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From Algorithms to Pedagogy: A Web of Science-Based Bibliometric Study of Artificial Intelligence in English Reading Education

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Abstract. The swift advancement of artificial intelligence (AI) has reshaped English reading education by enabling automation, personalization, and intelligent feedback. This study examined the intellectual structure, thematic evolution, and emerging research fronts of AI in English reading education from 2021 to 2025. A bibliometric analysis of 279 peer-reviewed articles from the Web of Science (WoS) Core Collection was conducted using VOSviewer and CiteSpace. Results showed steady growth in research productivity and citation impact, with 2,091 citations and an H-index of 22. Bibliographic coupling identified three major intellectual streams: educational applications, technological algorithms, and cross-disciplinary extensions involving AI-enhanced readability, text complexity, and English for Medical Purposes. Keyword co-occurrence analysis revealed three thematic clusters focusing on AI-supported comprehension, deep-learning-driven machine reading

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comprehension (MRC) and natural language processing (NLP), and machine-learning-based readability research. Burst detection further indicated a shift from computational mechanisms such as "question answering" and "deep learning" toward pedagogical perspectives including "education," "reading skills," and "large language models." Drawing on the Technology Acceptance Model (TAM), this study interpreted this transformation as a socio-technical process and provided transferable implications for responsible AI integration in English reading education.

Keywords: artificial intelligence; English reading education; bibliometric analysis; TAM

1. Introduction

Since 2021, research on AI-driven English reading instruction has expanded rapidly, reflecting the growing intersection of artificial intelligence (AI), large language models (LLMs), and educational linguistics (Peña-Acuña & Durão, 2024). These developments have significantly transformed English language education. AI technologies such as machine-learning-based comprehension systems and adaptive feedback platforms are reshaping how learners engage with texts and receive feedback (Shafiee Rad, 2025). Recent advances highlight the increasing role of AI in designing and evaluating educational content to improve textual clarity and cognitive accessibility (Pohl et al., 2024).

In digital education contexts, AI is increasingly viewed as a socio-cognitive mediator that personalizes learning and supports metacognitive engagement in reading (Pan et al., 2024). AI-driven reading tools, including generative text systems and adaptive learning platforms, have improved vocabulary learning, reading accuracy, and assessment efficiency (Rees & Lew, 2024; Wu et al., 2025). Beyond language learning, AI-mediated systems also enhance readability and academic engagement across disciplines (Boscardin et al., 2024). However, existing studies still show theoretical fragmentation and methodological inconsistency. Many focus on localized pedagogical applications or technological optimization without integrating perspectives from education and computational science. Consequently, a systematic and data-driven overview of AI in English reading education remains limited. In addition, theoretical models such as the Unified Theory of Acceptance and Use of Technology (UTAUT) have rarely been systematically applied to AI-mediated reading contexts (Dwivedi et al., 2019).

To close these gaps, the present study applied a bibliometric mapping approach to systematically analyze research on AI in English reading education published between 2021 and 2025. Drawing upon the Web of Science (WoS) Core Collection and using visualization tools such as VOSviewer and CiteSpace, this study identified the intellectual structures, thematic clusters, and emerging research fronts, including temporal surges of attention captured through burst detection analysis. Through a reproducible and data-driven overview, this research advanced a quantitative knowledge map that traces how AI in English reading has evolved–from computational mechanisms to human-centered pedagogical innovation. By combining bibliometric analytics with theoretical perspectives

such as TAM and socio-affective learning frameworks, this study built a link between technological innovation and pedagogical inquiry. Specifically, it aimed to address the following questions:
RQ1: What are the publication and citation patterns that indicate the research productivity and academic influence of AI in English reading education?
RQ2: What dominant intellectual structures and thematic configurations emerge, and in what ways are they conceptually connected?
RQ3: Based on burst keyword analysis and temporal evolution, what new research frontiers and developmental trends can be identified?

Using this analytical framework, the study offered a systematic and data-driven overview of the field. It also highlighted theoretical and practical insights into how AI innovations are reshaping English reading pedagogy.

2. Literature Review

2.1 The evolution of AI in English Reading Education

With the rise of deep learning and large language models (LLMs), research on AI in English reading education has evolved through three main phases. The initial phase (pre-2020) focused on computational modelling and machine reading comprehension (MRC), emphasizing algorithmic accuracy and text-processing efficiency (Yang et al., 2020). The second phase (2021–2023) marked a pedagogical shift, with growing integration of AI tools such as intelligent feedback, adaptive assessment, and chatbot-based scaffolding into reading instruction (Xu et al., 2022).

The third phase (2024–2025) reflected the emergence of generative AI and socio-affective pedagogy, moving from automation toward augmentation, where AI supports learner motivation, engagement, and self-regulation (Alarifi et al., 2025; Boscardin et al., 2024). Across these phases, AI has shifted from a technical aid to a cognitive and affective collaborator, transforming reading into a more interactive, multimodal, and data-driven literacy practice. However, limited attention has been paid to how AI-mediated reading reshapes learners' cognitive and interpretative processes, leaving the pedagogical implications of this transition underexplored.

2.2 Theoretical and Pedagogical Dimensions

Within English as a Foreign Language (EFL) and English for Specific Purposes (ESP) contexts, AI is increasingly conceptualized as a socio-cognitive scaffold supporting reading comprehension and learner autonomy. Empirical studies on AI-enhanced reading tutors, adaptive assessments, and AI-generated reading-comprehension items have shown their potential to support vocabulary development, inferential reasoning, assessment design, and learner motivation (Lin & Chen, 2024; Shin et al., 2025). These effects are commonly interpreted through frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) (Peng et al., 2023b), Self-Determination Theory (SDT), and affective–cognitive learning models. Together, these frameworks explain how perceived usefulness, autonomy, and emotional engagement shape learners' interaction with intelligent systems. However, limited efforts have integrated

technology adoption, cognitive load, and socio-affective mediation into a unified framework, resulting in a fragmented theoretical landscape (Liu & Qiao, 2025). This fragmentation constrains cumulative theorization by treating AI as a discrete tool rather than an embedded pedagogical agent. Consequently, recent studies highlight the need for integrative, human-centered frameworks linking computational intelligence with learning theories. Systematic evidence on AI integration in language education shows that while technological interventions are increasingly adopted, theoretical and pedagogical alignment remains fragmented (Yan et al., 2025). Bibliometric mapping can further address this need by revealing conceptual connections and emerging paradigms, as demonstrated by recent bibliometric analyses of AI in EFL education (Zhou et al., 2026a).

2.3 Methodological Gaps and Rationale for Bibliometric Mapping

Despite the growing body of research, studies on AI in English reading education still show methodological fragmentation. Three recurring weaknesses can be identified. First, most studies rely on limited classroom implementations or tool-specific experiments, which constrain the external validity of their results (de Winter, 2024). Second, disciplinary divergence remains evident: computational research focuses on algorithmic optimization, while educational inquiry emphasizes pedagogical outcomes, resulting in limited interdisciplinary integration (Liu et al., 2023). Third, there is an absence of meta-synthesis, as quantitative efforts to trace intellectual structures, bibliographic coupling, or thematic evolution remain limited. A bibliometric mapping approach provides a systematic and transparent method to address these issues by visualizing publication patterns, citation linkages, and keyword dynamics (Öztürk, 2024).

This approach reveals the intellectual structure and emerging research trajectories shaping this interdisciplinary field (Bo et al., 2025a). It also deepens empirical understanding and connects computational progress with pedagogical innovation in the age of generative AI. By addressing these methodological deficiencies, bibliometric mapping challenges prior narrative syntheses and offers an evidence-based platform for theory building and pedagogical innovation. However, comprehensive bibliometric mapping of the intellectual structure and emerging research trends of AI in English reading education remains limited. Therefore, this study conducted a bibliometric analysis to address this gap.

3. Methodology

3.1 Bibliometric Research Design

This study adopted a bibliometric research design to examine research on AI in English reading education. Bibliometric analysis has increasingly been used as a quantitative approach to map scientific knowledge and trace the evolution of research fields over time (Lim et al., 2025; Wider et al., 2025; Zhou et al., 2026b). This method integrates statistical indicators with network visualization techniques to identify emerging topics and intellectual linkages among publications (Morál-Muñoz et al., 2020). Compared with scoping reviews, which synthesize existing evidence through systematic identification and thematic interpretation of studies (Bo et al., 2025b), this data-driven approach provides transparent and visual representations of research structures and their dynamic

changes with greater precision (Öztürk et al., 2024). In this study, bibliometric techniques were used to map the intellectual landscape of AI research in English reading education. The analysis identified key thematic directions and tracked the field's development, offering an empirical basis for understanding AI's contribution to reading pedagogy and future educational reform.

3.2 Bibliometric Data Collection

The data collection criteria are summarized in Table 1. Bibliographic records were retrieved from the WoS Core Collection because of its broad disciplinary coverage and consistent indexing standards. In bibliometric studies of education and linguistics, WoS is widely used due to its academic credibility and cleaner metadata (Donthu et al., 2021; Zawacki-Richter et al., 2019). This study examined research on AI use in English reading education. Publications from 2021 to 2025 were included to reflect the rapid development of generative AI and its integration into English language teaching. Boolean operators, including AND and OR, were used to combine keywords (e.g., "artificial intelligence" AND "English language learning"). Searches were conducted across SSCI, ESCI, and SCI-EXPANDED to retrieve all relevant peer-reviewed articles. ESCI-indexed journals were included to capture emerging and interdisciplinary research not yet represented in SSCI or SCI-Expanded.

The search query was as follows:

TS = (("artificial intelligence" OR "AI" OR "ChatGPT" OR "machine learning" OR "deep learning" OR "generative AI") AND ("English reading" OR "reading comprehension" OR "reading skills" OR "reading instruction" OR "reading education"))

All records were retrieved on January 1, 2026, and analyzed using visualization and mapping techniques.

Table 1: Inclusion Criteria for Bibliometric Analysis

WoS Database	Core Collection
Time period	2021 to 2025
Search field	TS
Search keywords	TS = (("artificial intelligence" OR "AI" OR "ChatGPT" OR "machine learning" OR "deep learning" OR "generative AI") AND ("English reading" OR "reading comprehension" OR "reading skills" OR "reading instruction" OR "reading education"))
Document type	Article
Language	English
WoS Index	SSCI OR ESCI OR SCI-EXPANDED

3.3 Screening Process

The screening and selection procedure followed the PRISMA framework and is summarized in Figure 1. It included four stages: identification, screening, eligibility, and inclusion. From the WoS Core Collection, 495 bibliographic records were initially retrieved. After restricting the time span to 2021–2025, 107 papers were excluded because they fell outside the target period. The remaining 388

records were screened by document type. A total of 106 non-research materials, including editorials, conference proceedings, and book reviews, were removed. Then 282 full-text articles were assessed for eligibility. Three papers were excluded because they were written in languages other than English. Consequently, 279 studies met all inclusion criteria and were used for the bibliometric analysis. This multi-step screening ensured that the final dataset included only peer-reviewed English-language publications on AI in English reading education and that the selection process was transparent and systematic.

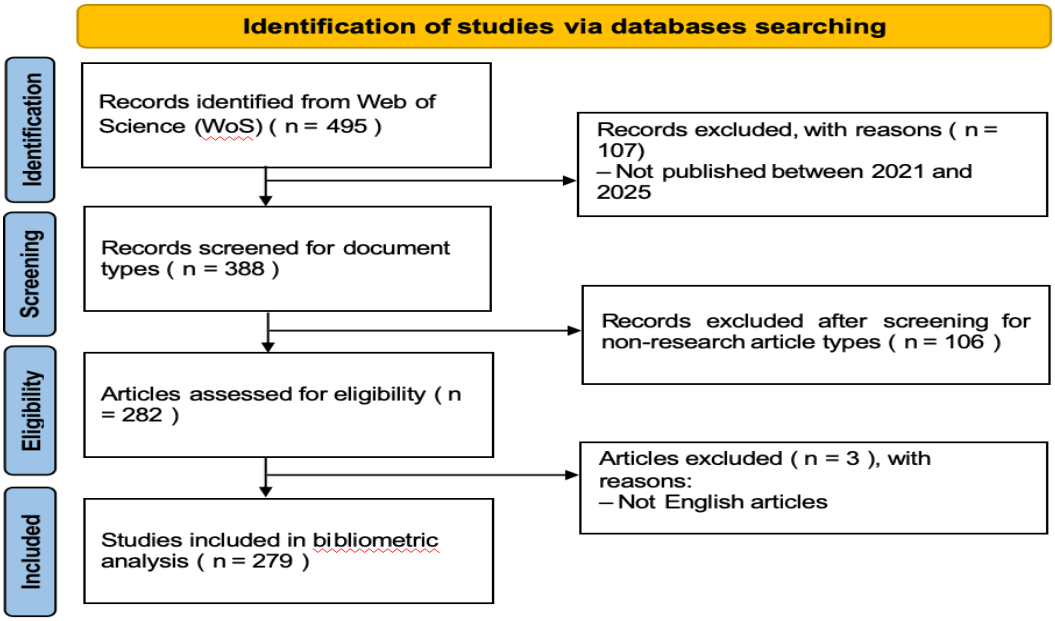

Figure 1: PRISMA Flowchart

3.4 Data Analysis

Bibliometric analyses were conducted using VOSviewer (version 1.6.20) and CiteSpace (version 6.3.R1, 64-bit Advanced) to examine the intellectual structure and thematic development of the field of research. These tools construct and visualize scientific knowledge networks by combining performance indicators with science-mapping techniques. Four complementary bibliometric approaches were applied to ensure analytical rigor and reproducibility. Performance analysis examined publication productivity and citation impact using indicators such as annual publication trends, citation counts, and h-index values (Donthu et al., 2021).

Bibliographic coupling analysis explored intellectual linkages among studies based on shared references, revealing current thematic connections within the field (Ma et al., 2022). Co-occurrence analysis identified three main research themes: AI-supported reading comprehension in education, computational reading comprehension and deep learning models, and machine learning approaches to language and readability. Burst-detection analysis was also conducted to identify emerging research fronts by detecting keywords with sudden increases in occurrence or citation intensity over time (An, 2024). Together,

these analyses provided an integrated framework for examining the structure and thematic evolution of the field.

4. Results

4.1 Bibliometric Performance and Annual Trends

The performance analysis of studies on AI in English reading education (2021–2025) offered an overview of the field's research productivity and citation impact. As shown in Table 2, the main bibliometric indicators derived from the WoS Core Collection included total publications, citing articles, total citations, average citations per study, and the H-index. Overall, 279 publications were identified, which received 2,091 citations in total (2,014 excluding self-citations). These papers were cited by 1,944 unique citing articles, resulting in an average of 7.49 citations per paper. The H-index of 22 indicated that at least 22 papers have been cited 22 times or more, reflecting a solid and steadily increasing academic influence within this expanding interdisciplinary domain.

Table 2: General Bibliometric Indicators from WoS (2021 to 2025)

Metric	Value (2021 to 2025)
Total Publications	279
Total Citing Articles	1,944 (1,894 excluding self-citations)
Total Citations	2,091 (2,014 excluding self-citations)
Average Citations per Item	7.49
H-Index	22

Figure 2 illustrates the annual distribution of publications and citations related to AI in English reading education from 2021 to 2025. The light-purple bars indicated the number of publications, while the dark-blue line represented citation trends. Both indicators exhibited a steady upward trajectory over the five-year period, peaking in 2025. This trend reflected increasing scholarly interest driven by the rapid advancement of generative AI technologies, such as ChatGPT, and their growing application in reading comprehension, assessment, and instructional design. Overall, the rising publication and citation patterns suggest that AI-based approaches are becoming increasingly influential in English reading education.

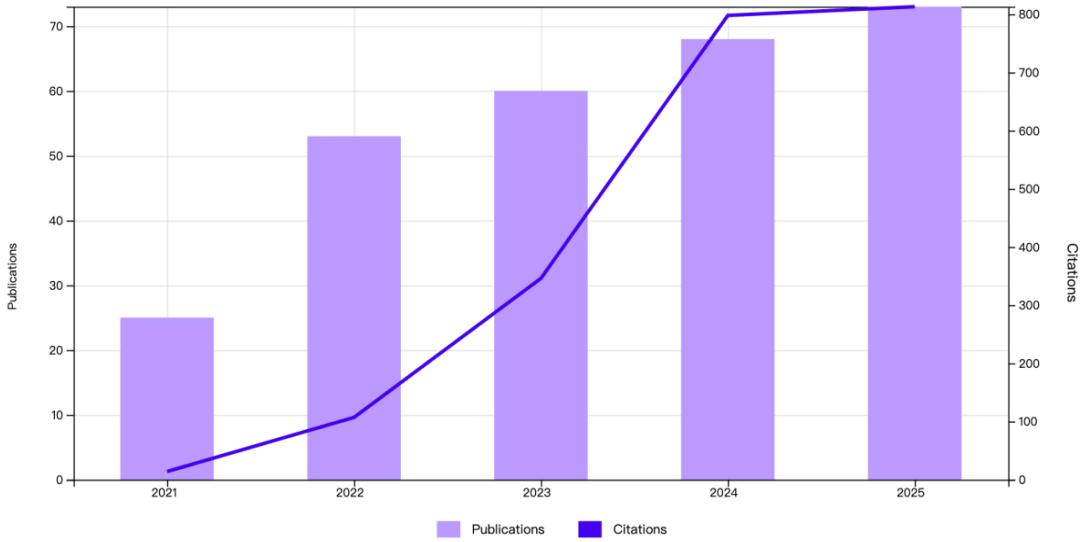

Figure 2: Annual Publications and Citations (Source: WoS Database)

4.2 Bibliographic coupling analysis by clusters

In the bibliographic coupling analysis, a citation threshold of 10 was applied to include only studies with notable scholarly influence. Among the 279 papers extracted from the WoS Core Collection, 47 met this criterion and were incorporated into the final network. As shown in Figure 3, these 47 studies formed three coherent clusters that reveal the main lines of intellectual development in AI-driven English reading research. Table 3 summarizes the thematic focus of the three clusters, which correspond to three intellectual streams in the field: Educational Application, Technological-Algorithmic, and Cross-disciplinary Application.

The first cluster (red) represented the Educational Application intellectual stream, comprising 18 works focused on the pedagogical incorporation of AI into English reading comprehension and assessment processes. These studies often built on concepts from educational psychology and technology adoption frameworks such as TAM and TPACK, reflecting a common interest in improving learner experience and instructional design. Representative studies, such as Lin and Chen (2024) and Shin and Lee (2023), examined ChatGPT's capacity to generate reading-comprehension items comparable to those created by human experts, whereas Wang et al. (2024) and de Winter (2024) investigated adaptive AI platforms designed to improve learner engagement and understanding.

Collectively, these studies signaled a pedagogical redirection–from technology-centered evaluation toward learner-oriented adaptation–that aligns with ongoing developments in AI-mediated language learning. This cluster represented the application layer of AI in English reading pedagogy, showing how intelligent systems are being integrated into educational practice to advance personalization and assessment innovation.

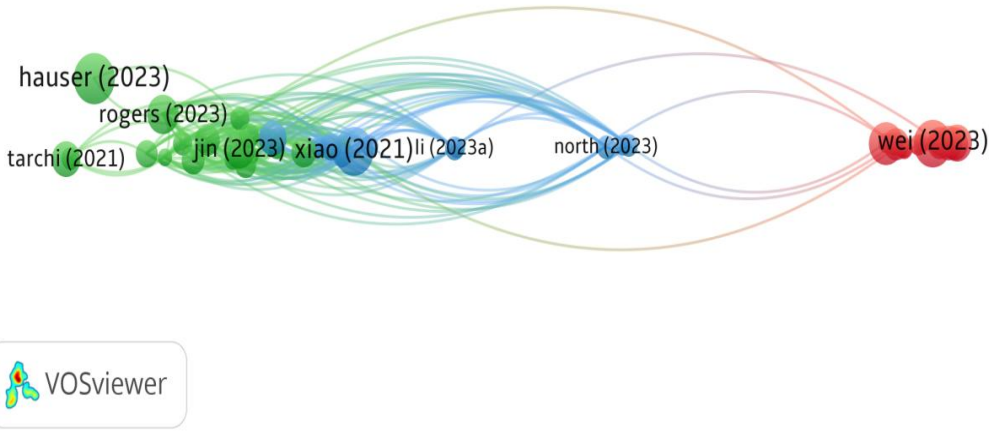

Figure 3: Bibliographic Coupling Analysis (Source: VOSviewer Visualization)

The second cluster (green) consisted of 18 studies that form the Technological-Algorithmic intellectual stream, focusing on the computational foundations of MRC. Foundational works such as Baradaran et al. (2022) and Kazi et al. (2023) outlined major advances in deep learning for MRC, while subsequent studies including Guan et al. (2024) developed interpretable and transformer-based models for automatic question generation. The strong bibliographic coupling among these publications showed that AI-related reading research is becoming increasingly anchored in computational linguistics and natural language processing (NLP).

For instance, Cui et al. (2022) demonstrated how data-driven reading models can improve evidence-based instructional design, further integrating NLP advances into educational contexts. Serving as the algorithmic backbone of the field, this cluster linked theoretical perspectives on language learning with technological implementation, reflecting a gradual convergence between educational research and data-driven NLP modeling. In sum, this body of research lays the technical groundwork for future progress in AI-enhanced reading assessment and adaptive pedagogy.

The third cluster (blue) comprised 11 articles and represented the Cross-disciplinary Application intellectual stream, showing how AI-assisted reading research has moved beyond general EFL contexts into specialized and professional domains. This cluster reflects progression from domain-specific text processing to pedagogical application. Li and Xu (2023) and Peng et al. (2023b) applied MRC frameworks to the summarization and semantic extraction of scientific and medical texts, demonstrating how AI models can support the processing of specialized language.

In medical and health-related English contexts, Chen (2025) and Pohl et al. (2024) highlighted the importance of disciplinary discourse and readability in shaping readers' comprehension of professional texts. At the instructional level, Rees and Lew (2024) and Boscardin et al. (2024) further demonstrated the pedagogical potential of GPT-based and generative AI tools, particularly for supporting

vocabulary comprehension, learner engagement, and medical education. Overall, this cluster illustrates the expansion of AI-assisted English reading research from general language-learning contexts to discipline-specific applications, where AI technologies are increasingly used to support text understanding, readability, and instructional practice.

Table 3: Bibliographic Coupling by Cluster

Cluster No. & Colour	Cluster Labels	No. of Articles	Representative Publications
Cluster 1 (Red)	AI-Driven English Reading Comprehension and Assessment Systems	18	De Winter (2024), Lee et al. (2023), Lin and Chen (2024), Shin and Lee (2023), Wang et al. (2024), Liu and Ardakani (2022), Peng et al. (2023a), Xia et al. (2024), Xu et al. (2022)
Cluster 2 (Green)	Computational Reading Comprehension as the Interdisciplinary Bridge between AI and English Reading	18	Baradaran et al. (2022), Guan et al. (2024), Cui et al. (2022), Kazi et al. (2023), Bulut and Yildirim-Erbasli (2022) Liu et al. (2023), Rogers et al. (2023), Yang et al. (2020)
Cluster 3 (Blue)	AI-Enhanced Readability, Text Complexity, and English for Medical Purposes	11	Li and Xu (2023), Peng et al. (2023b), Chen (2025), Pohl et al. (2024), Rees and Lew (2024), North et al. (2023), Boscardin et al. (2024)

4.3 Co-occurrence analysis by clusters

To trace the conceptual and thematic development of AI in English reading education, a keyword co-occurrence analysis was conducted using VOSviewer. After applying a minimum occurrence threshold of 22, 56 keywords were obtained and organized into three clusters. As shown in Figure 4 and Table 4, these clusters represent three major thematic orientations within the field: pedagogical applications, computational modeling, and language readability. This structure mirrors a coherent and well-defined research landscape in AI-supported English reading.

Cluster 1 consisted of 25 keywords and stood out as the largest and most connected group within the co-occurrence network. Representative keywords included "artificial intelligence", "technology", "reading", "comprehension", "education", "student", and "skill". Studies in this cluster looked into how intelligent technologies contribute to reading comprehension by giving adaptive feedback, creating automated questions, and tracking learners' performance in real time. Evidence suggests that AI-based systems help develop learners' metacognitive awareness, text-annotation habits, and deeper reading-for-meaning abilities (Pan et al., 2024; Xu et al., 2022). Over time, research has moved from seeing AI as a teaching aid to viewing it as a learning partner that supports autonomy and continuous engagement. When integrated into real classroom

contexts, adaptive AI tools appear to increase students' motivation, participation, and reading achievement (Peng et al., 2023b; Wu et al., 2025).

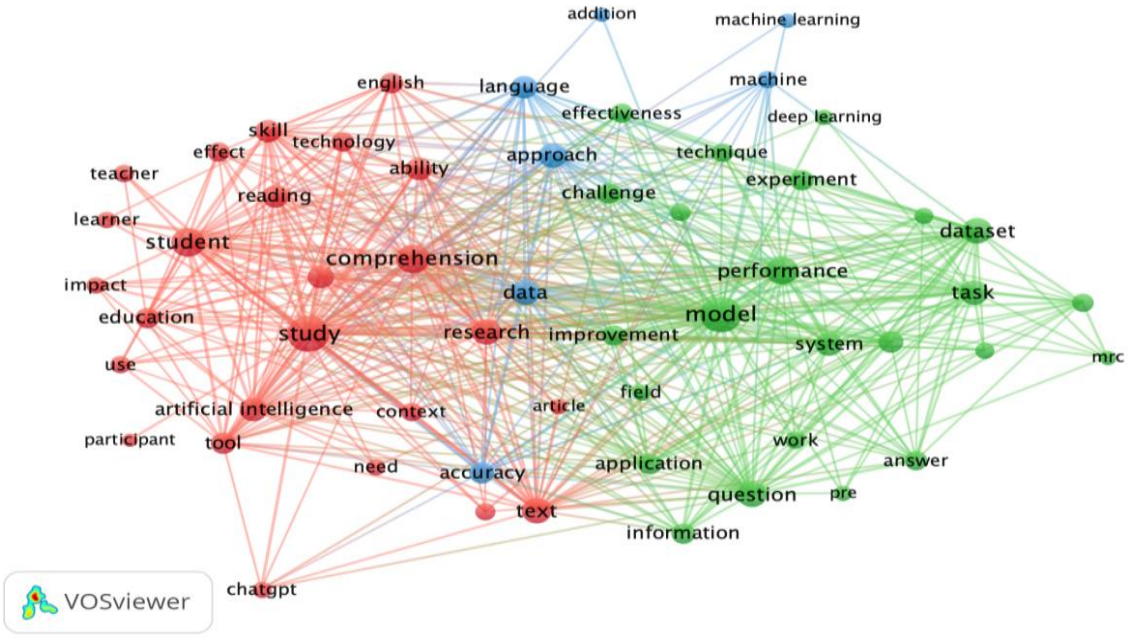

Figure 4: Co-Occurrence Analysis (Source: VOSviewer Visualization)

Cluster 2 is made up of 24 keywords that reflect the computational core of AI-based English reading research. Keywords like "machine reading comprehension", "deep learning", and "natural language processing" emphasized its focus on algorithmic approaches to language understanding. This cluster gathered studies employing neural and transformer-based architectures to model or evaluate human reading comprehension with greater accuracy and contextual sensitivity.

Bulut and Yildirim-Erbasli (2022) demonstrated how transformer models can automatically generate human-like reading items, whereas Liu et al. (2023) analyzed semantic-matching mechanisms that improve MRC performance and generalization. At a broader level, Rogers et al. (2023) analyzed QA and MRC datasets to expose benchmark limitations and their impact on AI literacy assessment. Moving toward pedagogical use, Shin et al. (2025) contrasted generative AI and human-constructed tests, demonstrating that LLMs enhance reading-assessment design through scalable and adaptive generation.

Cluster 3 included 7 keywords and focused on how machine learning supports language processing and readability analysis. Key terms–"accuracy", "approach", "readability", "language", and "machine learning"–indicated its emphasis on computational methods. The research grouped in this cluster suggested a move away from rule-based linguistic analysis to data-driven modeling, where algorithms learn lexical, syntactic, and semantic patterns that contribute to reading comprehension. Liu and Ardakani (2022) created a machine-learning-supported affective model that adjusts reading tasks to learners' cognitive and emotional needs, promoting individualized learning. Likewise, Xia et al. (2024)

designed an interpretable eye-tracking model for assessing reading ability, linking cognitive behaviors with AI evaluation. From a pedagogical view, Lee et al. (2023) showed that AI-generated content can improve EFL learners' reading enjoyment and engagement, while North et al. (2023) advanced lexical complexity prediction models that improve readability assessment and inform curriculum design across proficiency levels.

Table 4: Co-Occurrence Analysis by Cluster

Cluster No. & Colour	Cluster Labels	No. of keywords	Representative keywords
Cluster 1 (Red)	AI-Supported English Reading Comprehension in Education	25	"artificial intelligence", "technology", "development", "reading", "skill", "tool", "English", "student", "comprehension", "education", "text", "ability"
Cluster 2 (Green)	Computational Reading Comprehension and Deep Learning Models	24	"machine reading comprehension (MRC)", "application", "deep learning", "natural language processing", "task", "performance", "experiment", "dataset", "model", "question", "problem", "field"
Cluster 3 (Blue)	Machine Learning-Based Language and Readability Analysis	7	"accuracy", "addition", "approach", "data", "language", "readability", "machine learning"

4.4 Burst Detection Analysis by keywords

To explore emerging research directions and temporal dynamics in AI-assisted English reading education, a burst detection analysis was conducted using CiteSpace. Following Kleinberg's (2002) burst detection model, this technique identified keywords exhibiting abrupt increases in frequency over specific periods, indicating heightened scholarly attention. The parameters were set as $\alpha_1/\alpha_0 = 2.0$, $\alpha_i/\alpha_{i-1} = 2.0$, number of states = 2, $\gamma = 0.8$, and a minimum duration of one year. Based on these settings, ten burst keywords were identified. Table 5 presents the keywords with the strongest citation bursts from 2021 to 2025, highlighting shifts in research priorities within AI-assisted English reading education.

From 2021 to 2022, burst keywords were primarily associated with algorithmic and computational themes, including "machine reading comprehension," "deep learning," and "question answering." These terms reflect a research focus on developing AI models capable of simulating human reading processes through large-scale data and neural architectures (Cui et al., 2022). Between 2022 and 2023, attention shifted toward linguistic and semantic dimensions, as indicated by bursts in "natural language understanding," "neural network," "English language," and "text," with studies increasingly addressing language processing and bilingual or EFL reading contexts (Liu et al., 2023). From 2024 onward, the emergence of keywords such as "education," "reading skills," and "large

language models" suggested a clear expansion toward pedagogical applications and contextualized literacy development.

Table 5: Keywords with Strongest Bursts (Source: CiteSpace)

Keywords	Year	Strength	Begin	End	2021 - 2025
question answering	2021	2.15	**2021**	2023	
deep learning	2021	2.47	**2022**	2023	
machine reading comprehension	2021	3.91	**2022**	2023	
natural language understanding	2022	1.57	**2022**	2023	
neural network	2022	1.25	**2022**	2023	
English language	2022	1.06	**2022**	2022	
text	2023	1.44	**2023**	2023	
reading skills	2024	1.38	**2024**	2025	
education	2024	1.37	**2024**	2025	
Large language models	2024	1.25	**2024**	2025	

5. Discussion

The results of this bibliometric investigation of publications on AI in English reading education from 2021 to 2025 reveal several important patterns that are consistent with and extend previous research. Performance analysis shows a steady increase in publications and citations, indicating that AI-supported language learning has become a rapidly expanding interdisciplinary field (Zawacki-Richter et al., 2019). Bibliographic coupling identifies three major intellectual streams: educational applications, technological algorithms, and cross-disciplinary applications.

In addition, keyword co-occurrence and burst detection analyses reveal a clear development trend. Early studies mainly focused on algorithmic topics such as machine reading comprehension and deep learning (Kazi et al., 2023), whereas recent research increasingly emphasizes pedagogical applications of AI in reading comprehension and learner engagement (Pan et al., 2024). This shift reflects perspectives in technology-enhanced language learning, which view AI as a pedagogical partner supporting personalized learning and learner autonomy.

5.1 Theoretical Implications

Based on the bibliometric analysis, this study examined how AI in English reading education evolved across technological, pedagogical, and ethical dimensions. It contributes to the theoretical understanding of AI integration by demonstrating the roles of technological innovation, pedagogical flexibility, and socio-affective engagement in transforming reading processes. According to TAM, technology adoption is largely shaped by perceived usefulness and ease of use. However, the present findings indicated that AI adoption in English reading education is not a single, one-time act but a continuous and adaptive process shaped by learners' perceptions, institutional environments, and ethical awareness. These findings

suggest that AI adoption should be viewed as a socio-technical evolution that unfolds across cognitive, organizational, and ethical dimensions over time.

The bibliometric coupling and co-occurrence analyses revealed that most studies still emphasize technological functionality, such as machine reading comprehension, deep learning, and LLMs (Kazi et al., 2023), rather than pedagogical mediation. This gap supports Dwivedi et al.'s (2019) view that technology acceptance should include institutional, ethical, and contextual factors, rather than centering solely on individual perception. In addition, the clusters found in this study indicated that theoretical integration between educational psychology, AI-based cognitive modeling, and reading pedagogy remains limited. Representative studies such as Lin and Chen (2024) and Xu et al. (2022) highlight the need to connect AI functionalities with learner cognition, motivation, and metacognitive regulation.

These findings imply that AI in English reading education should be regarded not merely as a set of technological tools but as a socio-affective learning support system that reshapes how learners engage with texts, collaborate with peers, and interact with digital systems. Furthermore, the appearance of "education," "health literacy," and "large language models" in the burst detection analysis mirrors a conceptual movement toward human-centered AI. This evolution articulates the significance of integrating ethical principles–such as transparency, fairness, and inclusivity–into theoretical frameworks of AI adoption, in line with UNESCO's SDG 4 vision of equitable and quality education (UNESCO, 2021).

5.2 Practical Implications

This study translates its bibliometric findings into practical strategies for integrating AI in English reading comprehension education. First, the growth of publications and the emergence of burst keywords such as "education," "reading skills," and "large language models" suggest the need for structured AI literacy programs for teachers and students. These programs can promote the responsible use of tools such as ChatGPT, Grammarly, and intelligent reading assistants (Shin & Lee, 2023). They should emphasize ethical awareness, data privacy, academic integrity, and pedagogically appropriate use of AI-supported reading tools (Boscardin et al., 2024). AI training can be organized progressively, beginning with basic awareness of AI-assisted reading and ethical use, followed by practical training in adaptive feedback and vocabulary development, and finally extending to the design of AI-supported reading tasks and assessment systems (de Winter, 2024; Lee et al., 2023; Shin et al., 2025).

Second, the bibliographic coupling results revealed three intellectual streams involving educational applications, technological algorithms, and cross-disciplinary applications in specialized reading contexts. This finding suggests that effective AI integration requires collaboration among language educators, computer scientists, cognitive psychologists, and EdTech developers. The development of AI-integrated reading environments should not focus only on technical innovation but also on pedagogical relevance, learner engagement, and ethical implementation. Cross-domain collaboration can support the design of

adaptive systems that personalize reading materials, feedback, and comprehension tasks while remaining aligned with instructional goals (Dwivedi et al., 2023; Liu & Ardakani, 2022; Wang et al., 2024). Institutions should also establish evaluation mechanisms, such as classroom observations, learner feedback, and learning analytics, to assess the long-term effectiveness and transparency of AI-supported reading initiatives (Wu et al., 2025).

Third, the keyword co-occurrence results showed that AI-supported comprehension, MRC/NLP, and machine-learning-based readability research have become central themes. These findings indicate the need to strengthen individualized learning support so that AI functions as a facilitative tool rather than a replacement for learners' cognitive engagement. AI-driven reading platforms can adjust text difficulty, feedback type, and task complexity according to learners' proficiency, motivation, and learning progress (Xia et al., 2024). Such adaptive support can enhance self-regulation, metacognitive awareness, and reading comprehension while preserving the teacher's role as a guide and facilitator. In this sense, personalized AI-supported learning should be used to scaffold comprehension, vocabulary development, inferencing, and critical reading rather than replace human instruction (Alarifi et al., 2025; Liu & Qiao, 2025; Wangdi & Shimray, 2025).

5.3 Limitations and Future Directions

Despite providing a comprehensive bibliometric overview, this study has several limitations. First, the analysis relied only on the WoS Core Collection, which may not fully represent the diversity of global scholarship, especially studies published in non-English or regional contexts. Second, the time span (2021–2025) focused on recent developments and may overlook earlier research conducted before the rise of generative AI. Third, as a quantitative bibliometric analysis, this study could not capture qualitative aspects of AI-supported English reading instruction, such as classroom practices and learners' experiences. Future research should therefore combine bibliometric methods with qualitative approaches to better understand how AI affects reading engagement and comprehension. Expanding datasets to include additional sources such as Scopus and ERIC and examining diverse linguistic and educational contexts would further enhance the understanding of AI's role in English reading education.

6. Conclusion

This bibliometric investigation examined 279 publications (2021–2025) to trace the intellectual structure and thematic progression of research on AI in English reading education. The analysis showed a shift from computational mechanisms, such as deep learning and machine reading comprehension, to pedagogical innovation and learner-centered approaches. The findings illustrated that AI increasingly functions as a socio-affective mediator. It enhances learners' motivation, engagement, and metacognitive growth rather than acting only as a technological tool. In line with UNESCO's SDG 4 (Quality Education), the study highlighted AI's potential to support inclusive, ethical, and high-quality learning through AI literacy training, ongoing evaluation, interdisciplinary collaboration, and adaptive instructional systems. These initiatives reinforced the view that AI

should complement, not replace, critical reading instruction. Future research should integrate quantitative and qualitative approaches and expand datasets across different databases and learning contexts. It should also examine the long-term effects of adaptive AI feedback on reading comprehension and learner autonomy. The findings may also provide transferable insights for educators and policymakers in diverse educational contexts where AI technologies are increasingly integrated into language learning.

Conflict of Interest
The authors declare no conflict of interest.

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