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# Understanding AI-Supported Personalised Learning in Research Writing: A Systematic Review of Technologies, Pedagogy, and Learning Outcomes

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**Abstract**
Artificial Intelligence (AI) has emerged as a transformative force in education, particularly in supporting personalised learning and research writing processes. However, existing studies remain fragmented, with limited synthesis of implementation strategies, pedagogical design, and learning outcomes. This study presents an SLR of AI-supported personalised learning in research writing. 27 studies issued between 2023 and 2026 were examined using descriptive statistics, thematic synthesis, and VOSviewer-based bibliometric analysis within the PRISMA 2020 framework. The findings indicate that generative AI and large language models (LLMs) are the dominant technologies, primarily supporting adaptive feedback, iterative writing processes, and self-regulated learning (SRL). While AI-supported learning is generally associated with improvements in writing performance, engagement, and learner autonomy, the strength of evidence varies across study designs, with limited and inconclusive findings regarding critical thinking and deeper learning outcomes. Four key themes emerged: (1) pedagogical integration of AI in writing processes, (2) AI-driven personalisation and SRL, (3) learning effectiveness and outcome variability, and (4) emerging trends related to generative AI, AI literacy, and ethical challenges. The review concludes that AI functions as a pedagogically mediated system rather than a standalone solution, with effectiveness dependent on instructional design, learner engagement, and responsible use. Future research should prioritise longitudinal designs, diverse educational contexts, and the integration of AI literacy within pedagogical frameworks.
**Keywords:** Artificial Intelligence, Personalised Learning, Research Writing, Generative AI, Self-Regulated Learning

## Introduction

The rapid advancement of artificial intelligence (AI) is reshaping educational practices worldwide, particularly in higher education where digital transformation and data-driven learning are becoming increasingly prominent. The integration of AI technologies into teaching and learning has created new opportunities for personalised learning, enabling tailored instructional support, real-time feedback, and scalable learning environments. At the same time, the growing reliance on AI raises important questions regarding its impact on learning processes, academic integrity, and the development of higher-order cognitive skills.

From a theoretical perspective, AI-supported personalised learning can be understood through the lens of self-regulated learning (SRL) theory, which emphasises learners' ability to plan, monitor, and evaluate their own learning processes (Zimmerman, 2002). AI technologies, particularly those providing adaptive feedback and interactive scaffolding, have the potential to support these processes by enabling continuous feedback and iterative improvement. However, the extent to which AI facilitates deep learning, rather than surface-level task completion, remains an important area of inquiry.

With the advancement of Generative AI (GenAI) technologies and large language models (LLMs), learners are now able to engage with intelligent systems that provide real-time feedback, adaptive scaffolding, and interactive support throughout the writing process. These developments have shifted academic writing instruction from static, teacher-centred models towards dynamic, learner-centred environments supported by real-time feedback and adaptive scaffolding.

Despite rapid advancements, existing research on AI-supported personalised learning in research writing remains fragmented across technological, pedagogical, and learning dimensions. Many studies focus on specific AI tools or isolated learning outcomes, with limited integration of how AI is implemented, how it enables personalisation, and how it influences learning processes holistically. Furthermore, recent reviews tend to adopt either narrative approaches or narrow thematic focuses, limiting the ability to draw comprehensive and evidence-based conclusions (e.g., Singh et al., 2026). In addition, a substantial proportion of existing studies are small-scale or perception-based, raising concerns about the robustness and generalisability of reported outcomes.

Recent studies suggest that AI-supported personalised learning can enhance writing performance, engagement, and self-regulated learning through adaptive feedback and iterative writing processes. However, these findings remain context-dependent and methodologically uneven.

Therefore, this study aims to systematically synthesise existing literature on AI-supported personalised learning in research writing. By integrating findings from empirical studies and review-based research, this systematic literature review seeks to provide a comprehensive understanding of implementation strategies, pedagogical design, learning outcomes, and emerging research trends. To ensure a clear and organised alignment between the study objectives and data synthesis procedure, the research questions were created using SPIDER model.

Table 1
*The SPIDER model*

| The Element | Information in the Study |
|---|---|
| **S: Sample** | Students and educators involved in research writing across various educational levels (secondary, pre-university, and tertiary education), including students, academic writers, and supervisors. |
| **PI: Phenomenon of Interest** | The use of Artificial Intelligence (AI) technologies (e.g., AI chatbots, generative AI, intelligent tutoring systems) to support personalised learning in research writing processes, including idea generation, literature review, academic writing, feedback, and revision. |
| D: Design | Experimental studies, quasi-experiments, case studies, and design-based research are examples of empirical studies using quantitative, qualitative, or mixed-method study approaches. |
| **E: Evaluation** | Learning outcomes related to research writing development, including writing quality, critical thinking, self-regulated learning, feedback effectiveness, learner engagement, and academic performance. |
| **R: Research Type** | Empirical investigations carried out in academic writing, learning, and educational settings, including specific review studies such bibliometric analyses and systematic literature reviews. |

The research questions of this systematic literature review were formulated based on the SPIDER model presented in **Table 1** to ensure a systematic, transparent, and structured alignment between the study scope, research objectives, and data synthesis process.

What are the key characteristics of studies on AI-supported personalised learning in research writing in terms of research objectives, design, sample, educational level, and methodological strengths and limitations?

How is artificial intelligence implemented to support personalised learning in research writing, particularly in terms of personalisation mechanisms, technological approaches, pedagogical design, and stages of the research writing process?

What learning outcomes are associated with AI-supported personalised learning in research writing, particularly in relation to writing quality, critical thinking, self-regulated learning, learner engagement, and academic performance?

What are the emerging research trends, themes, and gaps in AI-supported personalised learning in research writing, based on both empirical studies and prior review-based research?

This study makes three key contributions. First, it provides a comprehensive synthesis of AI-supported personalised learning in research writing across technological, pedagogical, and learning dimensions. Second, it develops a multi-layer analytical framework that explains how AI implementation, personalisation mechanisms, and pedagogical design interact to influence learning outcomes. Third, it identifies critical gaps related to higher-order learning, methodological limitations, and AI literacy, providing directions for future research.

## Literature Review

*Artificial Intelligence and Personalised Learning*

AI has become a key enabler of personalised learning by providing adaptive, data-driven support tailored to individual learner needs. Recent systematic reviews highlight that AI technologies, including machine learning, learning analytics, and generative AI, facilitate personalised learning through mechanisms such as adaptive feedback, recommendation systems, and learner modelling (Peng & Li, 2025). These technologies enable real-time monitoring of learner progress and support the development of customised learning pathways, thereby enhancing learner engagement and performance.

In particular, generative AI and large language models (LLMs) have introduced new possibilities for interactive and scalable personalised learning environments. Studies show that these tools can provide immediate feedback, generate learning content, and support iterative learning processes (Lizano-Sánchez et al., 2025). However, despite these advancements, the effectiveness of AI-driven personalisation remains dependent on pedagogical integration and learner characteristics.

*AI in Research Writing and Self-Regulated Learning*

This study is conceptually grounded in self-regulated learning (SRL) theory (Zimmerman, 2002), which emphasises the cyclical processes of planning, monitoring, and reflection. AI-supported personalised learning aligns with this framework by enabling adaptive feedback, real-time monitoring, and iterative revision processes. In addition, constructivist learning theory supports the role of AI as a facilitator of active knowledge construction rather than passive content generation. The application of AI in academic writing has gained significant attention, particularly with the emergence of generative AI tools such as ChatGPT. Existing research indicates that AI can support various stages of the writing process, including idea generation, drafting, revision, and feedback (Sydorenko et al., 2024). These tools are often associated with improvements in writing quality, efficiency, and learner confidence.

A key mechanism through which AI supports writing is self-regulated learning (SRL). AI systems can facilitate SRL by enabling learners to plan, monitor, and evaluate their writing processes through continuous feedback and interaction. For instance, AI-driven feedback systems and recommendation engines have been shown to enhance learners' ability to revise and refine their work iteratively. Nevertheless, concerns have been raised regarding over-reliance on AI and the potential reduction in critical thinking and deep learning (Chen et al., 2020; Palacios-Núñez et al., 2025). While existing studies consistently report improvements in writing performance and engagement, the evidence remains methodologically uneven. Experimental studies demonstrate measurable gains, whereas perception-based studies often overestimate effectiveness due to self-reported bias. Furthermore, inconsistencies in research design and outcome measurement limit the comparability of findings across studies.

### Limitations of Existing Reviews and Research Gap

Despite the growing body of research on AI in education, existing reviews remain fragmented and limited in scope. Several systematic reviews have examined AI-supported personalised learning broadly (Hardaker & Glenn, 2025; Peng & Li, 2025), while others focus specifically on generative AI or self-regulated learning (Ren et al., 2025). Additionally, reviews on AI in academic writing tend to concentrate on tool usage or ethical implications rather than pedagogical integration and learning processes (Li & Wu, 2025).

Existing reviews on AI-supported academic writing have largely adopted narrative approaches, focusing on challenges and emerging practices rather than systematic synthesis (e.g. Singh et al., 2026), thereby limiting the ability to draw comprehensive and evidence-based conclusions.

Importantly, there is a lack of integrative reviews that simultaneously examine AI technologies, personalisation mechanisms, pedagogical design, and learning outcomes within the context of research writing. Existing studies often treat these dimensions in isolation, resulting in a limited understanding of how AI supports personalised learning holistically.

Furthermore, current literature is dominated by higher education contexts and short-term studies, with limited attention to longitudinal outcomes, critical thinking development, and the role of AI literacy. These gaps demonstrate the necessity of a thorough and methodical synthesis that links learning, pedagogical, and technological aspects.

Taken together, these limitations indicate that existing literature lacks a comprehensive, evidence-based synthesis that integrates technological, pedagogical, and learning dimensions. As a result, current understanding of AI-supported personalised learning in research writing remains fragmented and insufficiently theorised.

Therefore, there is a need for a systematic and integrative review that synthesises AI technologies, personalisation mechanisms, pedagogical design, and learning outcomes within a unified analytical framework. Such an approach is essential to move beyond descriptive accounts of AI use and towards a deeper understanding of how and under what conditions AI can effectively support personalised learning in research writing.

**Contribution of This Study**

This study goes beyond prior reviews by developing a multi-layer analytical framework that explicitly links AI technologies, personalisation mechanisms, pedagogical design, and learning outcomes within research writing contexts. Unlike existing reviews that treat these elements separately, this study explains the interdependencies between these dimensions and how they collectively shape learning effectiveness. This enables a deeper understanding of not only whether AI is effective, but also how and under what conditions it supports personalised learning in research writing.

**Methodology**

This study employed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to guide the systematic literature review process, ensuring methodological rigour, transparency, and reproducibility (Page et al., 2021). The PRISMA approach provides a structured workflow consisting of four key stages: identification, screening, eligibility assessment, and inclusion, supported by clearly defined inclusion and exclusion criteria. The review focuses on examining the implementation of Artificial Intelligence (AI) in personalised learning for research writing, with particular emphasis on pedagogical design, AI-driven personalisation mechanisms, and learning effectiveness. To

ensure the inclusion of high-quality scholarly evidence, two major databases, Scopus and Web of Science (WoS), were selected due to their comprehensive coverage of peer-reviewed journals across education, technology, and interdisciplinary domains. The building of Boolean search strings, the use of database filtering criteria, and the recording of the selection procedure were all directed by the PRISMA protocol.
The specific search strings employed for both Scopus and Web of Science are presented in Table 2**.**

Table 2
*Search string utilised in the process of SLR*

| Database | Boolean Operator Utilised |
|---|---|
| **Scopus** | TITLE-ABS-KEY (("artificial intelligence" OR AI OR "generative AI" OR "large language model*" OR "AI chatbot*" OR "conversational AI" OR ChatGPT OR "intelligent tutoring system*" OR "AI tutor*" OR "AI research assistant*" OR "AI writing assistant*" OR "intelligent writing assistant*" OR "AI-assisted writing") AND ("personalised learning" OR "personalized learning" OR "adaptive learning" OR "individualized learning" OR "self-regulated learning" OR "learner-centered learning" OR "inquiry learning" OR "inquiry-based learning") AND ("academic writing" OR "research writing" OR "scientific writing" OR "essay writing" OR "thesis writing" OR "research skills" OR "student research" OR "independent research" OR "project-based learning")) |
| **Web of Science** | ((TS= ("artificial intelligence" OR AI OR "generative AI" OR "large language model*" OR "AI chatbot*" OR "conversational AI" OR ChatGPT OR "intelligent tutoring system*" OR "AI tutor*" OR "AI research assistant*")) AND TS= ("personalised learning" OR "personalized learning" OR "adaptive learning" OR "individualized learning" OR "self-regulated learning" OR "learner-centered learning" OR "learning analytics")) AND TS= ("academic writing" OR "research writing" OR "research skills" OR "student research" OR "inquiry learning" OR "inquiry-based learning" OR "independent research" OR "project-based learning") |

The PRISMA framework ensures transparency, replicability, and methodological rigour through systematic study selection and reporting procedures. First, it supports the formulation of clearly defined and focused research questions. Second, it ensures the application of systematic and replicable inclusion and exclusion criteria. Third, it facilitates the structured synthesis of a large body of scientific literature within a defined timeframe.
As a result, the three primary methodological steps of this systematic review were identification, screening, and eligibility evaluation, as shown in Figure 1. A systematic search was conducted across Scopus and Web of Science using predefined Boolean search strings related to artificial intelligence, personalised learning, and research writing contexts. The initial search yielded a total of 217 records, comprising 149 records from Scopus and 68 records from Web of Science.

Subsequently, records were filtered using predefined inclusion and exclusion criteria, including publication year (2023–2026), subject area relevance (Social Sciences and Computer Sciences), document type (journal articles), and language (English). Automated filtering tools available within the databases were applied, followed by manual screening to ensure accuracy and relevance.

The study selection process resulted in 27 articles that met all inclusion criteria and were deemed suitable for further analysis. The inclusion criteria were defined as follows:

The study investigates the application of AI technologies in personalised learning contexts;
The study focuses on research writing or academic learning processes, and
The study presents empirical findings, systematic reviews, or relevant analytical discussions.

Following the selection process, all included studies were analysed systematically to identify patterns in AI implementation, pedagogical approaches, personalisation mechanisms, and learning outcomes. The findings of the review are synthesised and presented in the subsequent sections, including structured tables and thematic analysis.

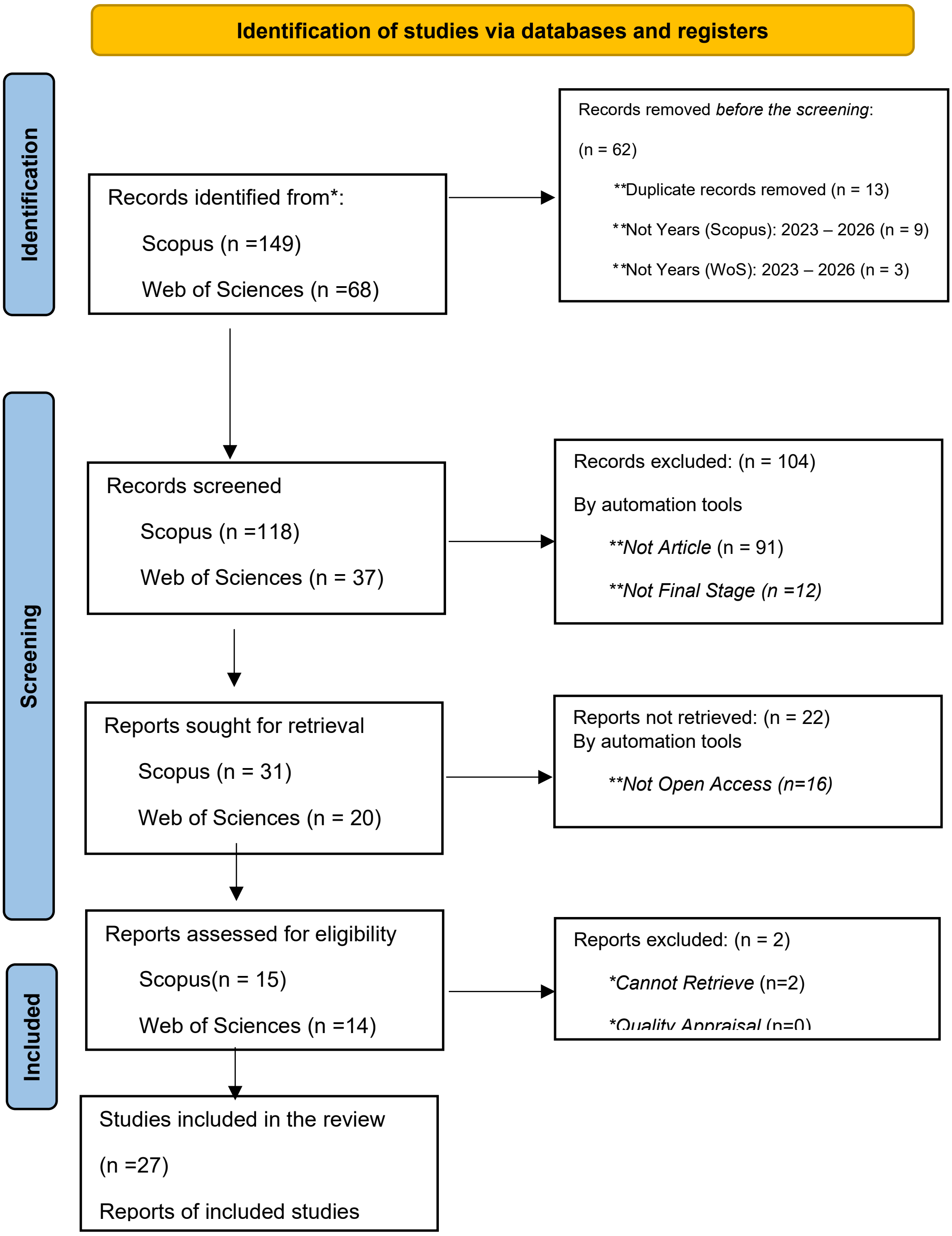

Figure 1. PRISMA 2020 flow diagram illustrating the study selection process. Adapted from Page et al. (2021). **Manual screening processes were applied. **Automation tools were used for preliminary screening and filtering.*

*Identification*
The identification phase involved a systematic search of two major databases, namely Scopus and Web of Science (WoS). A total of 217 records were initially identified, comprising 149 records from Scopus and 68 records from Web of Science, as illustrated in the PRISMA flow diagram (Figure 1). Prior to the screening stage, records were removed based on predefined exclusion criteria. A total of 62 records were excluded, including 13 duplicate records, 12 records that did not meet the publication year criteria (2023–2026), and 37 records that were not aligned with the relevant subject areas (i.e., Social Sciences and Computer Sciences). After applying these criteria, 155 records remained and were retained for the screening phase.

*Screening*
Based on their abstracts and titles, 155 records were reviewed during the screening stage. Consequently, 104 entries were eliminated, mostly because they were not written in English (n = 1), were not at the final publication stage (n = 12), or were not categorised as journal articles (n = 91). 51 reports were requested for full-text retrieval after the screening procedure. Nevertheless, 22 reports were not retrievable, primarily because of restricted access and unavailability of open access. Due to access constraints, some non-open-access studies could not be included. While this may introduce potential selection bias, efforts were made to ensure comprehensive coverage through two major databases (Scopus and WoS), which index high-quality peer-reviewed research. Consequently, 29 reports were successfully retrieved and advanced to the eligibility assessment stage.

*Included*
At the eligibility assessment stage, a total of 29 full-text articles were critically evaluated against the predefined inclusion and exclusion criteria. Following this assessment, 2 studies were excluded due to retrieval limitations. Subsequently, all remaining studies were subjected to quality appraisal. As a result, 27 studies met all inclusion and quality criteria and were included in the final systematic review. This study aimed to systematically examine the implementation of AI-supported personalised learning in research writing, with a particular focus on AI technologies, personalisation mechanisms, pedagogical design, and learning outcomes. Accordingly, the 27 included studies formed the final dataset for analysis in this systematic literature review.

*Quality Appraisal*
To ensure the inclusion of high-quality studies, a systematic quality appraisal was conducted for all selected articles. The evaluation criteria were adapted from Abouzahra et al. (2020) and comprised six key dimensions: clarity and specificity of research objectives, relevance and contribution of the study, transparency of methodological procedures, appropriateness of the conceptual framework, integration with existing literature, and the extent to which study limitations were explicitly acknowledged and discussed.

A 3-point Likert scale was used to evaluate each quality appraisal criterion; "Yes" received one point, "Partially" received half a point, and "No" received zero points. Each article may receive a maximum of six points, which represented complete adherence to all six quality standards (C1–C6). Only publications that scored higher than 3.0 (i.e., more than 50%) were deemed to be of sufficient quality and added to the systematic literature review (SLR) in accordance with the predetermined inclusion criteria.

Based on the quality appraisal results presented in Table 3, the majority of the reviewed articles demonstrated high methodological quality. Most studies (A1–A7, A10–A17, A19–A21, A24–A25, and A27) achieved scores ranging between 5.0 and 5.5, indicating that they clearly articulated their research objectives (C1), demonstrated strong relevance and applicability (C2), employed appropriate and transparent methodologies (C3), and defined key concepts effectively (C4). In several cases, these studies also provided adequate comparisons with existing literature (C5). Although many articles only partially addressed the reporting of study limitations (C6), this did not substantially affect their overall methodological quality.

A group of studies (A3, A18, A22, and A26) obtained scores of 4.5**,** reflecting good methodological quality with minor limitations**.** These studies met most of the quality criteria, particularly in terms of clarity of research objectives, methodological rigour, and conceptual alignment, but demonstrated partial weaknesses in methodological transparency (C3) or comparative discussion with prior literature (C5).

Several studies (A8, A9, and A23) recorded scores between 3.5 and 4.0, indicating moderate methodological quality**.** While these studies satisfied the minimum inclusion threshold and demonstrated clear research purposes (C1), relevance (C2), and conceptual definitions (C4), they exhibited notable limitations in comparative analysis (C5) and insufficient reporting of study limitations (C6). Despite these shortcomings, their scores exceeded the predefined threshold of 3.0, and they were therefore retained for inclusion in the systematic review.

Importantly, no articles fell below the minimum quality threshold, and all twenty-seven studies were deemed methodologically acceptable for inclusion in the final synthesis.

Overall, the quality appraisal process confirms that the selected studies provide a robust and credible evidence base**,** with the majority demonstrating strong methodological rigour. This systematic and transparent evaluation enhances the validity, reliability, and trustworthiness of the findings presented in this study.

Table 3
*Article Quality Appraisal Results*

| ID | C1 | C2 | C3 | C4 | C5 | C6 | Score |
|---|---|---|---|---|---|---|---|
| **A1** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |
| **A2** | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | **5.5** |
| **A3** | 1.0 | 1.0 | 0.5 | 1.0 | 0.5 | 0.5 | **4.5** |
| **A4** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |
| **A5** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |
| **A6** | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | **5.5** |
| **A7** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |
| **A8** | 1.0 | 1.0 | 0.5 | 1.0 | 0.0 | 0.0 | **3.5** |
| **A9** | 1.0 | 1.0 | 0.5 | 1.0 | 0.0 | 0.0 | **3.5** |
| **A10** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **A11** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |
| **A12** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |
| **A13** | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | **5.5** |
| **A14** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |
| **A15** | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | **5.5** |
| **A16** | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | **5.5** |
| **A17** | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | **5.5** |
| **A18** | 1.0 | 1.0 | 0.5 | 1.0 | 0.5 | 0.5 | **4.5** |
| **A19** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |
| **A20** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |
| **A21** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |
| **A22** | 1.0 | 1.0 | 0.5 | 1.0 | 0.5 | 0.5 | **4.5** |
| **A23** | 1.0 | 1.0 | 0.5 | 1.0 | 0.0 | 0.5 | **4.0** |
| **A24** | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | 0.5 | **5.0** |
| **A25** | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | **5.5** |
| **A26** | 1.0 | 1.0 | 0.5 | 1.0 | 0.5 | 0.5 | **4.5** |
| **A27** | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.5 | **5.5** |

A = Article, C = Criterion Question

*Data Analysis*

Data analysis was carried out in two methodical phases after the research selection procedure.

In order to summarise the salient features of the included research, a descriptive analysis was first carried out. Publication year, educational attainment, sample characteristics, research design, subject focus, and learning setting were all included. This phase made it possible to identify methodological tendencies, research trends, and distributions among papers pertaining to AI-supported personalised learning in research writing.

Second, research on the application and results of Artificial Intelligence (AI) in customised learning environments was synthesised using a thematic analysis. Each study's pertinent data was methodically processed and grouped according to recurrent ideas and trends. After that, these codes were arranged into higher-order topics, allowing for an ordered analysis of how AI technologies.

This analytical process facilitated an integrative understanding of key outcomes reported in the literature, including learning effectiveness, student engagement, self-regulated learning, feedback mechanisms, and writing performance. Additionally, it allowed for the identification of emerging patterns in AI-driven personalisation strategies and pedagogical approaches within research writing contexts.

To ensure the reliability of the coding process, two researchers independently coded all included studies based on predefined analytical categories. Inter-rater reliability was assessed using Cohen’s kappa, with a value of $\kappa = 0.82$ indicating strong agreement. Any discrepancies in coding were resolved through discussion until consensus was achieved.

Bibliometric analysis was conducted using VOSviewer to identify co-occurrence patterns and thematic clusters within the selected studies. Keywords were extracted from titles and abstracts, and a minimum occurrence threshold of 3 was applied to ensure the inclusion of relevant and frequently used terms. The analysis employed full counting and association strength normalisation to construct the network. Clustering was performed using the default VOSviewer algorithm, resulting in distinct thematic groups representing key research areas. The network visualisation was interpreted based on node size (frequency of occurrence) and link strength (co-occurrence relationships), allowing for the identification of dominant themes and their interconnections.

## Results

*Characteristics of the Studies in AI-Supported Personalised Learning for Research Writing*

The reviewed studies demonstrate a strong concentration of research on AI-supported personalised learning in research writing within higher education contexts**.** The majority of the studies were conducted among undergraduate, postgraduate, and doctoral students, with only limited representation from secondary education settings such as Lämsä et al. (2025). This indicates that AI-supported writing tools are predominantly implemented in contexts that demand advanced academic literacy, critical thinking, and research competencies**.**

In terms of research design, the included studies exhibit considerable methodological diversity. A significant proportion employed **mixed-method approaches**, combining experimental or survey data with qualitative insights, enabling a more holistic understanding of both learning outcomes and learner experiences (e.g. Ren et al., 2025; Tran et al., 2025). Quantitative methods, such as **structural equation modelling (SEM), learning analytics, and configurational analysis (fsQCA)**, were also widely utilised to examine relationships between AI use and learning effectiveness (e.g., Ngo et al., 2024; Wu & Chiu, 2025). In contrast, several studies adopted **qualitative or narrative approaches** to explore user perceptions, pedagogical practices, and ethical considerations (e.g., Lo, 2025; Palacios-Núñez et al., 2025). Additionally, a number of **conceptual and review-based studies** (Kong et al., 2024; Siva Prasad Reddy et al., 2026) contributed theoretical and framework-driven perspectives, although these lacked empirical validation.

Regarding **sample characteristics**, most empirical studies involved **student participants**, with sample sizes ranging from very small exploratory groups (e.g., 10 participants in A. Nguyen et al., 2024) to larger datasets exceeding 400 participants (e.g., Tran et al., 2025; Kaur & Kapoor, 2025). A smaller number of studies included **educators or faculty members,** offering insights into instructional practices and institutional perspectives (e.g., Nurchurifiani et al., 2025). However, the prevalence of small and context-specific samples suggests limitations in **generalisability across broader educational populations.**

The **educational context** of the studies is largely centred on **academic writing, thesis development, language learning, and research skill acquisition,** often within **English as a Foreign Language (EFL)** or discipline-specific settings such as STEM (e.g., Lizano-Sánchez et al., 2025). AI tools—particularly **generative AI and large language models (LLMs)** such as ChatGPT and writing assistants—were commonly integrated to support tasks such as **idea generation, drafting, revision, feedback provision, and self-regulated learning.**

Across the reviewed studies, several **key strengths** can be identified. These include the integration of **advanced analytical techniques** (e.g., process mining, multimodal analytics), the development of **innovative pedagogical frameworks** (e.g., the 6-P model, CoRL-based virtual teachers), and the use of **real-world classroom implementations.** These contributions highlight the growing sophistication of AI-supported personalised learning environments.

However, notable **limitations and research gaps** persist. Many studies are constrained by **small sample sizes, short intervention durations, and context-specific implementations**, limiting their external validity. Additionally, several studies rely heavily on **self-reported data**, which may introduce bias. Conceptual and review studies, while valuable, often lack **empirical validation,** and there remains a limited number of **longitudinal and large-scale studies** examining sustained learning impacts. Ethical concerns, including **over-reliance on AI, academic integrity, and unequal access**, are also recurring issues highlighted across the literature.

Overall, the findings indicate that while AI-supported personalised learning in research writing is an **emerging and rapidly evolving field**, further research is needed to strengthen empirical evidence, expand across diverse educational contexts, and address ethical and pedagogical challenges. A detailed critical analysis of the reviewed studies is presented in **Table 4**, which summarises the research objectives, methodological approaches, sample characteristics, key findings, strengths, and identified limitations.

To provide an overview of the included studies, a quantitative aggregation of study characteristics was conducted as in **Table 5**. The majority of studies employed experimental or mixed-method designs, with a strong dominance of higher education contexts. Generative AI was the most frequently investigated technology, and most studies focused on drafting and revision stages of writing. Noticeably, the total number of studies is 27. Categories such as AI technology type, writing stages, and learning outcomes are not mutually exclusive; therefore, frequencies may exceed 27. All studies were classified into a single category for research design and educational level. These patterns indicate a field that is methodologically diverse but still dominated by small-scale and context-specific studies, highlighting the need for more robust and generalisable research designs.

Table 5
*Summary of Study Characteristics (n = 27)*

| Category | Subcategory | Frequency (n) | Percentage (%) |
|---|---|---|---|
| Research Design ***(mutually exclusive)*** | Experimental | 8 | 29.6 |
| | Quasi-experimental | 5 | 18.5 |
| | Mixed-methods | 6 | 22.2 |
| | Qualitative | 4 | 14.8 |
| | Survey / Perception | 3 | 11.1 |
| | Not specified | 1 | 3.7 |
| Educational Level ***(mutually exclusive)*** | Higher Education | 20 | 74.1 |
| | Secondary Education | 4 | 14.8 |
| | Mixed / Other | 3 | 11.1 |
| AI Technology Type ***(non-mutually exclusive)*** | Generative AI (LLMs) | 16 | 59.3 |
| | Adaptive Feedback Systems | 7 | 25.9 |
| | Learning Analytics AI | 5 | 18.5 |
| | Intelligent Tutoring Systems | 5 | 18.5 |

| | | | |
|---|---|---|---|
| Writing Stage Supported ***(non-mutually exclusive)*** | Idea Generation / Planning | 13 | 48.1 |
| | Drafting | 19 | 70.4 |
| | Revision / Editing | 17 | 63.0 |
| | Full Writing Cycle | 11 | 40.7 |
| Learning Outcomes ***(non-mutually exclusive)*** | Writing Performance | 21 | 77.8 |
| | SRL Development | 16 | 59.3 |
| | Engagement | 13 | 48.1 |
| | Critical Thinking | 7 | 25.9 |

Table 4
*Critical Analysis of the Studies*

| **Author (Year)** | **Scope of Research** | **Research Design** | **Samples (Education Level)** | **Findings** | **Strengths** | **Limitations (Gaps)** |
|---|---|---|---|---|---|---|
| **Ren et al. (2025)** | AI scaffolding using LLM-generated error correction for L2 writing | Mixed-method (experiment + interviews) | 44 UG students (higher education) | AI scaffolding significantly improves writing; proficiency moderates the effect. | Strong intervention design; personalised AI scaffolding | Small sample; short duration; limited generalisability |
| **Kong et al. (2024)** | 6-P pedagogy integrating GenAI for self-regulated academic writing | Conceptual / pedagogical design | Not applicable (framework study) | Structured AI integration enhances SRL and critical thinking. | Clear pedagogical model; practical framework | No empirical validation |
| **Nguyen et al. (2024)** | Human-AI collaboration patterns in academic writing | Learning analytics (quantitative + sequence analysis) | 10 doctoral students (higher education) | Iterative AI interaction improves writing performance. | Advanced analytics (HMM, process mining) | Very small sample; niche population |
| **Wu & Chiu (2025)** | GenAI + learner characteristics in enhancing SRL | fsQCA (mixed-method configurational analysis) | Undergraduate & postgraduate students (higher education) | SRL improves through the interaction of AI affordances + learner traits. | Strong methodological approach (fsQCA) | Complex interpretation; lacks causal clarity |
| **Chen et al. (2025)** | Help-seeking behaviour: AI vs. human expert | Experimental (multimodal analytics) | 38 university students (higher education) | AI leads to nonlinear help-seeking; risk of over-reliance | Innovative multimodal data (eye-tracking, logs) | Lab-based setting; limited ecological validity |
| **Tran et al. (2025)** | Self-determination in using MT/GenAI for | Mixed-method (survey + interviews) | 416 students + 17 interviews (higher education) | Motivation influences AI use; contextual differences exist | Large dataset; strong theoretical grounding (SDT) | Self-reported bias; contextual limitations |

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| | academic writing | | | | | |
| **Kaur & Kapoor (2025)** | Students' perceived benefits of ChatGPT | Quantitative (EFA + CFA) | 515 university students (higher education) | Identifies 6 benefit categories (learning, efficiency, writing, etc.) | Large sample; strong statistical validation | Perception-based; no performance outcomes |
| **Perifanou & Economides (2025)** | GenAI in collaborative project-based learning | Mixed-method (project + survey + focus group) | 30 postgraduate students (higher education) | Enhances collaboration but risks dependency & inaccuracies | Real classroom implementation | Small sample; limited scalability |
| **Çela (2025)** | Digital tools (incl. AI) in academic writing | Systematic literature review | Literature studies (tertiary focus) | Improves engagement & revision; depends on integration | Comprehensive synthesis | Lacks empirical validation |
| **Ngo et al. (2024)** | ChatGPT usage: satisfaction & continuance intention (ECM model) | Quantitative (SEM) | 435 university students (higher education) | Satisfaction & usefulness drive continued use | Strong theoretical model (ECM) | Does not measure learning outcomes |
| **Jantassova et al. (2026)** | AI-enhanced STEM language learning framework | Experimental (pedagogical intervention) | Technical university students (higher education) | Improves scientific communication & language skills | Integrated STEM + AI approach | Context-specific; limited transferability |
| **Bevilacqua & Dell'erba (2024)** | Educational tech in assessment-as-learning | Qualitative | 206 pre-service teachers | Enhances metacognition & reflective skills | Large qualitative dataset | Not AI-focused explicitly |
| **Mizumoto & Teng (2025)** | Accuracy of LLMs in classifying learner responses | Quantitative comparison | 143 students (higher education) | LLMs show moderate accuracy; need human oversight | Strong methodological rigour | Limited reliability of AI |
| **Lo (2025)** | Grammarly in ESL academic writing | Qualitative (interviews + focus groups) | 30 students + 5 instructors (higher education) | Improves writing, motivation, SRL | Rich qualitative insights | Limited depth of feedback from AI |
| **Lizano-Sánchez et al. (2025)** | AI assistant in remote chemistry lab | Mixed-method | chemistry students (higher education) | AI supports procedural, conceptual, and writing tasks | Domain-specific (STEM lab) evidence | Context-specific; limited generalisation |

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| **Reddy et al. (2026)** | Review ChatGPT applications, benefits, constraints, ethics in education | Systematic literature review | 65 studies; mixed levels, mainly higher education | ChatGPT supports writing, literacy, efficiency; raises ethical concerns | Broad synthesis; comparative discussion across AI tools | Limited longitudinal evidence; higher-education dominant |
| **Yang et al. (2025)** | Examine CoRL-guided AI virtual teacher for English writing | Quasi-experimental with teacher interview | 61 undergraduates; higher education | CoRL-VT improved writing, organization, lexical development | Strong theoretical grounding; pre-post assessment | Small sample; exploratory evidence only |
| **Butarbutar & González Vallejo (2025)** | Explore factors influencing AI-assisted thesis writing adoption | Narrative inquiry | 10 university students; higher education | AI supports thesis stages but raises ethics, dependency concerns | Clear PPM framework; rich process insights | Very small sample; single-university context |
| **Singh et al. (2026)** | Review AI-supported academic writing assessment challenges, practices, strategies | Narrative review | Literature; higher education focus | Process-based assessment and AI literacy are essential | Strong integrative synthesis; policy relevance | No empirical testing; not systematic review |
| **Bansal et al. (2025)** | Explore AI-driven pedagogical advancement in DSIP education | Survey-based pedagogical analysis | Engineering students; higher education | AI supports engagement, conceptual understanding, problem-solving | Practical engineering pedagogy focus | Weak writing-specific relevance; limited validation |
| **Nguyen & Doan (2025)** | Compare ChatGPT vs teacher-facilitated PBL autonomy effects | Explanatory sequential mixed-methods | 50 EFL learners; language centre / likely pre-tertiary-adult bridging | ChatGPT improved autonomy; self-efficacy gains were similar | Comparative design; mixed evidence | Context-specific; not explicit academic writing focus |
| **Wen et al. (2025)** | Investigate learner differences in BIM knowledge construction | Qualitative interview study | 10 undergraduate/postgraduate students; higher education | Personalised, collaborative strategies improve knowledge construction | Focus on learner diversity | Not AI-implemented directly; very small sample |
| **Lamsa et al. (2025)** | Measure secondary students' | Quantitative modelling | 179 secondary students; secondary education | AI trace data identifies | Rare secondary-level | Not directly AI writing |

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| | SRL processes with AI trace data | / learning analytics | | SRL patterns for personalised support | evidence; advanced analytics | intervention |
| **Palacios-Núñez et al. (2025)** | Explore teachers' uses and beliefs about ChatGPT in writing | Qualitative interviews | 10 writing teachers; higher education | ChatGPT mostly used in revision; ethical tensions persist | Valuable teacher perspective | Small sample; unreflective use reported |
| **Nurchurifiani et al. (2025)** | Examine faculty use of AI tools in writing and research | Mixed-methods | 16 English faculty; higher education | AI improves efficiency in planning, reviewing, publishing | Faculty-centred perspective | Small sample; indirect student-learning evidence |
| **Sydorenko et al. (2024)** | Analyse digital divide in higher education transformation | Conceptual / policy analysis | Not applicable; higher education system | Digital divide constrains equitable digital transformation | Strong systemic perspective | Not academic-writing specific; limited AI depth |
| **Ou et al. (2024)** | Conceptualise and cultivate critical GAI literacy in doctoral writing | Conceptual + pedagogical intervention | 60 PhD students; doctoral / higher education | Students developed ethical awareness, prompting, critical evaluation | Strong theoretical integration; writing-specific | Limited scalability; doctoral context only |

*Implementation of AI-Supported Personalised Learning in Research Writing*

This section synthesises AI implementation through a multi-layered analytical framework encompassing AI technology types, personalisation mechanisms, pedagogical design, and writing stages (Table 6 and Figure 2). Moving beyond descriptive categorisation, the analysis organises AI implementation into four functional categories: (1) generative AI, (2) adaptive feedback systems, (3) learning analytics-based AI, and (4) intelligent tutoring systems (ITS). This classification is consistent with emerging systematic reviews that conceptualise AI in education as a layered ecosystem linking technological affordances with pedagogical functions and learning outcomes (Farhood et al., 2025; Peng & Li, 2025; Banihashem et al., 2025).

The findings indicate that generative AI tools and large language models (LLMs)—such as ChatGPT—represent the most dominant category across the reviewed studies. These tools primarily support idea generation, drafting, and content structuring through prompt-based interactions and iterative human–AI collaboration (Kong et al., 2024; A. Nguyen et al., 2024). In contrast, adaptive feedback systems, including AI writing assistants and LLM-based correction tools, are predominantly used in revision and editing stages, providing real-time, personalised feedback that enables iterative improvement of writing quality (Lo, 2025; Ren et al., 2025). This distinction reflects broader findings in the literature that different AI types serve functionally differentiated roles within the learning process (Naznin et al., 2025; Farhood et al., 2025).

A second layer of analysis highlights the role of AI-driven personalisation mechanisms, which act as the core mediating factor between technology and learning outcomes. Across the studies, key mechanisms include adaptive feedback, prompt scaffolding, learner modelling, recommendation systems, and learning analytics–based monitoring. Learning analytics tools, for example, enable the tracking and prediction of learner behaviours to support self-regulated learning (SRL) processes (Lämsä et al., 2025; Wu & Chiu, 2025), while ITS provide context-aware scaffolding and guided instruction across the writing cycle (A. Chen et al., 2025; Yang et al., 2025) These findings align with prior research emphasising that personalisation, rather than AI tools alone, is the critical driver of effective learning (Lan & Zhou, 2025; Chang et al., 2023).

The pedagogical design supporting the integration of AI is predominantly focused on approaches that emphasise student engagement and process-oriented learning. This includes methodologies such as self-regulated learning (SRL), guided writing, inquiry-based learning, project-based learning, and collaborative learning. Within this framework, AI functions as a pedagogical mediator, supporting learners in planning, monitoring, and revising their writing. For instance, SRL-based designs leverage AI for goal setting and feedback regulation, while collaborative and project-based approaches integrate AI as a tool for co-construction of knowledge and sustained writing development (Q. N. Nguyen & Doan, 2025; Perifanou & Economides, 2025). This reinforces the growing consensus that the effectiveness of AI is contingent upon its alignment with pedagogical strategies, rather than its standalone use (Peng & Li, 2025; Banihashem et al., 2025).

With regard to the stages of the research writing process, the analysis reveals a differentiated pattern of AI support. Generative AI is most frequently applied in early-stage writing activities, such as idea generation and structuring, whereas adaptive feedback systems dominate drafting and revision stages. Learning analytics tools and ITS extend support across the full writing cycle, including monitoring and reflection. However, relatively few studies address advanced stages such as literature synthesis, critical argumentation, and knowledge construction, indicating a gap in supporting higher-order academic writing skills. Similar gaps have been identified in recent systematic reviews, which note that AI applications tend to prioritise efficiency and surface-level improvements over deep cognitive engagement (Muñoz et al., 2025; Zhang et al., 2025).

Several key implementation insights emerge from this framework-based synthesis. First, AI implementation in research writing is functionally differentiated, with distinct AI types supporting specific writing stages and learning processes. Second, personalisation mechanisms serve as the central linkage between AI technologies, pedagogical design, and learning outcomes. Third, while AI enhances writing efficiency, feedback accessibility, and learner engagement, its effectiveness is strongly influenced by learner characteristics, including motivation, prior knowledge, and self-regulation capabilities. These findings are consistent with meta-analytic evidence demonstrating that AI-supported learning outcomes are context-dependent and mediated by learner engagement (Xu et al., 2026; Lan & Zhou, 2025).

Nevertheless, several challenges persist. Across the reviewed studies, concerns related to academic integrity, ethical use, and over-reliance on AI are consistently reported. In particular, excessive dependence on generative AI may lead to reduced critical thinking and shallow engagement, especially in the absence of structured pedagogical guidance (A. Chen et al., 2025; Palacios-Núñez et al., 2025). Additionally, many implementations remain short-term and context-specific, limiting the generalisability of findings. These issues highlight the need for more longitudinal, theory-driven, and pedagogically grounded research to ensure that AI supports not only writing performance but also deeper learning processes.

To further synthesise the relationships identified in Table 6, Figure 2 presents a conceptual framework illustrating how AI technologies support personalised learning in research writing. The framework demonstrates the interaction between AI types, personalisation mechanisms, pedagogical design, and learning outcomes, highlighting the role of personalisation as a mediating layer linking technology and learning processes. This framework serves as a unifying structure that integrates the findings across RQ2 and RQ3, illustrating how implementation design influences learning outcomes.

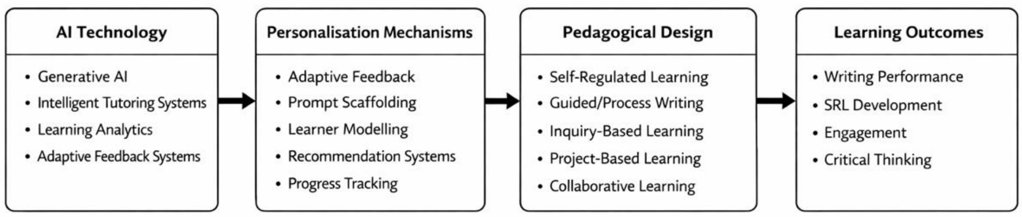


Figure 2. Conceptual framework of AI-supported personalised learning in research writing.

Table 6
*Implementation Characteristics of AI-Supported Personalised Learning in Research Writing*

| Author (Year) | AI Type | Personalisation Mechanism | Pedagogical Design | Writing Stage | Outcome Insight |
|---|---|---|---|---|---|
| **Ren et al. (2025)** | Adaptive Feedback System (LLM correction) | Adaptive feedback (error correction) | Guided writing; SRL | Drafting; Revision | Improves accuracy via iterative feedback loops |
| **Kong et al. (2024)** | Generative AI (LLM prompting) | Prompt scaffolding | SRL-based learning | Idea generation; Structuring | Enhances structured thinking & planning |
| **Nguyen et al. (2024)** | Generative AI (LLM interaction) | Iterative human–AI interaction | Process-based writing | Drafting; Revision | Continuous refinement improves performance |
| **Wu & Chiu (2025)** | Learning Analytics AI | Learner modelling; adaptive pathways | Personalised SRL pedagogy | Full writing cycle | Aligns feedback with learner traits |
| **Chen et al. (2025)** | Intelligent Tutoring System (AI chatbot) | Help-seeking support | Self-directed learning | Drafting; Feedback | Enhances autonomy but risks shallow learning |

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|---|---|---|---|---|---|
| **Tran et al. (2025)** | Adaptive AI System | Motivation-based personalisation | Motivation-based learning | Drafting; Revision | Effectiveness depends on learner motivation |
| **Kaur & Kapoor (2025)** | Generative AI (ChatGPT) | Content generation support | Independent learning | Idea generation; Drafting | Increases engagement and efficiency |
| **Perifanou & Economides (2025)** | Generative AI (collaborative tools) | Collaborative scaffolding | Collaborative learning | Drafting; Revision | Enhances peer interaction; risk of dependency |
| **Çela (2025)** | Adaptive Feedback System | Automated feedback | Guided writing | Revision | Improves revision efficiency |
| **Ngo et al. (2024)** | Generative AI (ChatGPT) | On-demand assistance | Informal learning | Idea generation | Drives engagement and usability |
| **Jantassova et al. (2026)** | Intelligent Tutoring System | Adaptive learning pathways | STEM-integrated pedagogy | Full writing cycle | Improves structured learning & performance |
| **Bevilacqua & Dell'erba (2024)** | Learning Analytics AI | Reflective feedback | Reflective learning | Revision; Reflection | Enhances metacognitive awareness |
| **Mizumoto & Teng (2025)** | Adaptive AI Classification Tool | Automated evaluation | Analytical learning | Literature review | Limited reliability affects outcomes |
| **Lo (2025)** | Adaptive Feedback System (Grammarly) | Real-time corrective feedback | Guided writing | Drafting; Revision | Improves grammar and writing quality |
| **Lizano-Sánchez et al. (2025)** | Intelligent Tutoring System | Context-aware assistance | Inquiry-based learning | Reporting; Writing | Supports domain-specific writing tasks |
| **Reddy et al. (2026)** | Generative AI | Generalised assistance | Independent learning | Drafting; Revision | Improves efficiency; raises ethical concerns |
| **Yang et al. (2025)** | Intelligent Tutoring System (AI tutor) | Real-time scaffolding | Tutoring-based learning | Drafting | Improves writing performance |
| **Butarbutar & Vallejo (2025)** | Generative AI | Process support across stages | Project-based learning | Full writing cycle | Supports long-term writing development |
| **Singh et al. (2026)** | Adaptive Assessment AI | Feedback + evaluation system | Inquiry-based learning | Drafting; Evaluation | Enhances analytical and evaluative skills |
| **Bansal et al. (2025)** | Intelligent Tutoring / Applied AI | Contextual support | Active learning | Reporting; Writing | Improves applied understanding |
| **Nguyen & Doan (2025)** | Generative AI (ChatGPT) | Autonomy support | Project-based learning | Full writing cycle | Promotes autonomy and engagement |
| **Wen et al. (2025)** | Learning Analytics AI | Differentiated learning pathways | Differentiated learning | Drafting; Revision | Effect varies by learner differences |

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|---|---|---|---|---|---|
| **Lamsa et al. (2025)** | Learning Analytics AI | SRL monitoring & prediction | SRL-based learning | Monitoring; Reflection | Supports personalised intervention |
| **Palacios-Núñez et al. (2025)** | Generative AI (ChatGPT) | Revision assistance | Guided writing | Revision | Improves surface writing; limits depth |
| **Nurchurifiani et al. (2025)** | Generative AI | Workflow support | Process-based learning | Full writing cycle | Enhances organisation and efficiency |
| **Sydorenko et al. (2024)** | System-level AI | Infrastructure-level personalisation | Institutional implementation | Not specified | Focus on system-level transformation |
| **Ou et al. (2024)** | Generative AI + Literacy Tools | Critical AI literacy scaffolding | Critical literacy pedagogy | Drafting; Reflection | Develops critical evaluation skills |

*Outcomes of AI-Supported Personalised Learning in Research Writing*

The outcomes of AI-supported personalised learning in research writing vary across studies depending on research design, methodological rigour, and measurement approaches. To provide a more nuanced interpretation, the evidence is categorised into experimental, mixed-method, perception-based, and conceptual studies, representing different levels of evidential strength. Importantly, these categories do not contribute equally to conclusions regarding effectiveness, with experimental studies providing stronger causal evidence and perception-based studies offering more limited support.

Strong empirical evidence from experimental and quasi-experimental studies indicates that AI-supported interventions can improve writing performance and specific aspects of self-regulated learning. For example, Ren et al. (2025) and Yang et al. (2025) reported measurable improvements in writing accuracy and organisation following AI-supported feedback and tutoring interventions. Similarly, Chen et al. (2025) demonstrated that AI-assisted help-seeking influences learning behaviours, although with potential risks of over-reliance.

In contrast, mixed-method and learning analytics studies provide moderate evidence, highlighting patterns of improved engagement, SRL processes, and writing development. These findings are consistent with prior research highlighting the role of AI in supporting self-regulated learning processes (Lämsä et al., 2025; Wen et al., 2025; Wu & Chiu, 2025). However, these findings are largely correlational and context-dependent.

A substantial proportion of studies rely on perception-based data, reporting positive student attitudes, increased engagement, and perceived improvements in writing (Kaur & Kapoor, 2025; Ngo et al., 2024; Tran et al., 2025). While these findings suggest high acceptance of AI tools, they do not necessarily reflect actual learning gains.

Additionally, conceptual and review-based studies propose theoretical benefits of AI-supported learning but lack empirical validation (Kong et al., 2024; Siva Prasad Reddy et al., 2026). Therefore, claims regarding the effectiveness of AI should be interpreted with caution, as the overall evidence base remains methodologically heterogeneous. Building on this evidence structure, the following analysis synthesises the key learning outcomes identified across the reviewed studies.

Across these categories, a clear hierarchy of evidence emerges. Experimental and quasi-experimental studies provide the most robust support for improvements in writing performance and self-regulated learning (e.g., Jantassova et al., 2026; Ren et al., 2025; Yang et al., 2025). However, perception-based studies primarily reflect user satisfaction rather than measurable learning gains. Mixed-method studies occupy an intermediate position, offering contextual insights but limited causal inference.

Synthesising across evidence types, the findings indicate that AI-supported personalised learning is generally associated with improvements in writing performance, particularly in structured and experimentally validated contexts. Many studies reported improvements in **writing accuracy, organisation, clarity, and overall quality**, particularly through the use of adaptive feedback and iterative AI-supported revision processes (e.g., Lo, 2025; A. Nguyen et al., 2024; Ren et al., 2025).

A second dominant outcome domain is **self-regulated learning (SRL).** Several studies highlight that AI tools enhance learners' ability to **plan, monitor, and evaluate their own writing processes**, contributing to greater autonomy and independent learning (e.g., Wu & Chiu, 2025; Lamsa et al., 2025; Butarbutar & Vallejo, 2025). This is particularly evident in AI systems that provide personalised feedback, progress tracking, and adaptive learning pathways. However, the effectiveness of SRL development is often influenced by **learner characteristics**, including motivation and prior knowledge. This suggests that SRL outcomes are mediated not only by AI functionality but also by pedagogical design and learner characteristics.

In addition, **student engagement** emerges as a key outcome across the majority of studies. AI-supported tools increase engagement by providing **immediate feedback, interactive learning experiences, and ease of use** (e.g., Kaur & Kapoor, 2025; Ngo et al., 2024). However, increased engagement does not necessarily translate into deeper learning, as some learners may rely excessively on AI-generated outputs without sufficient critical evaluation (e.g., Chen et al., 2025; Palacios-Núñez et al., 2025). Notably, evidence for engagement is predominantly derived from perception-based studies, indicating that this outcome may be over-represented relative to more rigorously measured learning gains.

The impact of AI on critical thinking remains inconclusive, with limited and methodologically weaker evidence compared to other outcome domains. While some studies report improvements in **analytical and reflective skills**, particularly when AI is integrated within structured pedagogical designs (e.g. Bevilacqua & Dell'erba, 2024; Ou et al., 2024) others indicate potential limitations. In particular, the use of AI for automated feedback or content generation may reduce opportunities for **deep cognitive processing and critical evaluation**, especially when learners adopt a passive approach.

Despite these positive outcomes, several **limitations and concerns** are consistently identified across the literature. These include issues related to **over-reliance on AI, reduced depth of learning, ethical considerations, and variability in AI reliability** (e.g. Mizumoto & Teng, 2025; Siva Prasad Reddy et al., 2026) Additionally, some studies provide only **perception-based evidence** without directly measuring learning outcomes, highlighting the need for more **robust empirical and longitudinal research**.

Overall, synthesising across evidence types, AI-supported personalised learning confirms that the strongest empirical evidence supports improvements in writing performance and aspects of self-regulated learning, particularly when implemented within structured pedagogical designs. However, evidence for engagement is largely perception-based, and the impact on critical thinking remains limited and inconclusive. These findings, as summarised in Table 7, indicate that the effectiveness of AI is not uniform but conditional upon the strength of evidence, implementation design, and learner engagement, reinforcing the need for cautious interpretation and more rigorous future research.

Table 7
*Outcomes of AI-Supported Personalised Learning: Outcome Domains and Learning Effectiveness*

| Author (Year) | AI PL Implementation | Outcome Domain | Learning Effectiveness |
|---|---|---|---|
| **Ren et al. (2025)** | Adaptive LLM feedback | Writing; SRL; Engagement | Improved writing accuracy, SRL autonomy, and engagement through adaptive feedback |
| **Kong et al. (2024)** | Prompt-based AI scaffolding | Writing; SRL; Critical Thinking | Enhanced SRL, structured thinking, and improved writing organisation |
| **Nguyen et al. (2024)** | Iterative human-AI writing | Writing; Engagement; Performance | Improved writing quality and performance through iterative refinement cycles |
| **Wu & Chiu (2025)** | AI adaptive SRL system | Writing; SRL; Engagement | Increased SRL, engagement, and personalised writing development |
| **Chen et al. (2025)** | AI help-seeking chatbot | SRL; Engagement; Critical Thinking | Improved engagement and SRL but reduced depth of critical evaluation |
| **Tran et al. (2025)** | Motivation-based AI support | Writing; Engagement; SRL | Enhanced motivation and engagement, with mixed impact on writing depth |
| **Kaur & Kapoor (2025)** | ChatGPT-assisted writing | Writing; Engagement | Improved perceived writing quality and engagement |
| **Perifanou & Economides (2025)** | Collaborative GenAI learning | Writing; SRL; Engagement | Improved collaboration, engagement, and shared knowledge construction |
| **Çela (2025)** | AI feedback tools | Writing; Engagement | Improved writing refinement and revision effectiveness |
| **Ngo et al. (2024)** | ChatGPT learning support | Engagement; Performance | Increased engagement and continued usage, with perception-based effectiveness |
| **Jantassova et al. (2026)** | Adaptive AI learning platform | Writing; SRL; Performance | Improved academic performance, SRL, and conceptual understanding |
| **Bevilacqua & Dell'erba (2024)** | Reflective AI learning tools | SRL; Critical Thinking | Enhanced metacognitive awareness and critical reflection skills |
| **Mizumoto & Teng (2025)** | LLM classification tool | Critical Thinking; SRL | Limited reliability reduced effectiveness in analytical accuracy |
| **Lo (2025)** | AI writing assistant | Writing; SRL; Engagement | Significant improvement in writing quality and learner autonomy |
| **Lizano-Sánchez et al. (2025)** | AI lab assistant | Writing; SRL; Performance | Improved writing clarity, performance, and structured learning |
| **Reddy et al. (2026)** | General AI tools | Writing; SRL; Engagement | Improved writing and engagement but raised ethical concerns |
| **Yang et al. (2025)** | AI virtual tutor | Writing; Performance | Enhanced writing performance and task completion efficiency |

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| **Butarbutar & Vallejo (2025)** | AI thesis support | Writing; SRL; Engagement | Improved thesis writing quality and independent learning |
| **Singh et al. (2026)** | AI assessment system | SRL; Critical Thinking | Enhanced process-based learning and analytical thinking skills |
| **Bansal et al. (2025)** | AI-supported STEM learning | Engagement; Performance | Improved engagement, understanding, and academic performance |
| **Nguyen & Doan (2025)** | ChatGPT in PBL | SRL; Engagement; Performance | Increased autonomy, engagement, and learning performance |
| **Wen et al. (2025)** | Adaptive AI tools | Critical Thinking; SRL | Mixed effectiveness depending on learner differences |
| **Lamsa et al. (2025)** | AI learning analytics | SRL | Improved monitoring, prediction, and self-regulated learning behaviours |
| **Palacios-Núñez et al. (2025)** | ChatGPT writing support | Writing; Engagement | Improved writing revision but limited depth of understanding |
| **Nurchurifiani et al. (2025)** | AI research writing tools | Writing; Engagement; Performance | Enhanced writing workflow, engagement, and performance outcomes |
| **Sydorenko et al. (2024)** | System-level AI integration | — | Limited direct evidence on learning effectiveness |
| **Ou et al. (2024)** | AI literacy pedagogy | Writing; SRL; Critical Thinking | Improved critical AI literacy, writing skills, and self-regulation |

*Conceptual Network Analysis on AI-Supported Personalised Learning in Research Writing*

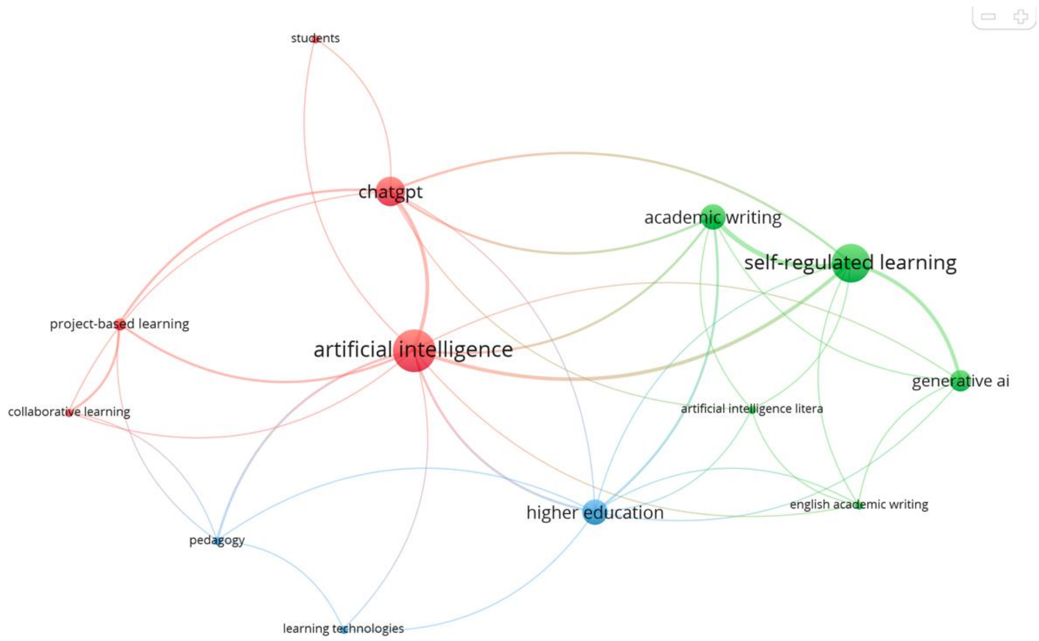


Figure 3. Keyword co-occurrence network of authors' keywords in studies on artificial intelligence (AI)–supported personalised learning in research writing.

The conceptual framework of research on artificial intelligence (AI), self-regulated learning, academic writing, and pedagogical techniques in higher education is depicted in the keyword co-occurrence network shown in Figure 3. The visualisation identifies major research themes, conceptual connections, and new paths in AI-supported customised learning for research writing by assessing the frequency and co-occurrence of terms.

The first cluster (red) centres on “artificial intelligence” as the most prominent and highly connected node, indicating its central role in the research landscape. This cluster is strongly associated with keywords such as "ChatGPT", "students", “project-based learning,” and “collaborative learning". The concentration of these terms suggests that a substantial body of literature focuses on the integration of AI tools—particularly generative AI systems like ChatGPT—within student-centred and active learning environments. The presence of project-based and collaborative learning indicates that AI is frequently positioned as a facilitator of interactive, inquiry-based, and socially mediated learning processes. Overall, this cluster reflects a pedagogical orientation in which AI is used to enhance engagement, participation, and learner autonomy within authentic learning contexts.

The second cluster (green) is anchored by “self-regulated learning”, which is closely connected to “academic writing", “generative AI", “English academic writing", and “artificial intelligence literacy". This cluster highlights the growing emphasis on learning processes and cognitive development, particularly in the context of research writing. The strong linkage between self-regulated learning and academic writing suggests that AI is increasingly utilised to support learners in managing their own writing processes, including planning, monitoring, and revising. The inclusion of generative AI and AI literacy further indicates that recent studies are not only focusing on writing performance but also on developing learners’ critical awareness and responsible use of AI tools. This cluster therefore reflects a shift towards metacognitive and process-orientated perspectives, where AI supports both skill development and learner independence.

The third cluster (blue) is associated with educational contexts and technological systems, with “higher education” serving as the central node. It is linked to keywords such as “pedagogy” and “learning technologies". The strong connections between these terms indicate that research in this cluster emphasises the institutional and systemic integration of AI within higher education environments. This includes the adoption of AI tools within broader teaching strategies, curriculum design, and digital learning infrastructures. The positioning of higher education as a bridging node suggests that most empirical studies are situated within tertiary-level settings, where academic writing and AI-supported learning are most intensively explored.

An important observation from this conceptual map is the presence of cross-cluster linkages, particularly through the nodes “artificial intelligence", “academic writing", and “higher education". These nodes function as bridging concepts that connect pedagogical applications (red cluster), learning processes (green cluster), and educational contexts (blue cluster). This interconnected structure highlights that AI in research writing is not studied in isolation but rather as part of a multi-dimensional ecosystem that integrates technological tools, pedagogical strategies, and learner-centred processes.

These clusters align with the study’s analytical framework, particularly highlighting the intersection between AI implementation (RQ2), self-regulated learning processes, and learning outcomes (RQ3), thereby reinforcing the interconnected nature of technology, pedagogy, and learning in AI-supported writing. Together, these clusters reflect a shift from technology-focused research towards integrated models that combine AI implementation, pedagogical design, and learner-centred processes.

A temporal analysis of the included studies indicates a clear evolution of research focus over time. Early studies (2023–2024) primarily concentrated on the adoption of AI tools and their general impact on writing performance. From 2024 onwards, there is a noticeable shift towards the integration of self-regulated learning (SRL) frameworks and pedagogical design. More recent studies (2025–2026) increasingly emphasise generative AI, AI literacy, and ethical considerations, reflecting a transition from tool-centric to learner- and pedagogy-centred research. This trend suggests a maturation of the field, with growing attention to deeper learning processes and responsible AI use.

In summary, the VOSviewer network analysis demonstrates that research on AI-supported personalised learning in research writing is multi-layered and evolving. Earlier and dominant studies focus on the integration of AI within pedagogical practices and student engagement, while more recent work emphasises self-regulated learning, generative AI, and AI literacy. These findings indicate that future research should adopt a more integrated and holistic perspective, combining pedagogical design, cognitive development, and responsible AI use to fully realise the potential of AI in supporting personalised research writing.

## Discussion

### *AI as a Pedagogically Mediated System in Research Writing*

This review conceptualises AI-supported personalised learning in research writing as a pedagogically mediated system in which learning outcomes emerge from the interaction between AI capabilities, instructional design, and learner engagement. As synthesised in Table 7, AI implementation operates across interconnected layers, which are AI type, personalisation mechanism, pedagogical design, and writing stage, collectively shaping how learning is supported.

Empirical evidence from the reviewed studies reinforces this interpretation. For instance, structured pedagogical integration of generative AI within self-regulated learning (SRL) frameworks has been shown to enhance writing organisation and planning (Kong et al., 2024), while guided writing supported by adaptive AI feedback significantly improves writing accuracy and performance (Lo, 2025; Ren et al., 2025). Similarly, project-based and collaborative learning designs incorporating AI tools facilitate knowledge co-construction and sustained writing development (Q. N. Nguyen & Doan, 2025; Perifanou & Economides, 2025). These findings indicate that AI functions as a pedagogical amplifier, rather than an autonomous instructional agent.

Furthermore, the analysis reveals a functional differentiation of AI roles across the writing process. Generative AI is predominantly used in early stages such as idea generation and structuring (Kaur & Kapoor, 2025; Ngo et al., 2024), whereas adaptive feedback systems are more closely associated with drafting and revision (Çela, 2025; Ren et al., 2025). Learning analytics tools and intelligent tutoring systems extend support across the full writing cycle, particularly in monitoring and reflection (Wu & Chiu, 2025; Lamsa et al., 2025). This stage-specific alignment suggests that AI contributes to learning through targeted pedagogical affordances, rather than uniform effects.

*Personalisation Mechanisms as the Core Driver of Learning Outcomes*
A central contribution of this review is the identification of personalisation mechanisms as the primary drivers of learning outcomes. Across the reviewed studies, mechanisms such as adaptive feedback, prompt scaffolding, learner modelling, and progress monitoring consistently underpin effective learning.

For example, adaptive feedback systems enable iterative refinement of writing, leading to measurable improvements in writing quality (Lo, 2025; Ren et al., 2025), while prompt-based scaffolding supports idea generation and structured thinking (Kong et al., 2024). Learning analytics approaches further enhance personalisation by aligning feedback with learner characteristics and behavioural patterns (Lämsä et al., 2025; Wu & Chiu, 2025) Intelligent tutoring systems extend this support through context-aware scaffolding and guided instruction (A. Chen et al., 2025; Yang et al., 2025).

These findings align with SRL theory, where learning is conceptualised as a cyclical process of planning, monitoring, and reflection. Empirical studies in this review demonstrate that AI tools can support each of these phases—for instance, enabling learners to plan writing tasks through AI-generated prompts, monitor progress via feedback systems, and reflect through revision cycles (Bevilacqua & Dell'erba, 2024; Butarbutar & González Vallejo, 2025). However, several studies caution that these benefits are contingent upon active learner engagement, as passive reliance on AI may limit the development of self-regulation skills.

*Explaining Learning Outcomes Through Implementation Design*
A key contribution of this review is its ability to explain how and why AI influences learning outcomes, rather than merely reporting them. By linking implementation characteristics (RQ2) with learning outcomes (RQ3), the findings demonstrate that learning effects are mediated by pedagogical design and usage patterns.

Positive outcomes, particularly in writing performance, engagement, and SRL, are consistently observed in studies employing structured and interactive designs. For example, iterative human–AI writing processes have been shown to improve writing quality and performance (A. Nguyen et al., 2024), while AI-supported SRL systems enhance both engagement and autonomous learning behaviours (Lämsä et al., 2025; Wu & Chiu, 2025). Similarly, AI-supported thesis writing and project-based learning environments promote long-term writing development and autonomy (Butarbutar & González Vallejo, 2025; Q. N. Nguyen & Doan, 2025)

In contrast, studies reporting weaker or mixed outcomes often involve less structured or perception-based implementations. For instance, perception-focused studies highlight increased engagement and usability (Kaur & Kapoor, 2025; Ngo et al., 2024), but do not always demonstrate measurable improvements in writing performance. Additionally, some experimental studies indicate that while AI enhances efficiency, it may reduce depth of cognitive engagement when learners rely heavily on automated outputs (A. Chen et al., 2025; Palacios-Núñez et al., 2025).

These findings suggest that AI is more effective in supporting lower- to mid-level cognitive processes, such as writing accuracy, organisation, and revision, than higher-order processes like critical thinking and argumentation. This aligns with evidence showing that AI-assisted feedback improves surface-level writing features, while deeper cognitive gains require structured pedagogical support (Bevilacqua & Dell'erba, 2024; Ou et al., 2024). This confirms that learning outcomes are not determined by AI tools alone, but by how they are embedded within pedagogical and interactional contexts.

*The Tension between Efficiency and Deep Learning*

A key tension identified across studies is the trade-off between efficiency and cognitive depth. AI tools, particularly generative AI, significantly enhance efficiency by reducing the time and effort required for idea generation, drafting, and revision (Nurchurifiani et al., 2025; Siva Prasad Reddy et al., 2026). These benefits contribute to increased engagement and accessibility of the writing process (Kaur & Kapoor, 2025; Ngo et al., 2024).

However, multiple studies highlight the potential trade-offs associated with this efficiency. For example, A. Chen et al. (2025) found that AI-supported help-seeking can lead to nonlinear learning behaviours and over-reliance, while Palacios-Núñez et al. (2025) observed that AI use in revision may improve surface-level writing but limit deeper understanding. Similarly, Mizumoto & Teng (2025) reported limitations in the reliability of AI outputs, raising concerns about their impact on analytical accuracy.

These findings suggest that while AI can enhance performance, it does not inherently promote deeper learning. Instead, cognitive engagement depends on how AI is used within pedagogical contexts. Approaches that incorporate reflective tasks, critical evaluation, and AI literacy, such as those proposed by (Ou et al., 2024), are essential for ensuring that AI supports higher-order thinking rather than replacing it.

*Contextual and Methodological Constraints in the Evidence Base*

The findings of this review must be interpreted in light of several limitations within the current evidence base. First, the majority of studies are conducted in higher education contexts, with limited representation from secondary education (Lämsä et al., 2025). Second, many studies involve small sample sizes or short-term interventions, which restrict the generalisability of findings (Butarbutar & González Vallejo, 2025; A. Nguyen et al., 2024).

Additionally, a substantial proportion of studies rely on self-reported perceptions rather than objective performance measures (Kaur & Kapoor, 2025; Tran et al., 2025), which may overestimate the effectiveness of AI-supported learning. While experimental and mixed-method studies provide stronger evidence (Ren et al., 2025; Yang et al., 2025), the overall evidence base remains methodologically heterogeneous, limiting the ability to draw definitive causal conclusions.

Furthermore, some AI applications included in the review are context-specific or not exclusively focused on research writing (e.g., STEM or general learning contexts), which may affect the consistency of findings (Bansal et al., 2025; Lizano-Sánchez et al., 2025). These limitations highlight the need for more rigorous, large-scale, and longitudinal research.

*Implications for Pedagogy, Research, and Policy*

The findings of this review have several important implications. From a pedagogical perspective, AI should be embedded within structured instructional designs that promote active learning, self-regulation, and critical engagement. Educators play a key role in guiding learners to use AI tools effectively, ensuring that AI supports rather than replaces cognitive effort (Kong et al., 2024; Perifanou & Economides, 2025).

For learners, the increasing use of AI underscores the importance of AI literacy and ethical awareness, particularly in evaluating AI-generated content and maintaining academic integrity (Ou et al., 2024). Without these competencies, learners may become overly dependent on AI, limiting their ability to develop independent writing skills.

From a research perspective, future studies should prioritise longitudinal designs, diverse educational contexts, and deeper investigation into higher-order cognitive outcomes. There is also a need for more theory-driven research that integrates AI within established learning frameworks, such as SRL and cognitive development models (Siva Prasad Reddy et al., 2026).

*Overall Synthesis*

Overall, this review positions AI-supported personalised learning in research writing as an integrated and context-dependent system, where effectiveness is shaped by the interaction between AI technologies, personalisation mechanisms, pedagogical design, and learner engagement. While AI demonstrates strong potential to enhance writing performance, engagement, and self-regulated learning, its impact on deeper cognitive processes remains conditional. This study addresses the limitations identified in prior reviews by providing an integrated, multi-dimensional synthesis that connects AI implementation, pedagogical design, and learning outcomes within a unified framework.

The findings suggest an emerging shift towards a human–AI co-regulation paradigm, in which learners and AI systems collaboratively support the writing process. However, realising this potential requires careful alignment between technology, pedagogy, and ethical practice. Future research should therefore adopt a holistic approach that balances efficiency with deep learning, ensuring that AI functions as a tool for cognitive enhancement rather than substitution.

**Conclusion**

This systematic literature review provides a comprehensive synthesis of research on AI-supported personalised learning in research writing, addressing critical gaps in the existing literature. By analysing 27 studies published between 2023 and 2026, this study demonstrates that AI is not a standalone instructional tool but a pedagogically mediated system, where learning outcomes emerge from the interaction between AI technologies, personalisation mechanisms, pedagogical design, and learner engagement.

A key contribution of this study is the development of a multi-layer analytical framework that explains how AI supports personalised learning in research writing. The findings reveal that different AI technologies serve functionally distinct roles across the writing process, with generative AI supporting idea generation and structuring, while adaptive feedback systems and intelligent tutoring systems facilitate drafting, revision, and iterative improvement. More importantly, the review highlights that personalisation mechanisms—such as adaptive feedback, prompt scaffolding, and learner modelling—act as the central drivers of learning outcomes, rather than AI technologies alone.

In terms of learning outcomes, the evidence indicates that AI-supported personalised learning is most effective in improving writing performance and supporting self-regulated learning (SRL), particularly within structured pedagogical designs. However, the impact on higher-order cognitive outcomes, such as critical thinking and deep learning, remains limited and inconclusive. Furthermore, the strength of evidence varies significantly across study designs, with experimental studies providing stronger support, while perception-based studies tend to overestimate effectiveness. These findings underscore the importance of interpreting AI-related learning outcomes with caution, given the methodological heterogeneity of the current evidence base.

This study also highlights a fundamental tension between efficiency and cognitive depth. While AI enhances writing efficiency, accessibility, and engagement, it may also lead to over-reliance and reduced critical engagement if not carefully integrated within pedagogical frameworks. Therefore, the effectiveness of AI in research writing is contingent not only on technological capabilities but also on instructional design, learner agency, and responsible use.

From a practical perspective, the findings suggest that educators should adopt a pedagogy-first approach, embedding AI within structured learning environments that promote self-regulation, critical thinking, and reflective practice. Additionally, the integration of AI literacy is essential to ensure that learners can critically evaluate and responsibly use AI-generated content. From a policy perspective, institutions should develop guidelines and frameworks that support ethical AI use while maintaining academic integrity.

Despite its contributions, this review is subject to several limitations. The inclusion of only Scopus and Web of Science databases and the exclusion of some non-open-access studies may introduce selection bias. Moreover, the dominance of higher education contexts and short-term studies limits the generalisability of findings. Future research should prioritise longitudinal and large-scale studies, expand to diverse educational contexts, and focus on higher-order cognitive outcomes such as critical thinking, argumentation, and knowledge construction. There is also a need for more theory-driven and design-based research that integrates AI within established pedagogical frameworks.

In conclusion, AI-supported personalised learning in research writing represents a rapidly evolving field with significant potential. However, its effectiveness depends not on the technology itself, but on how it is designed, implemented, and used within pedagogically meaningful contexts. Advancing this field requires a shift from tool-centric approaches towards integrated, learner-centred, and ethically grounded models of AI-supported learning.

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