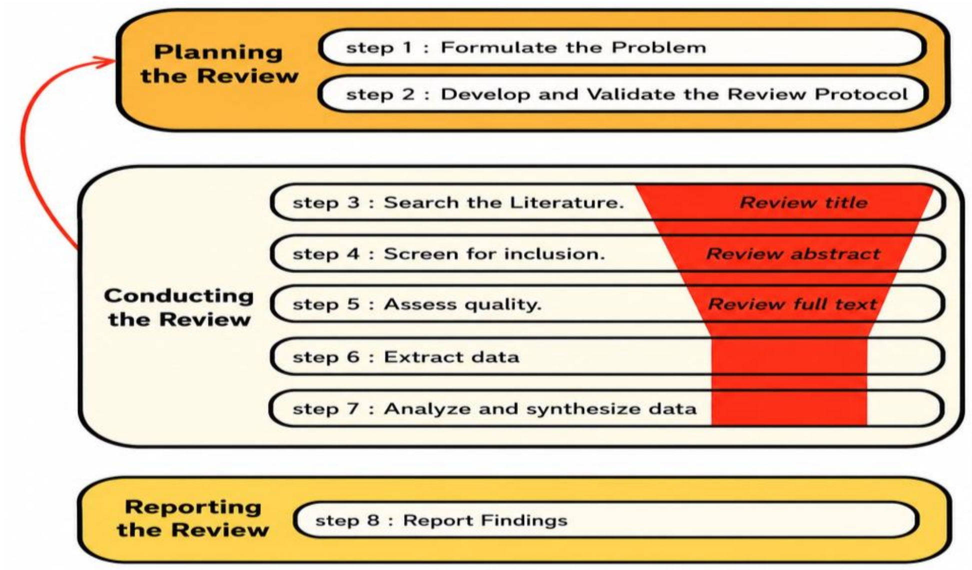

Figure 1 : Stages of the SLR construction process

Review Planning

The planning phase began with operationalizing the research questions (RQ1–RQ3). A review protocol was then developed, encompassing the search strategy, data-source selection, inclusion and exclusion criteria, and quality-assessment procedures. Three keyword combinations were applied: “Literacy numeracy and learning style,” “Literacy numeracy and Artificial Intelligence,” and “Learning Style and Artificial Intelligence.” These terms were entered into Scopus and ScienceDirect, platforms recognized for their credibility and international scope. Table 1 presents the complete inclusion and exclusion criteria.

Table 1. Inclusion and Exclusion Criteria for the Systematic Literature Review

Criteria	Description
Database	Scopus (primary); ScienceDirect (secondary)
Inclusion Criteria	1. Keyword appears in title, abstract, keywords, or full text 2. Written in English

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	3. Published in one of the selected databases 4. Journal-article format 5. Published between 2015 and 2025
Exclusion Criteria	1. Keywords absent from title, abstract, or full text 2. Not written in English 3. Unclear publisher 4. Outside the field of mathematics education 5. Full text inaccessible
Search Keywords	“Literacy numeracy and learning style” “Literacy numeracy and Artificial Intelligence” “Learning Style and Artificial Intelligence”

Conducting the Review

As shown in Table 2, the initial search yielded 6,519 records (Scopus = 3,387; ScienceDirect = 3,132). In Table 2.

Table 2. Search Results Before Filtering

Title Terms	Keyword Combination	Scopus	ScienceDirect
Numeracy literacy; learning style; AI tutor	"Literacy numeracy and learning style" "Literacy numeracy and Artificial Intelligence" "Learning Style and Artificial Intelligence"	24 18 3,345	1,321 379 1,432
Total		**3,387**	**3,132**

Following title-, keyword-, and abstract-based screening, 161 documents were retained in Table 3.

Table 3. Filtered Article Search Results

Title Terms	Keyword Combination	Scopus	ScienceDirect
Numeracy literacy; learning style; AI tutor	"Literacy numeracy and learning style" "Literacy numeracy and Artificial Intelligence" "Learning Style and Artificial Intelligence"	2 1 57	76 10 15
Total		**60**	**101**

The selection process then followed PRISMA guidelines (Page et al., 2021), as depicted in Figure 2. A quality-screening step reduced the 6,519 initial records to 161 documents based on title and abstract review. Full-text eligibility screening

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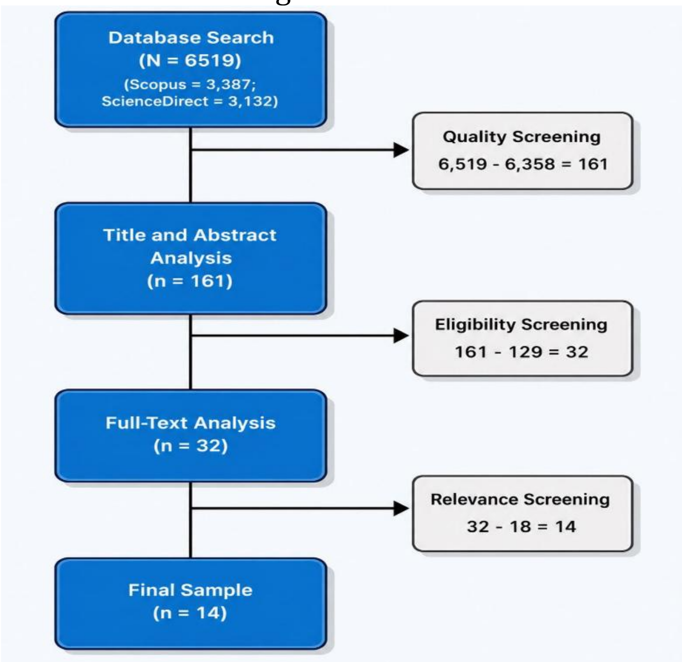
further reduced this set from 161 to 32 articles, and a final relevance-screening step narrowed the sample to 14 articles for in-depth analysis in Figure 2

Figure 2. PRISMA Flow Diagram of the Article Selection Process



Each of the 14 selected articles was further appraised using the five-criterion quality-assessment instrument in Table 4, covering the clarity of research objectives, the appropriateness of study design, the adequacy of data-collection description, the clarity of reported results, and the acknowledgment of limitations. Only articles meeting at least three of the five criteria (score ≥ 3 of 5) were retained for the final synthesis, after which each article was coded by title, authorship, year, country, context, methodology, and design to support the subsequent thematic and bibliometric analysis in Table 4.

Table 4. Quality Assessment Criteria

Code	Quality Assessment Criterion	Scoring
QA1	Is the research objective clearly stated?	Yes = 1; Partial = 0.5; No = 0
QA2	Is the study design appropriate for the research question?	Yes = 1; Partial = 0.5; No = 0
QA3	Are the data-collection methods adequately described?	Yes = 1; Partial = 0.5; No = 0
QA4	Are the results clearly reported and analyzed?	Yes = 1; Partial = 0.5; No = 0
QA5	Are the limitations of the study acknowledged?	Yes = 1; Partial = 0.5; No = 0

Bibliometric analysis using VOSViewer and word-cloud visualization was then employed to map keyword co-occurrence patterns, publication trends, and thematic clusters across the reviewed literature.

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Reporting of Review Findings

The findings are organized into three sections: (1) a literature profile encompassing author trends, country distributions, and methodological characteristics; (2) an analysis of numeracy literacy in relation to learning styles and AI Tutor use, addressing RQ1–RQ3; and (3) identified research gaps and recommendations for future investigation.

Results and Discussion

Bibliometric Profile of the Reviewed Literature

Table 5 summarizes the 14 articles included in this review. The studies span 2018–2025, with 86% published between 2023 and 2025 reflecting heightened global interest in AI-assisted education following the COVID-19 pandemic. Geographically, contributions originate predominantly from the Netherlands (4 articles), Indonesia (3 articles), and Switzerland (2 articles) (Gligorea et al., 2023; Bajaj & Sharma, 2018; Begum et al., 2021; Tudorache, 2023; Otero et al., 2023) in Table 5.

Table 5. Summary of the 14 Reviewed Articles

No	Author (Year)	Journal	Design	Key Findings
1	Kestin et al. (2025)	*npj Science of Learning*	RCT	AI tutoring (GPT-4) outperformed conventional active learning by 0.52 SD on the post-test; students using AI showed 48% higher conceptual-comprehension gains.
2	Byrd Hornbug et al. (2024)	*Journal of Experimental Child Psychology*	Longitudinal study	Mathematical language (β=0.43, p<.001) and emergent literacy (β=0.38, p<.01) significantly predicted early numeracy.
3	Sari et al. (2025)	*ASPIRASI*	Quasi-experimental	AI implementation improved numeracy literacy by 32% (p<.05). Visual learners showed the highest gains (42%), followed by auditory (35%), kinesthetic (28%), and read/write (25%).
4	Herwandi et al. (2024)	*Jurnal Pendidikan dan Pembelajaran*	Quasi-experimental	AI-based interactive learning improved numeracy literacy by 28.7% (d=0.84). Experimental-group mean: 82.4 vs. control: 64.3 (p<.001).
5	Gligorea et al. (2023)	*Education Sciences*	SLR	Identified five key barriers: technical complexity (68%), institutional resistance (54%), teacher learning curve (61%),

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				infrastructure (72%), and implementation cost (49%).
6	Bajaj & Sharma (2018)	*Procedia Computer Science*	Experimental (ML algorithm)	AI detected learning styles with 87.3% accuracy. Self-regulated learning increased 41% in adaptive-AI groups vs. 18% in conventional groups.
7	Begum et al. (2021)	*International Journal of Educational Research*	Multilevel mediation analysis	Self-efficacy mediated the numeracy-mathematics performance relationship (indirect effect=0.23, $p<.01$); effects stronger for females ($\beta=0.31$) than males ($\beta=0.18$).
8	Tudorache (2023)	*Education Sciences (MDPI)*	Narrative review	AI can reduce achievement gaps by up to 27% when implemented equitably; 78% of studies showed positive impact on marginalized populations.
9	Otero et al. (2023)	*International Journal of STEM Education*	SLR	Identified five AI-literacy competencies; AI integration in STEM increased engagement by 52%.
10	Swargiary (2023)	*Journal of Learning Analytics*	Longitudinal quasi-experimental	AI personalized learning increased engagement by 47% and achievement by 34% ($p<.001$); digital divide significant (51% gain vs. 12% for low-access students).
11	Chang & Owen (2023)	*Smart Learning Environments*	Systematic review	AI-based ITS effective in 82% of studies ($n=60$); mean effect size $d=0.66$; reduced teacher workload by 38%.
12	Ratnaya & Fitriyani (2024)	*Al-Adzka*	Correlational/path analysis	Strong literacy-numeracy correlation ($r=0.68$, $p<.001$); mathematical language as mediator ($\beta=0.54$), explaining 62% of variance.
13	Chang (2023)	*Large-Scale Assessments in Education*	Moderated mediation (TIMSS 2019)	Early literacy predicted math achievement ($\beta=0.42$, $p<.001$), mediated by early numeracy; SES moderated the effect (model $R^2=58\%$).

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14	Karaali (2023)	*Numeracy*	Theoretical/critical review	AI struggles with contextual knowledge transfer (78% failure rate), qualitative reasoning (65%), and problem-posing (71%); numeracy ≠ computation.

RQ1: Numeracy Literacy Profiles by Learning Style

Figure 3 presents the VOSViewer network visualization based on keyword co-occurrence frequency across the 14 articles, distinguishing four thematic clusters: a cluster centered on AI, technology, and educational practice; a cluster centered on study, performance, and assessment; a cluster centered on early numeracy and literacy skill development, including mathematical language; and a cluster centered on learning style, model, and tool. Keywords such as "study," "student," and "education" constitute the largest nodes, while "ChatGPT," "artificial intelligence," and "learning style" occupy central, bridging positions—indicating their prominence in connecting the numeracy-literacy core to AI-based pedagogical approaches. VOSViewer in Figure 3.

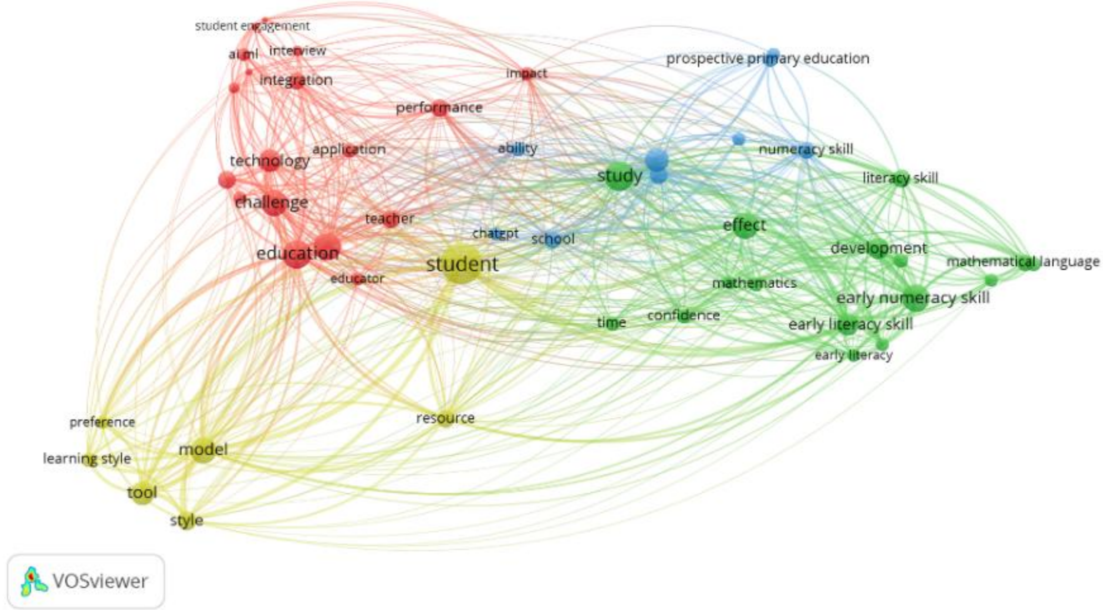

Figure 3. VOSViewer Network Visualization of Keyword Co-occurrence

The overlay visualization in Figure 4 reveals a temporal shift in research focus from 2021 to 2024 (indicated by the color gradient from purple/blue to yellow). Earlier publications (2021–2022, purple-blue) clustered around "learning style," "model," and "tool," whereas more recent studies (2023–2024, green-yellow) concentrate on "early numeracy skill," "mathematical language," and "student engagement." This shift indicates a transition from generic AI-learning-style frameworks toward more granular, numeracy-specific applications of AI tutoring In Figure 4.

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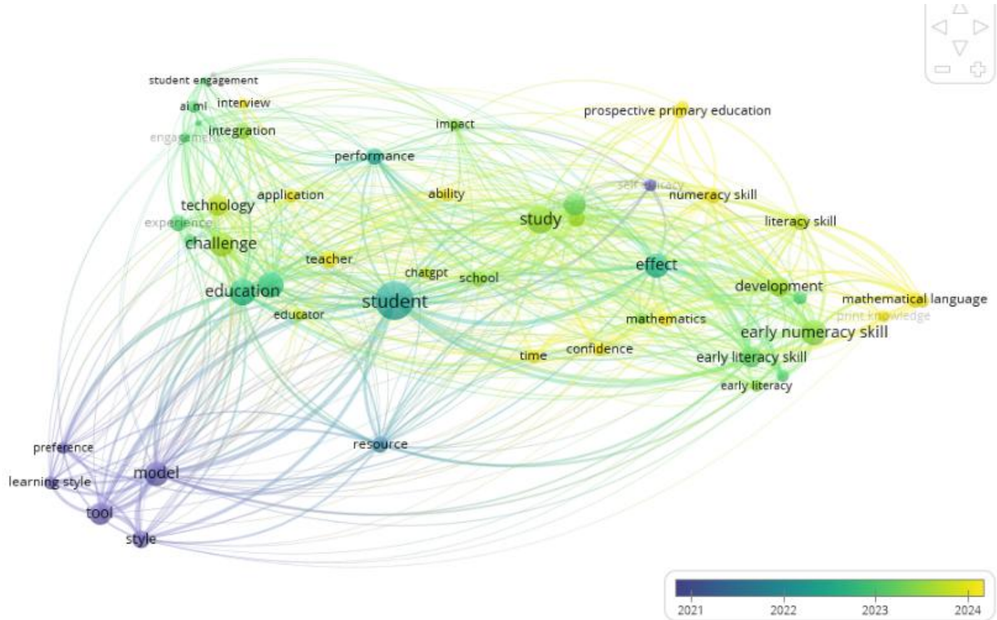

Figure 4. VOSViewer Overlay Visualization by Publication Year

Figure 5 illustrates keyword density, with “student,” “education,” “technology,” and “early numeracy skill” exhibiting the highest co-occurrence intensity (brightest regions). This density map confirms a hierarchical structure in which numeracy literacy constitutes the theoretical core, AI functions as the primary technological construct, learning style serves as the application context, and students represent the central research subject in Figure 5.

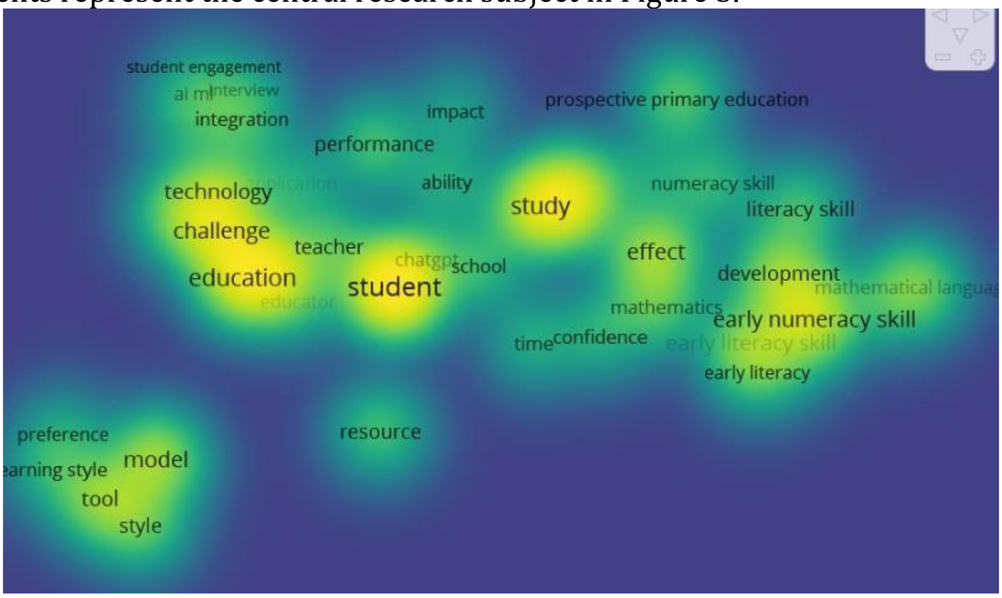

Figure 5. VOSViewer Density Visualization of Keyword Frequency

Empirically, Kestin et al. (2025) demonstrated through a Randomized Controlled Trial (RCT) that AI-guided instruction (GPT-4) surpassed conventional active learning by 0.52 standard deviations on post-test performance, with students exhibiting 48% higher conceptual-comprehension gains. Sari et al. (2025) reported that AI implementation improved numeracy literacy by 32% overall ($p < .05$), with

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differential gains by learning style: visual learners showed the highest improvement (42%), followed by auditory (35%), kinesthetic (28%), and read/write (25%), with a significant interaction effect ($F = 4.21$, $p < .01$). These findings corroborate Bajaj and Sharma (2018), whose adaptive AI system achieved 87.3% accuracy in learning-style detection and yielded a 41% increase in self-regulated learning among AI-assisted students compared with 18% in conventional groups.

Collectively, this evidence indicates that AI tutors do not exert uniform effects across learners; rather, their impact is modulated by individual learning-style preferences, with visual learners deriving particularly strong benefit from AI-generated graphical representations and data visualizations (Herwandi et al., 2024).

RQ2: Student Responses and AI Tutor Interaction Patterns

The reviewed literature identifies distinct interaction patterns between students of different learning styles and AI Tutor features. Visual learners benefit markedly from graphical feedback and dynamic data representations, whereas auditory and kinesthetic learners demonstrate higher engagement with interactive simulations and conversational AI interfaces (Herwandi et al., 2024). These interaction patterns align with Dai and Ke's (2022) systematic mapping review, which found that simulation- and AI-based learning environments particularly benefit learners through experiential, hands-on engagement consistent with the gains reported among kinesthetic learners in the present synthesis. Swargiary (2023) further reported that AI personalization systems increased long-term engagement by 47% and academic achievement by 34% ($p < .001$).

Self-efficacy emerges as a critical mediator of these interaction effects. Begum et al. (2021) found that self-efficacy mediates the link between numeracy expectations and mathematics performance (indirect effect = 0.23, $p < .01$), with stronger effects among female students ($\beta = 0.31$) than male students ($\beta = 0.18$). This suggests that the immediate, non-judgmental feedback characteristic of AI tutors may differentially enhance self-efficacy across gender groups, an avenue that warrants closer examination in future AI-tutor research.

The temporal bibliometric shift documented in Figure 4 further indicates that research on AI-learning-style interactions has evolved from static style classification toward dynamic, adaptive AI responses a development aligned with the emergence of large language models such as ChatGPT in educational settings.

RQ3: Factors Influencing Numeracy Literacy in AI-Mediated Learning

Three categories of factors were identified as shaping numeracy-literacy outcomes in AI-mediated learning environments. First, cognitive and linguistic factors play a foundational role. Byrd Hornbug et al. (2024) established that mathematical language ($\beta = 0.43$, $p < .001$) and emergent literacy ($\beta = 0.38$, $p < .01$) are significant longitudinal predictors of early numeracy. Ratnaya and Fitriyani (2024) corroborated these findings, identifying a strong literacy-numeracy correlation ($r = 0.68$, $p < .001$) and confirming mathematical language as a mediating variable ($\beta = 0.54$). Using TIMSS 2019 data, Chang (2023) further showed that early literacy predicts fourth-grade mathematics achievement ($\beta = 0.42$, $p < .001$), mediated by early numeracy and moderated by socioeconomic status, with the model explaining 58% of variance in mathematics performance.

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Second, sociocontextual and infrastructural factors substantially moderate implementation outcomes. Swargiary (2023) documented a pronounced digital divide, with high access students gaining 51% more than low access peers (12%). Herwandi et al. (2024) and Sari et al. (2025) similarly emphasized that socio-cultural adaptation and local infrastructure readiness are prerequisites for effective AI integration in Indonesian educational contexts. Tudorache (2023) argues that equitable AI implementation can reduce achievement gaps by up to 27%, contingent on principles of universal accessibility, inclusive personalization, algorithmic transparency, and data protection.

Third, institutional and pedagogical readiness constitute determining factors. Gligorea et al. (2023) identified five structural barriers: technical complexity (68% of studies), institutional resistance (54%), teacher learning curves (61%), inadequate infrastructure (72%), and high implementation costs (49%). Otero et al. (2023) emphasize that teacher AI literacy is itself a prerequisite for effective AI-enhanced numeracy instruction. Karaali (2023) cautions, from a philosophical standpoint, that AI systems remain limited in facilitating contextual knowledge transfer (78% failure rate), qualitative reasoning (65%), and problem-posing (71%) dimensions central to higher-order numeracy literacy and not reducible to computation alone.

These findings extend earlier syntheses by Chen et al. (2020), who emphasized AI's personalization potential in education generally, and by Roll and Wylie (2016), who anticipated the evolution of intelligent tutoring systems toward adaptive, learner-centered models. Likewise, Woolf et al. (2013) identified personalization and adaptive feedback as central "grand challenges" for AI in education; the studies reviewed here suggest that AI tutors have made measurable progress toward both objectives for visual and auditory learners, while contextual and qualitative reasoning as Karaali (2023) cautions, remain comparatively underdeveloped. The present review extends these perspectives by specifically synthesizing the intersection of AI tutoring, learning styles, and numeracy literacy, an integration not previously addressed in prior systematic reviews.

Taken together, the convergent evidence indicates that AI tutors function most effectively when embedded within institutional frameworks that prioritize infrastructure, teacher training, and equitable access, while being calibrated to students' learning-style profiles and linguistic-cognitive foundations.

Strengths and Limitations

This review's principal strength lies in its focused synthesis of two previously disconnected research strands, AI tutoring and learning-style-based pedagogy within the specific domain of numeracy literacy, following transparent, PRISMA-guided selection procedures. Nevertheless, several limitations warrant acknowledgment. First, reliance on two databases (Scopus and ScienceDirect) and English-language publications may have excluded relevant studies indexed elsewhere or published in Bahasa Indonesia. Second, the heterogeneity of study designs and outcome measures across the 14 included articles precluded meta-analytic pooling of effect sizes, limiting the precision of cross-study comparisons. Third, because most primary studies employed short-term, single-context interventions, conclusions regarding the durability of AI-tutor effects on numeracy literacy across learning styles remain provisional and should be interpreted with appropriate caution.

Conclusion and Suggestion

This systematic literature review examined the relationship between AI Tutor use, learning styles, and numeracy-literacy outcomes across 14 studies (2018–2025), yielding three principal findings that correspond to the research questions posed. With respect to RQ1, AI tutors outperform conventional active learning in authentic classroom settings (Kestin et al., 2025) and demonstrate differential effectiveness by learning style, with visual learners exhibiting the highest gains, followed by auditory, kinesthetic, and read/write learners. Bibliometric trends confirm a research shift toward AI-personalized and ChatGPT-integrated numeracy instruction.

With respect to RQ2, visual learners benefit most from graphical and visual AI features, while auditory and kinesthetic learners are better served by interactive and simulation-based AI elements; self-efficacy mediates AI's impact on numeracy outcomes, with gender-differentiated effects.

With respect to RQ3, cognitive-linguistic foundations (mathematical language and emergent literacy), sociocontextual infrastructure, and institutional-pedagogical readiness collectively determine the effectiveness of AI-mediated numeracy instruction. These findings carry implications for curriculum designers, educational technologists, and policymakers: AI integration in mathematics education should be preceded by teacher professional development in AI literacy, targeted infrastructure investment, and the design of culturally responsive, learning-style-aware instructional scaffolds.

Future research should pursue primary empirical studies particularly longitudinal and cross-cultural designs to examine the causal mechanisms through which AI tutors differentially influence numeracy literacy across learning-style profiles, including investigations into the long-term retention and transfer of numeracy skills in AI-assisted environments.

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