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Technology-enhanced Learning and Learning Analytics for personalized STEM learning: A scoping review

Umar Bin Qushem [a,*], Athanasios Christopoulos [a], Rogers Kaliisa [b], Mohammad Khalil [c], Tapio Salakoski [a], Mikko-Jussi Laakso [a]

[a] Turku Research Institute for Learning Analytics (TRILA), University of Turku, Finland
[b] Department of Education, University of Oslo, Norway
[c] Centre for the Science of Learning & Technology (SLATE), University of Bergen, Norway

A R T I C L E I N F O

Keywords:
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A B S T R A C T

Background: The increasing focus on Personalized STEM Learning (PSL) highlights the need to understand how Technology-Enhanced Learning (TEL) and Learning Analytics (LA) can be effectively integrated to support adaptive learning. While TEL-LA interventions have shown promise in optimizing learning pathways, an in-depth review is needed to evaluate their technological, pedagogical, and analytical characteristics, as well as their impact and implementation challenges.
Aim and method: The present study constitutes a systematic scoping review of 31 empirical intervention studies published between 2020 and 2024, analyzing recent developments in TEL-LA for PSL. The review examines the key characteristics of these interventions, their impact on learning outcomes, and the challenges in their implementation.
Results: The findings indicate that Intelligent Tutoring Systems (ITS) were the most widely applied technology in K–12 (mathematics), while Virtual Reality (VR) was utilized for immersive educational experiences in Higher Education (engineering). LA techniques, such as regression analysis, exploratory data analysis, and clustering, were crucial in monitoring engagement and providing personalized feedback. Self-regulated learning strategies were frequently embedded in TEL-LA interventions, with studies reporting improvements in student motivation, problem-solving skills, and academic performance.
Conclusions: The present study provides a robust foundation for understanding how TEL-LA for PSL can be effectively implemented to achieve Precision Education (PE), thereby offering evidence-based insights for educators, practitioners, and policymakers seeking to enhance personalized learning experiences in STEM education. It also expands the corpus of knowledge on how TEL-LA interventions are determining the learning outcomes and measuring the learning impact across education contexts.

Practitioner Notes

* Corresponding author: Turku Research Institute for Learning Analytics (TRILA), 20014 University of Turku, Turku, Finland.
E-mail addresses: umar.binqushem@utu.fi (U. Bin Qushem), athanasios.christopoulos@utu.fi (A. Christopoulos), rogers.kaliisa@iped.uio.no (R. Kaliisa), Mohammad.Khalil@uib.no (M. Khalil), tapio.salakoski@utu.fi (T. Salakoski), milaak@utu.fi (M.-J. Laakso).

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What is already known about this topic

While personalized approaches have gained prominence in education, their specific application in STEM contexts lacks systematic evaluation.

Educational technology and data-driven approaches exist separately, but their integration for personalized STEM learning remains underdeveloped.

The effectiveness of Learning Analytics (LA) in creating personalized STEM learning experiences has been theorized but lacks empirical validation across diverse educational contexts.

What this paper adds

A comprehensive analysis of which Technology-Enhanced Learning (TEL) approaches combined with Learning Analytics (LA) actually deliver measurable improvements in STEM learning outcomes.

Evidence that self-regulated learning strategies, when embedded within Intelligent Tutoring Systems (ITS), yield consistent improvements in both performance and engagement metrics.

A practical framework for understanding how different analytics techniques can be matched to specific STEM disciplines and educational levels.

Implications for practice and policy

K–12 instruction benefits most from ITS with embedded analytics, while Higher Education shows greater gains with immersive technologies.

Investment in LA infrastructure should prioritize systems that monitor engagement patterns and provide real-time feedback rather than summative assessment alone.

Educational technologists and curriculum designers should address the current scalability challenges by developing cross-platform solutions with standardized validation metrics.

Teacher training programs should incorporate LA literacy to help educators implement and interpret data from personalized learning technologies.

1. Introduction

The growing emphasis on personalized learning in education has been driven by the need to tailor instruction to individual learners' strengths, needs, and preferences. In science, technology, engineering, and mathematics (STEM) education, where students often engage in complex problem-solving and require diverse learning supports, personalization has been identified as a critical factor in improving engagement, motivation, and academic performance. Technology-Enhanced Learning (TEL) and Learning Analytics (LA) have emerged as powerful fields in this regard, enabling educators to analyze student data and implement adaptive learning strategies that support individualized learning experiences (Wong et al., 2023). By leveraging real-time insights, TEL-LA (Technology Enhanced Learning-Learning Analytics) interventions can facilitate more effective learning pathways, enhance student persistence, and address disparities in educational outcomes (Li & Wong, 2023).

The integration of LA into instructional practices allows for identifying students' strengths and weaknesses, real-time feedback, and personalized learning recommendations (Xu & Ouyang, 2022). Previous studies have shown that TEL-LA approaches, such as personalized feedback (Khor & Mutthulakshmi, 2023) and adaptive learning (Hilpert et al., 2023), can enhance students' engagement (Bond et al., 2023), cognitive skills development (Lim et al., 2021b; Leite et al., 2022), and time management (Iraj et al., 2020). The increasing role of AI-supported Learning Management Systems (LMS), computer-assisted platforms (Vanacore et al., 2023), and hybrid human-AI tutoring platforms (Thomas et al., 2024) further supports the potential for personalization in STEM learning environments.

Despite advancements in TEL-LA, existing research remains fragmented. Many studies focus on isolated aspects of personalized learning without providing a comprehensive understanding of how TEL-LA interventions function across different educational contexts (Li & Wong, 2020). Moreover, while LA has gained traction in education, its application to STEM disciplines has not been systematically examined with regard to the long-term impact and effectiveness of various intervention strategies (Xu & Ouyang, 2022; Wong et al., 2023). Therefore, there is a need for a more structured analysis of TEL-LA interventions in STEM education to identify best practices, challenges, and opportunities for improving student learning experiences through data-driven personalization.

1.1. Personalization in STEM education

Personalized learning has gained significant attention in recent years as a means of tailoring education to individual learners' needs, strengths, and preferences. However, despite the growing body of research, studies focusing on the application of such practices in STEM-related disciplines are limited (Li & Wong, 2023; Xu & Ouyang, 2022). Likewise, even though integrating LA practices in digital learning environments (DLEs) has been widely discussed, empirical evaluations of their effectiveness in STEM education are still underdeveloped (Wong et al., 2023).

The application of such practices has primarily focused on adaptive learning platforms (ALPs), data-driven instructional practices, and individualized feedback systems. A systematic review by Li et al. (2020) analyzed 798 articles published between 2000 and 2018 and found a growing trend in personalized STEM learning (PSL), particularly in Higher Education (HE) settings. The findings emphasized the increasing reliance on TEL to create customized learning pathways, although they noted that research on PSL at the K–12 levels remains scarce. A more recent review by Li and Wong (2023) examined 72 studies on PSL (including Arts–STEAM) education published between 2011 and 2020. The analysis revealed that blended learning environments and LA were the most commonly used personalization approaches. However, they also identified a critical gap; while many studies explored specific aspects of personalization, few provided a holistic analysis of how **ALP** and LA interact to enhance STEM education. Further highlighting the limitations in existing research, Xie et al. (2019) conducted a systematic review of technology-enhanced adaptive learning from 2007 to 2017. The findings showed the dominance of traditional computing devices in personalized learning, with little attention paid to emerging technologies such as artificial intelligence, immersive technologies, or data-driven personalization techniques.

1.2. Personalization in learning analytics

Learning Analytics (LA) has emerged as a powerful tool for enhancing personalized learning by leveraging student data to tailor instruction, provide real-time feedback, and optimize learning outcomes. Wong et al. (2023) reviewed 144 articles on LA and personalized learning published between 2012 and 2019. The findings indicated that while LA has been increasingly used to personalize learning experiences, most studies lack empirical validation as they rely primarily on theoretical frameworks and small-scale interventions.

Li and Wong (2020) also explored the role of LA in personalized learning environments and concluded that LA techniques—such as data mining, clustering, and predictive modeling—have been used to track student progress and recommend personalized learning pathways, but few studies have systematically assessed their long-term impact on student engagement and achievement.

Xu and Ouyang (2022) examined LA in adaptive learning and identified several key challenges, including data privacy concerns, limited scalability of personalization algorithms, and difficulty of integrating LA into traditional instructional practices. As part of the concluding remarks, the authors suggest that while LA holds promise for personalized education, more research is needed to understand its effectiveness in diverse learning contexts with special emphasis on STEM disciplines.

1.3. Theoretical and pedagogical foundations of AI-driven learning analytics

The integration of artificial intelligence (AI) into learning analytics (LA) has expanded opportunities to capture and analyze complex dimensions of learning. Yet, a persistent critique is that many LA interventions lack explicit theoretical grounding and pedagogical orientation (Ferguson & Clow, 2017; Khalil et al., 2023a). Without clear connections to learning theory, the effects of AI-driven LA applications on students' affective, cognitive, and metacognitive development remain inconsistent and fragmented. This section synthesizes insights from recent reviews and conceptual frameworks to outline how AI-driven and generative AI–based LA interventions engage with these learning dimensions and how pedagogical design principles and learning theories can guide their development.

Recent systematic reviews show that most AI-driven LA applications primarily emphasize cognitive engagement, such as analyzing discourse or tracking task performance (Ouyang & Zhang, 2024). While these tools demonstrate positive effects on participation and achievement, they often provide limited support for affective and metacognitive processes. Studies using multimodal learning analytics (MMLA) illustrate the potential to address this gap by capturing emotions, motivation, and regulatory strategies (Noroozi et al., 2019, 2020). Such work underscores that effective AI-driven LA interventions should move beyond surface-level monitoring to support learners' emotional regulation, motivational persistence, and reflective practices, all of which are critical in sustaining engagement in STEM learning.

Emerging research on generative AI further extends these possibilities. Unlike earlier AI-driven tools that largely provided visualizations or statistical feedback, generative AI systems enable conversational, adaptive, and context-sensitive forms of support. A systematic review by Misiejuk et al. (2025) shows that generative AI has been used in LA to scaffold reflection, guide self-regulated learning, and enhance learner agency. For instance, conversational agents powered by large language models can provide personalized prompts, explanations, or emotional support, thereby engaging affective and metacognitive processes more directly than static dashboards. At the same time, these developments raise concerns regarding transparency, ethical use, and pedagogical alignment, highlighting the need for generative AI to be embedded within robust learning theories rather than functioning as decontextualized technical add-ons.

Equally critical are the pedagogical design principles underpinning LA interventions. Feedback is among the most powerful drivers of learning (Wisniewski et al., 2020), and LA can strengthen feedback practices by making them timely, data-driven, and adaptive. Banihashem et al. (2022) emphasize that LA can enhance both the formative function of feedback and its role in supporting self- and co-regulation. Similarly, Mangaroska and Giannakos (2018) highlight the value of analytics-informed learning design, where dashboards and orchestration tools provide teachers with actionable insights to scaffold collaborative learning. Yet, as Ouyang and Zhang (2024) observe, most existing AI-driven LA applications lack explicit design principles, which limits their ability to connect analytics to meaningful pedagogical goals. Integrating design-based approaches such as scaffolding, mastery learning, and inquiry-based instruction is therefore essential for maximizing the educational value of AI-driven LA.

Finally, grounding LA interventions in learning theories provides a foundation for ensuring that their effects align with broader educational goals. Theories of self-regulated learning (Zimmerman, 2000), self-determination (Ryan & Deci, 2000), and socially shared regulation of learning (Järvelä et al., 2016) offer robust frameworks for understanding how learners plan, monitor, and reflect on their learning, individually and in groups. Khalil et al. (2023a) show that these theories are underutilized in LA research, despite their potential to guide the design of interventions that foster autonomy, motivation, and reflection. Generative AI's ability to deliver adaptive, dialogic feedback can be explicitly connected to these theories, supporting not only cognitive performance but also affective resilience and metacognitive growth. In this way, aligning AI-driven LA with established pedagogical principles and theories ensures that interventions address affective, cognitive, and metacognitive outcomes in a coherent and holistic manner.

1.4. Motivation and contribution of the current study

Despite the increasing attention to personalized and adaptive learning, several key gaps persist in the literature. First, while personalized learning has been widely studied in general education, research specifically targeting STEM learners remains limited (Li & Wong, 2023; Xu et al., 2022). Many reviews have examined adaptive learning broadly without distinguishing between STEM and non-STEM disciplines. Additionally, reviews exploring personalized learning in STEM tend to focus primarily on HE, overlooking its applicability in K–12 settings (Du Plooy et al., 2024; Khor & Mutthulakshmi, 2023).

Another limitation is the lack of empirical studies evaluating the impact of personalized learning technologies on student learning outcomes. For instance, Khor & Mutthulakshmi, 2023 examined the role of data and methods in personalizing adaptive learning but did not investigate how specific technologies influence student performance. Other studies have been confined to narrow disciplinary contexts such as computer science (Barbosa et al., 2024) and social sciences (del Pilar Gonzalez & Chiappe, 2024), limiting their generalizability to STEM education. Furthermore, some reviews have failed to include the most recent literature (Muñoz et al., 2022; Martin et al., 2020; Xu & Ouyang, 2022), and few have systematically analyzed intervention studies measuring learning outcomes (Xu & Ouyang, 2022; Wong et al., 2023).

A notable scoping review from 1998 to 2019 by Sáinz et al. (2022) examined STEM intervention studies but focused solely on gender participation. This leaves an important gap regarding how PSL has evolved in recent years, particularly with advancements in LA practices and ALPs. Other studies (e.g., Larrabee Sønderlund et al., 2019; van Haastrecht et al., 2024) have assessed the effectiveness of LA interventions, but questions remain about how these interventions can be integrated into existing educational practices to provide data-driven support for PSL. There is also a lack of research synthesizing collective practices that could enhance personalization efforts across STEM education.

While the field of PSL has begun to attract scholarly attention, significant gaps remain in our understanding of how TEL-LA interventions can effectively support personalized educational experiences. The current literature lacks a comprehensive synthesis of recent empirical studies that systematically evaluate the implementation and effectiveness of such interventions. Such a research gap is particularly concerning given the rapid technological advancements and the increasing emphasis on data-driven educational practices in STEM disciplines.

In the context of STEM education, the distinction between "personalized learning" and "adaptive learning" embodies both conceptual and operational differences, which merits critical examination. Personalized learning encourages learner autonomy and self-directed learning, often rooted in a constructivist framework that prioritizes the learner's agency in their educational journey (Peng et al., 2019). In contrast, adaptive learning relies on algorithmic adjustments to the learning experience based on real-time performance data, aiming to optimize engagement and efficiency through a system-driven approach that may sometimes overshadow individual learner agency (Ezzaim et al., 2024). The review is thereby guided by a conceptual framework that examines questions of control and agency in TEL-LA environments. In greater detail, we conceptualize agency as learners' capacity to make meaningful choices about their learning paths, while control refers to the distribution of decision-making power between learners, educators, and algorithmic systems. The framework helps to understand how different TEL-LA interventions balance automated personalization with learner autonomy and how various stakeholders exercise control over the learning processes.

To address these limitations, we contend that a thorough investigation of intervention-oriented empirical studies from 2020 to 2024 is essential. Such an analysis would unveil the critical characteristics of TEL-LA interventions, including the technologies employed, methodological approaches, learning strategies, and their measurable impact on student learning outcomes across diverse educational contexts. By synthesizing these findings, the present study aims to enhance understanding of TEL-LA interventional practices for PSL and demonstrate how personalized learning experiences could be implemented in STEM education. Guided by this objective, the following Research Questions (RQs) are formulated:

RQ1: What are the key characteristics of TEL-LA interventions in PSL?

A systematic understanding of the technological, pedagogical, and analytical characteristics of TEL-LA interventions is necessary because these design elements determine how personalization is enacted in practice. Prior reviews have shown that research in personalized STEM learning is fragmented, often examining technologies or analytics methods in isolation without connecting them to broader learning theories or frameworks (Li & Wong, 2020, 2023; Xie et al., 2019). By mapping intervention characteristics, this study situates TEL-LA practices within established theoretical perspectives such as self-regulated learning (SRL), metacognition, and learner agency, which highlight how adaptive technologies can scaffold meaningful learning pathways (Molenaar et al., 2021; Wong et al., 2023). Understanding these features also informs how personalization aligns with the goals of precision education (PE), where decisions about learning pathways are optimized through data-driven and contextually sensitive design (Qushem et al., 2021).

RQ2: What are the key impact areas and learning outcomes associated with TEL-LA interventions in PSL?

This question is grounded in the recognition that learning analytics must demonstrate measurable improvements in learning, rather than assume impact. Ferguson and Clow (2017) argue that the central test for LA is whether it improves learning and teaching in practice, yet the evidence base remains limited and often methodologically weak. More recent systematic reviews of LA dashboards further highlight that while some interventions show promise for increasing participation or motivation, their effects on achievement are often negligible or modest, raising questions about the extent to which LA has lived up to its promise (Kaliisa et al., 2024). Examining impact across domains such as achievement, engagement, motivation, and cognition provides a way to connect TEL-LA interventions to broader educational goals, including equity and student agency. This focus on impact is therefore crucial to move beyond the hype of technology and establish a clearer evidence base for how TEL-LA contributes to STEM learning outcomes.

RQ3: What are the challenges and limitations in implementing TEL-LA interventions for PSL?

Identifying challenges and limitations is theoretically important because the success of TEL-LA depends not only on design but also on contextual and methodological constraints. Ferguson and Clow (2017) emphasize that issues of validity, reliability, generalizability, and ethics remain underexplored in LA, which limits the credibility and transferability of findings. At the same time, questions of control and agency—how decision-making is distributed between learners, educators, and algorithms—frame key challenges in implementing personalized learning environments (Wong et al., 2023). Without attending to these issues, TEL-LA interventions risk perpetuating inequities or failing to scale beyond narrow contexts. By systematically analyzing the reported barriers, this study aims to highlight the structural, methodological, and ethical considerations necessary for ensuring that TEL-LA interventions can deliver sustainable and equitable impact in STEM education.

2. Methodology

The research study was carried out using the scoping review methodology presented by Arksey and O'Malley (2005). The study was structured to investigate the key interventions supported by TEL-LA intervention practices in STEM education, covering K–12 to higher education (HE) settings. Scoping reviews are appropriate for evaluating the extent of literature on a topic, where more research should be undertaken, and how research on a topic is carried out (Khalil et al., 2021; Pollock et al., 2021). As a result, the scoping review seems most justified for this study's objectives. As part of the review process, the following steps were considered: (*1)* search strategy and query design; *(2)* selection of relevant studies; and *(3)* data extraction, analysis, and synthesis.

2.1. Search strategy and query design

To identify relevant studies, we developed a structured search strategy incorporating specific terminology related to our research focus and targeting scholarly databases with strong coverage in educational technology. The search parameters were designed to capture the intersection of personalized learning approaches and STEM education within recent empirical literature. An important step of query design is the identification process of determining the right keywords and, to some extent, refining the keywords to locate the right resources. As the study seeks to explore technologies that are utilized for learning purposes and have prompted the provision of environments, a broad yet similar meaning of words capturing EdTech platforms was chosen. In addition, although the study aimed to search for STEM-related studies, query design has given priority to 'STEM Education' or 'STEM Learning' over the words of STEM, which may divert finding the resources covering studies that solely highlight how STEM education is being taught or different approaches played out during the students' learning. Following the establishment of the search parameters, search queries were applied to articles, keywords, and abstracts in various configurations according to each database structure. The search query was based on the following keyword combinations: ("Learning Environment" OR "Learning Intervention" OR "Education* Technology" OR "Learning* Technology") AND ("Learning Analytics") AND ("Science" OR "Technology" OR "Engineering" OR "Math*" OR "STEM* education" OR "STEM* learning").

The literature search was conducted using three major academic databases: Web of Science, Scopus, and ACM. The first two databases are widely recognized in the production of SLRs and are valued for their advanced search capabilities and reliability in yielding consistent results, including peer-reviewed works related to STEM educational research (Klokočka, 2025). Consequently, ACM is also a well-known database for technical and scientific magazines and materials. Since the LAK conference proceedings are indexed in ACM, it is likely to be a significant outlet for covering many related issues in learning analytics as well as learning interventions. Following

Table 1
The inclusion and exclusion criteria.

Inclusion	Exclusion
Empirical and experimental studies	Non-empirical and non-experimental studies
Published between 2020 and 2024	Published before 2020 and after 2024
Full texts are freely available and written in English.	Not freely accessible and written in other languages than English.
Studies in the domain of STEM	Studies in non-STEM fields.
Studies of interventional design or falling under the category of having some interventional effects in STEM-related education using learning platforms and LA practices.	Studies that were referred to utilize learning platforms and LA but did not have a proper interventional setup (e.g., controlled environment, randomized control trial, pre-post assessment, or experimental or directed intervention).
The targeted population includes primary, secondary, and higher education (K–12-HE).	Does not specify or belong to any population group between K–12 and HE.

the database search, a total of 1769 publications were yielded from the 3 databases that matched at least one of our search criteria.

2.2. Selection process

Our selection process, particularly filtering the relevant studies, has two parts: screening and eligibility, which were conducted according to the PRISMA guideline (Page et al., 2021). One of the important steps of this process is to ensure establishing the screening criteria for studies to be selected or excluded. All necessary criteria that guided the selection process can be read in Table 1. Prior to the screening phase, a total of 1287 studies were removed due to duplication, title, and availability. During the initial screening, identified studies were further checked against 1st criteria, particularly by type of study design, i.e., empirical and experimental. As review studies investigating interventional study designs should be grounded in empirical and experimental research, this approach has been

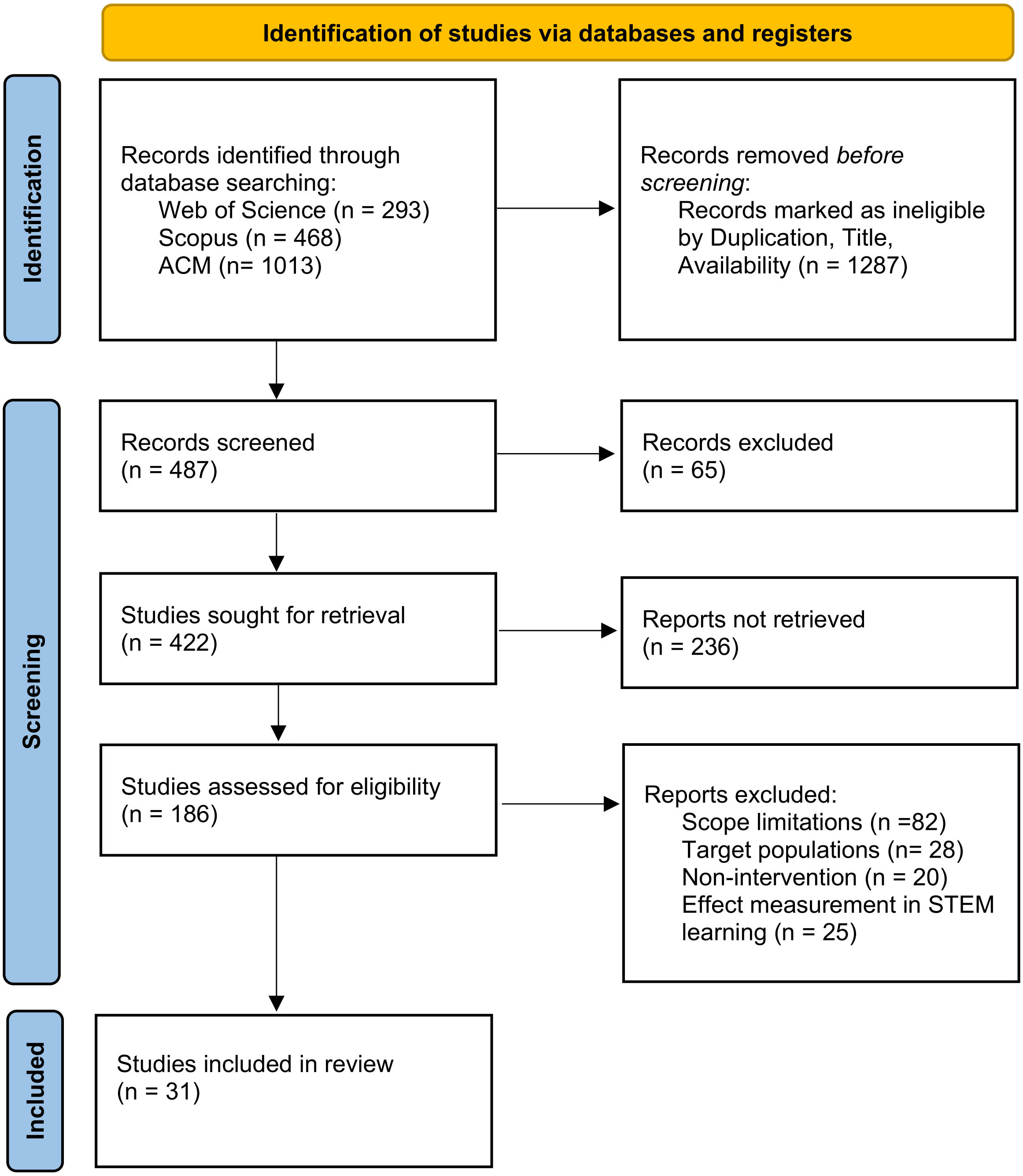

Fig. 1. PRISMA flow diagram (Page et al., 2021).

recommended by previous works (Nolan et al., 2025; Pasion et al., 2019). Based on the 1st and 2nd criteria, the remaining studies (n = 487) underwent screening to match with the study design and timeframe, which yielded 65 entries. The remaining articles (n = 422) were then further screened for relevance following the 3rd and 4th criteria, eliminating 236 articles due to language types other than English and lack of description concerning STEM learning and education. This screening stage yielded 186 eligible full-text articles for detailed assessment.

The last step in the selection process includes a more in-depth assessment to choose the eligibility of studies. During the final evaluation, two researchers assessed each article (full text) and ensured whether the studies were suitable and relevant for data extraction and further analysis. Researchers in this phase eliminated 155 articles due to the limited scope of incorporation of TEL-LA practices (n = 82), inappropriate target populations (n = 28), non-interventional methodologies (n = 20), and lack of intervention effect measurements (n = 25) according to the 4th and 5th criteria. The final corpus comprised 31 interventional studies that met all inclusion criteria (Fig. 1). To ensure methodological rigor, we included only true or quasi-experimental studies, randomized controlled trials, or investigations employing pre-test and post-test measurements (Aggarwal & Ranganathan, 2019).

2.3. Data extraction, analysis, and synthesis

Following the recommendations by Arksey and O'Malley (2005), we proceeded with data extraction, analysis, and synthesis. All selected articles initially stored in our repository were organized based on key information: title, year, domain, technology, intervention characteristics, study focus, and educational context. After verifying the initial metadata and annotations, we extracted the final corpus and all relevant information into an Excel file. It is publicly available on the Zenodo platform (Bin Qushem, 2025). The dataset of collected literatures was cleaned and used for information extraction and subsequent analysis using the coding framework outlined in Table 2. During the initial analysis stage, we restructured the extracted data to align with our research questions; these codes were crucial for locating relevant information and categorizing data throughout our analysis and synthesis process. Two researchers participated in this phase: one responsible for data extraction and another as a reviewer. The research team was involved from pre-screening through synthesis, particularly in resolving disagreements until consensus was achieved.

3. Results

3.1. Characteristics of TEL-LA intervention in PSL

PSL has been a growing field of research, as Fig. 2 illustrates. There were only 3 studies reported in 2020. However, that number started to experience a substantial increase in the following years, reaching 9 articles by 2021.

Most interventional studies were conducted in HE (n = 21), and the remaining (n = 10) were in K–12. Concerning the geographical distribution (Fig. 3), nearly half of the studies are from the USA (n = 14), followed by Australia (n = 5) and the Netherlands (n = 2). The remaining studies include a mixture of cross-country activities (n = 2). Other countries with one study each were Canada, China, Germany, Mexico, Norway, Taiwan, and the UAE. Interestingly, the sample size of the learners in the included studies varied greatly (min = 29, max = 18,925). Following Slavin and Smith (2009), studies with fewer than 100 students were categorized as 'small,' those with 100–250 students as 'medium,' and those exceeding 250 students as 'large.' The included studies consisted primarily of small-scale interventions (n = 19) (Lo & Tsai, 2022; Molenaar et al., 2021; Moltudal et al., 2020; Salehian Kia et al., 2021; Schütt et al., 2024; Suarez-Warden et al., 2023), followed by medium-sized samples (n = 6) (Carpenter et al., 2021; Choi et al., 2023; Cogliano et al., 2022; Günther, 2021; Hilpert et al., 2023; Iraj et al., 2020) and large sample studies (n = 6) (Cho et al., 2024; Cloude et al., 2024; Demszky et al., 2024; Fan et al., 2021; Garbers et al., 2023; Gurung et al., 2024; Gyamfi et al., 2022; Lang et al., 2020; Leite et al., 2022; Lim et al., 2021a, 2021b; Qushem et al., 2022; Tempelaar et al., 2021; Thomas et al., 2024; Vanacore et al., 2023; Wang et al., 2024a; Yeckehzaare et al., 2022; Zambrano & Baker, 2024; Zhang et al., 2022). intervention-related studies have mostly covered mathematics (n = 12) and science-based (n = 8) disciplines, although we noticed that, in some studies, student groups or participant groups had been part of cross- and/or inter-related disciplines, including Computer Science, Information Systems, and Data Science. There have also been some exceptions, including one interventional study where the participants studied 'math and statistics' and belonged to the business and economics program (HE). The main research design approach in common is quasi-experimental (n = 22), followed by randomized control trials (n = 7) and true experimental (n = 2).

Among the studies, various learning theories provided foundations for investigating learner behavior (Fig. 4). Self-regulated Learning (SRL) emerged as a key theoretical framework, appearing in studies across computer science (n = 2) (Cloude et al., 2024;

Table 2
The coding framework.

RQs	Coding category	Codes
RQ1	Characteristics of the TEL-LA intervention in PSL	Publication; Education Level; Population, Country; Domain; Learning theories; Learning technologies; Learning Analytics techniques; Learning strategies.
RQ2	Distribution of Learning Impact and Learning Outcomes in PSL	Impact areas; Learning outcomes (e.g., achievement, performance, and motivation).
RQ3	Challenges and Limitations	Personalization Issues; Data Issues; Methodological issues.

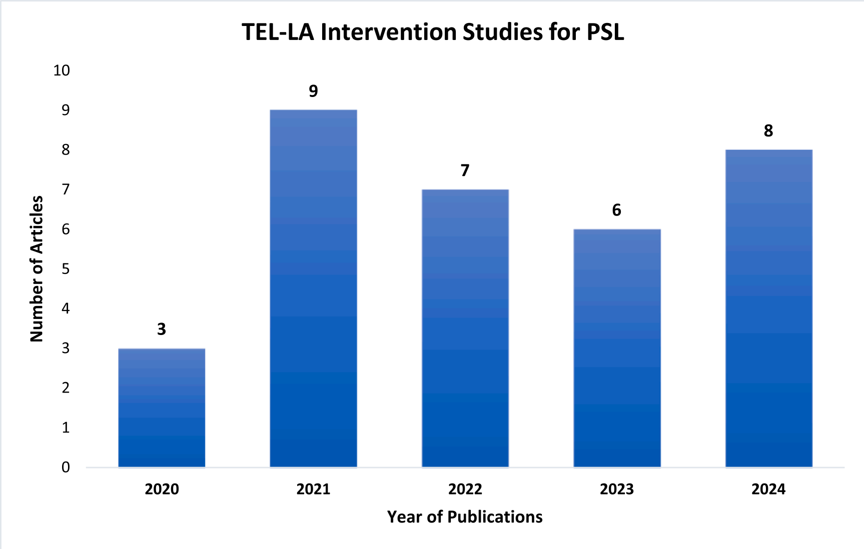

Fig. 2. Publication's trend in TEL-LA interventions for PSL.

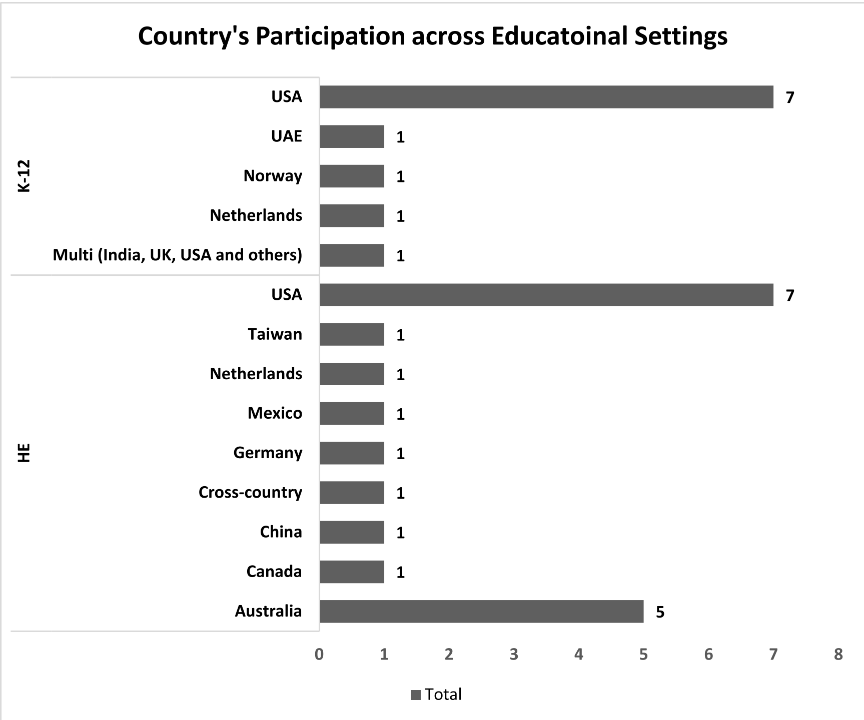

Fig. 3. Countries' participation represented by level of Education.

Fan et al., 2021), mathematics ($n = 1$) (Molenaar et al., 2021), and science ($n = 2$) (Cogliano et al., 2022; Hilpert et al., 2023). One study (Günther, 2021) applied both social comparison and social norms theories to contrast the positive and negative effects of such practices on student behavior, while another study (Vanacore et al., 2023) explored how students' motivation and behavior were influenced by explicitly adopting the social comparison model. Other theoretical frameworks included the Cognitive Theory ($n = 1$), which aimed at enhancing learning effectiveness (Lo & Tsai, 2022), the Goal Complex Theory ($n = 1$) which was used to examine the interplay between achievement goals (Choi et al., 2023), Planned Behavior Theory ($n = 1$), which shaped individual planning strategies towards goal-directed actions (Cho et al., 2024). Other key theories were the Self-determination Theory ($n = 2$) (Moltudal et al., 2020; Schütt et al., 2024), the Metacognition Theory ($n = 2$) (Lim et al., 2021a; Vanacore et al., 2023), and the Desirable Difficulties

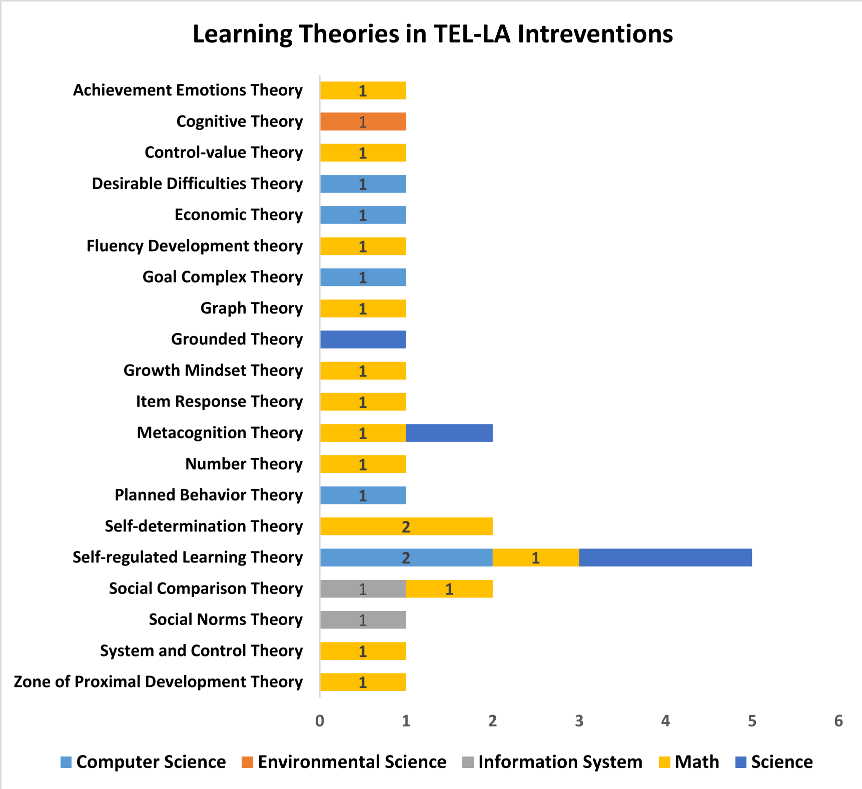

Fig. 4. Learning theories among TEL-LA intervention studies for PSL.

Theory ($n = 1$) (Yeckehzaare et al., 2022).

3.1.1. Technology platforms, analytics techniques and learning strategies

Researchers conducted interventions and ran experiments in pursuit of achieving PSL. That opened possibilities when different adaptive practices were integrated to create adaptive and data-informed educational experiences. Various technologies, analytics techniques, and learning strategies played important roles in shaping PSL. Table 3 presents descriptive findings on intervention practices, showing how technologies across different categories contributed to PSL, how analytical techniques were utilized to evaluate student learning traces from performance to outcome, and how learning strategies were considered by teachers or researchers to

Table 3
Summary of technologies, techniques, and strategies within TEL-LA intervention in PSL.

Intervention Practices	Categories	Number of Studies
Technology Platforms	Digital Learning Environments	21
	Adaptive Learning Platforms	12
	Technology-mediated Learning Environments	5
Analytics Techniques	Inferential Analyses	9
	Statistical Analyses	9
	Machine Learning	7
	Descriptive Analyses	5
	Predictive Analyses	3
	Casual Analysis	1
	Statistical Modelling	1
	Decision-based Analysis	1
Learning Strategies	Self-regulated and Metacognitive Learning	8
	Feedback-based Learning	7
	Motivation and Behavioral Strategies	4
	Problem-based Learning	3
	Personalized Learning	2
	Mastery-based Learning	2
	Practice-based Learning	2
	Game-based Learning	1

support learning enhancement. Looking at the granularity of the table for specific practices, it seems to have disparity in findings and approaches. For instance, a variety of terms were used to describe TEL environments in terms of the technology platforms, prompting their classification into three distinct technology categories: *1)* Adaptive Learning Platforms (ALPs), *2)* Digital Learning Environments (DLEs), and *3)* Technology-mediated Learning Environments (TMLEs). The scope of intervention practices in LA has broadened significantly and utilized a wide range of methodologies beyond mere statistical analysis. That is reflected in the category representing all different forms of analytics techniques being grouped together. In addition, a number of studies were found to be focused on different learning strategies that are instrumental to its interventional impact or learning outcome through TEL-LA practices.

Among the reviewed studies, the Digital Learning Environments (DLEs) made up more than half of the technology platforms (55 %), which serve as crucial infrastructure for delivering and testing impactful pedagogical innovations. The most frequently used technologies among those DLEs were MOOC ($n = 3$) and Canvas ($n = 3$) due to their productiveness hinging on careful and intentional instructional design. For instance, a digital training module focused on SRL skills has been shown to substantially close predicted achievement gaps for university students (Cogliano et al., 2022). Other intervention studies incorporated with these DLEs are also supported by strategies like behavioral nudges (Garbers et al., 2023), metacognitive ability (Salehian Kia et al., 2021), problem-solving (Wang et al., 2024a), and personalized feedback (Cho et al., 2024).

In addition to DLEs, Adaptive Learning Platforms have been utilized to provide personalized and adaptive learning experiences. Interestingly, the most frequent technology in ALP's category was ASSISTments ($n = 3$), an Intelligent Tutoring System (ITS). The ALPs used for K–12 math intervention, such as those investigated within the ASSISTments ecosystem, were highly advanced yet scalable platforms focused on mastery-based learning activities for middle school students (Vanacore et al., 2023; Zambrano & Baker, 2024; Gurung et al., 2024). This platform is equipped with features like robust data capture and algorithmic modelling, detailed logging of interaction data for estimating student knowledge, and employment of machine learning models for detecting non-cognitive states like confusion, concentration, and gaming the system (Zambrano & Baker, 2024).

Moving beyond DLEs and ALPs, Virtual Reality ($n = 2$), a Technology-mediated Learning Environment (TMLE), is increasingly integrated with data analytics (DA) to enhance visualization, collaboration, and learning for complex tasks in fields like design and engineering (Suarez-Warden et al., 2023; Lo & Tsai, 2022). These immersive technologies allow researchers to explore the dynamics of shared control and spatial arrangement, demonstrating that collaborative use can improve problem-solving efficiency and learning outcomes (Chen et al., 2021)

Moreover, the LA methods employed in intervention studies range from basic statistical modeling to more dynamic analytical techniques capable of uncovering the complex processes and psychological constructs. Most studies employed a mix of quantitative and qualitative analysis methods. Approximately one-quarter of them involved statistical analyses (25 %), while another quarter used inferential analyses (25 %). Among the inferential analyses, regression analysis ($n = 5$) emerged as particularly distinctive compared to other similar approaches and was utilized highly in analyzing K–12′s math learning outcomes. For instance, student-perceived trust measurement, feedback understanding, and actionable intelligence were analyzed through regression analysis in a data-driven intervention (Iraj et al., 2020). Consequently, statistical analysis was used for dissecting and quantifying crucial metacognitive factors and biases. For example, in a Codio-based intervention study, a statistical analysis was undertaken to comparatively assess confidence judgments (placement) against performance data, demonstrating a reversal of the hard-easy effect in programming learning underlying a complex and critical relationship between metacognitive monitoring accuracy and academic outcome (Cloude et al., 2024).

Besides, learning assessments in the remaining 50 % of interventions, excluding the first two quarters, were observed employing a set of techniques like machine learning and descriptive analyses, including exploratory data analysis ($n = 4$), clustering analysis ($n = 3$), and Bayesian Knowledge Tracing or BKT ($n = 2$). Considering analytics approaches in machine learning, which largely focused on predictive modeling based on aggregate institutional and platform data, often resulted in findings limited to the descriptive function of LA (Tempelaar et al., 2021). In addition, several studies have reported employing techniques capable of capturing the temporal and sequential nature of learning. For instance, dynamic methods like 'moment-by-moment learning curves' built upon BKT produced crucial insights into how students regulate their accuracy during learning within ALTs over time, which is necessary for understanding hybrid human-system regulation (Molenaar et al., 2021). Similarly, a complex approach like 'standardized treatment effects' in confirmatory analysis was applied to a large-scale MOOC experimental dataset, determining that modifications to content presentation, such as increasing video playback speed, effectively reduced the perceived temporal cost of the course, leading to higher rates of persistence and completion (Lang et al., 2020).

3.2. Impact of TEL-LA intervention on learning outcomes

3.2.1. Positive effects on learning outcomes

The majority of the studies ($n = 20$) reported to have a positive impact on learning performance ($n = 9$) as well as learner engagement ($n = 6$). The aforementioned findings are confirmed by post-intervention tests that examined performance (Leite et al., 2022), higher final course grades (Lim et al., 2021b; Suarez-Warden et al., 2023), course completion rates (Cho et al., 2024), weekly passed lessons (Thomas et al., 2024), unit exams and final exams (Cogliano et al., 2022), increased competence (Moltudal et al., 2020), and increased likelihood of solving problems correctly (Vanacore et al., 2023). Although one study (Garbers et al., 2023) did mention the impact of utilizing nudges to improve student engagement and learning outcomes in completing assignments, that was not as significant as seen on student engagement.

Among the studies reporting improved engagement, several showed specific measurable outcomes. Two studies demonstrated increased regularity of interaction with learning resources (Hilpert et al., 2023; Lo & Tsai, 2022), while another study using a 'Call to

Action' approach—where students received feedback messages requiring response—resulted in enhanced accountability. Personalized support interventions, integrating social norms-based feedback, also yielded positive results, reporting an increase in online active learning time by 25.4 % (Günther, 2021), whereas hybrid human-AI tutoring extended student practice time (Thomas et al., 2024). Furthermore, social presence and social identity were also found to be key drivers of substantially higher engagement when combined with personalized learning strategies (Garbers et al., 2023). Finally, SRL strategies embedded in e-books were also found to have enhanced student engagement (Iraj et al., 2020).

Beyond engagement, several studies revealed impact across various learning domains, including learning behavior ($n = 3$), cognition ($n = 3$), motivation ($n = 2$). Vanacore et al. (2023) found that help-seeking behaviors, such as accessing instructor-provided hints, positively influenced student performance, whereas two other studies demonstrated improved learning behavior through different approaches. Lim et al. (2021b) reported increased use of intensive high engagement strategies following LA-based feedback, while Lang et al. (2020) observed that students who adjusted video playback speed to 1.25x saved time while consuming more educational content. Regarding motivation, Wang et al. (2024a) explored how varying levels of student motivation influenced engagement in physics problem-solving tasks that utilized crowdsourced simulations. The findings indicated that the intervention group performed comparably to university students, with incorrect responses from the university group demonstrating low intrinsic motivation.

Cognitive improvements manifested in several ways across three studies. Gyamfi et al. (2022) noted enhanced quality judgment in students reviewing learning resources when using rubrics during assessment. Cho et al. (2024) found that students who applied planning tactics in their online course writing responses reported more structured learning experiences and better progress tracking. Meanwhile, Carpenter et al. (2021) discovered that students with higher reflection depth scores demonstrated greater learning effects when engaging with science-based content.

A subset of studies revealed multifaceted impact on student learning during interventions. Tempelaar et al. (2021) implemented LA for student profiling, which yielded benefits across multiple dimensions, including improved predictive capabilities, enhanced observation of learning patterns, more actionable feedback, better identification of at-risk students, more tailored interventions, and deeper student understanding. In a different approach, Lo and Tsai (2022) demonstrated that VR-based classroom environments enhanced flow experiences, provided richer learning interactions, increased learners' self-efficacy, and led to higher participation levels. Another research team explored long-term indicators affecting both student engagement and STEM career trajectories, concluding that mastery of fundamental mathematical concepts—particularly when accompanied by specific affective states such as productive confusion or focused engagement—influenced long-term educational outcomes. Zambrano and Baker (2024) took a different angle, focusing on how TalkMeter feature in CueMath functioned as both a motivational catalyst and feedback tool as a means of enhancing instructional effectiveness by promoting active learning and increasing student verbal participation.

3.2.2. Variation and complexity in learning outcomes

A total of 12 studies reported on mixed learning outcomes, underscoring the complexity of different learning interventions in dealing with individual differences and learning contexts in various areas, such as performance, behavior, engagement, motivation, cognition, and emotion. Among these areas, studies reported that students across educational settings had reported to have varied learning outcomes on performance ($n = 8$), behavior ($n = 4$), cognition ($n = 2$), engagement ($n = 2$), motivation ($n = 1$), and emotion ($n = 1$). However, it is important to note that few studies had one effect over another, driving students' learning outcomes. For instance, a student's behavior, like procrastination in study sessions, has a major influence on student exam performance (Yeckehzaare et al., 2022). Similarly, different practice behaviors and difficulty adjustments in an ALP influenced student learning gains or performance differently (Schütt et al., 2024). There has been one exceptional case reported where excessive practice led to a decline in performance because deliberate practice went beyond optimal (Qushem et al., 2022). On the other hand, it is common knowledge that an increase in student engagement has a substantial connection to student motivation and learning goals; however, that was not the case in Choi et al. (2023), who found a discrepancy between self-reported motivation and actual behavior. Regarding cognition, student perceptions (higher knowledge level) and learning curve patterns can vary based on a task's perceived difficulty level, which is associated with varied learning outcomes such as higher or lower post-test scores (Molenaar et al., 2021) and metacognitive accuracy or inaccuracy in doing home assignments (Cloude et al., 2024).

Nevertheless, while we also perceived different positive improvements or outcomes reported among the studies, there have been contradictory or varied outcomes as well, whereby some groups did not have expected improvement but rather decreased either learning, performing, or engagement. For instance, an ALT-based intervention has helped learning mathematics, though some pupils expressed resistance toward the adaptive learning technology and did not feel a particular platform was able to meet their demand. Thus, their perceived learning was decreased (Moltudal et al., 2020), regardless of finding evidence of increasing student motivation for 15 min of math homework every day. Moreover, one study described that digital learning environment-based tutoring intervention without math teacher support was not effective across educational contexts, particularly for students with higher grade levels compared with lower grades, and had slowed student progress until more accessibility with human-AI combined tutoring was given to them (Thomas et al., 2024). In addition, selection of problem type based on student prior math ability was seen influencing learning outcomes such that higher-performing students found it effective on fill-in problems, while lower-performing learners showed smaller or even negative effects (Gurung et al., 2024).

3.3. Challenges and limitations in PSL interventions

3.3.1. Personalization barriers

A total of 7 studies reported encountering challenges and limitations in providing PSL when it comes to identifying an individual's experience and opinion ($n = 1$), learning time ($n = 1$), learning effect and behavior, demographics ($n = 2$), achievement goal ($n = 1$), and level of content and support ($n = 1$). While studies utilized various technologies and tools in support of personalization, some studies raised concerns about the use of some tools in certain areas, such as capturing learning goals with a survey that might not be inclusive all the time, provided that it seems to have uncovered discrepancies between self-reported goals and how the student actually behaves during intervention (Choi et al., 2023); measuring student practicing and learning time in a feedback-oriented system did not reflect the effective time they spent on reading learning materials (Günther, 2021). Two studies acknowledged challenges in identifying additional support for learners (Molenaar et al., 2021) and in preserving learners' complex yet diverse experiences and opinions. The challenges are limited in ensuring more personalized support, which might have been different in outcomes if students' self-regulations with different educational levels were identified over time; in another case, use of a step-by-step deductive or inductive approach based on precision. Consequently, studies that did not consider paying attention to demographics (Gurung et al., 2024; Lim et al., 2021a) and an individual's learning characteristics (Lim et al., 2021a) as well as various perspectives of learning behaviors (Vanacore et al., 2023) faced challenges in understanding learners or ensuring personalized support.

3.3.2. Methodological constraints

Over 7 studies described several forms of methodological challenges and limitations expanded from data acquisition to data analysis: *1)* absence of random assignment ($n = 1$), *2)* limited content areas ($n = 1$), *3)* limited learning approach ($n = 1$), *4)* space constraints on instrument ($n = 1$), *5)* inaccurate measurement ($n = 1$), *6)* qualitative investigation ($n = 1$), and *7)* quantitative investigation ($n = 1$). Though field-wise, there are standard practices in conducting interventions, some of the challenges or limitations mentioned seem to have serious impacts or biases in interpreting learning outcomes or results. One key methodological limitation to have in a study is the possibility of having biases, such as selection bias (Thomas et al., 2024) and social desirability bias (Yeckehzaare et al., 2022). For instance, the study (Thomas et al., 2024) utilized 3 different platforms in teaching math, which was a potential threat to implementation fidelity, as different features with different tools may lead to varied learning experiences, which was harder to determine in classroom-based field studies compared to post-school program settings. Similarly, the study (Yeckehzaare et al., 2022), yet in a general context, emphasized concerns about inaccurate measurement over the use of the Procrastination Assessment Scale-Students (PASS). Although it is common practice in this field and poses the risk of social desirability bias, the study, however, utilized semester-level procrastination for a safe measurement. There were also limitations reported in conducting experiments due to limited content areas prompting the replication of other content areas across different subjects (Gurung et al., 2024), space constraints in writing the description of survey scales (Tempelaar et al., 2021), and a limited approach (only interaction-dominant) in capturing student engagement (Hilpert et al., 2023). Other key methodological limitations were identified, including quantitative investigations as a result of loss of information or erroneous statistics in certain problems (Suarez-Warden et al., 2023) and qualitative content analysis as lacking in detailed discussion in developing precise and generalizable coding schemes (Cho et al., 2024).

3.3.3. Data quality and validity issues

Data issues are crucial, and addressing these challenges is essential for ensuring a study with a robust methodology and a well-personalized process. While this process requires careful attention, studies have highlighted certain challenges and limitations that warrant further consideration. Despite the issues related to data analysis and data collection described under the methodological challenges, we shared other open data issues observed in seven studies ($n = 7$). One of the key issues is generalizability ($n = 2$), which is a barrier in generalizing the findings to broader contexts if the study's experiment or intervention was designed with a single learning system and over a certain period (Leite et al., 2022; Zambrano & Baker, 2024). Sample size and missing data ($n = 4$) were also reported to be another significant limitation in executing successful intervention and learning assessment, which was reflected by the reduction of sample datasets due to missing pre-post test data (Carpenter et al., 2021; Choi et al., 2023; Hilpert et al., 2023), while also checking significant differences among variables through the chi-squared test and the Fisher's exact test due to the small sample size (Schütt et al., 2024). Lastly, it is also a negative aspect; if used, the learning environment or particularly the LMS's trace data ($n = 1$) are questionable over quality (Fan et al., 2021).

4. Discussion

The present study expands the corpus of knowledge on how TEL-LA interventions are determining the learning outcomes and measuring the learning impact across education contexts. While there has been plenty of research on the topics of personalized learning, STEM research, TEL, and LA, very few studies have examined the integration of TEL-LA practices on learning outcomes in PSL. In fact, we have identified only three studies that share insights on the relativeness of intervention effectiveness with LA (Larrabee Sønderlund et al., 2019), the challenges and limitations over the use of evaluation and validation in TEL constructs (van Haastrecht et al., 2024), or looking into a bottom-up approach with gender participations over STEM learning (Sáinz et al., 2022). However, it should be pointed out that none of the existing research focuses on the PSL with an abstracted overview and impact of TEL-LA interventions.

In light of this, the present study addresses this gap by examining how TEL-LA shapes STEM education with personalization practices. The review led to the identification of various combinations of digital tools, analytics approaches, and adaptive strategies that transformed specific areas of STEM learning with measurable positive outcomes, though some yielded mixed results. Our analysis also revealed critical limitations within current intervention studies that researchers must address moving forward.

The integration of educational technology with LA creates compelling opportunities to customize STEM education to individual student needs. Despite persistent challenges in gathering reliable data, conducting meaningful analysis, and applying findings across diverse contexts, such approaches show remarkable promise. When implemented thoughtfully, they can significantly enhance how students master complex STEM concepts and develop crucial skills for future success, as demonstrated by recent work (Lim et al., 2021a; Qushem et al., 2022; Thomas et al., 2024).

Our study confirms trends identified in previous research (Li et al., 2020), showing growth in TEL-LA interventions supporting personalized student learning, particularly during 2023–2024, with 2021 as an interesting exception. This anomaly might relate to altered publishing dynamics during COVID-19 lockdowns, which potentially streamlined review processes (Sloane & Zimmerman, 2021). The geographical distribution of research raises important concerns that extend beyond mere numerical imbalance. The United States' dominance in this field (45 % of studies) reflects deeper structural factors, including funding priorities, technological infrastructure, and educational policy frameworks that prioritize data-driven approaches (Wang et al., 2024b; Allman et al., 2024). Such concentration suggests that current TEL-LA models may be inherently shaped by Western educational values, thus emphasizing individual achievement, standardized assessment, and technological solutionism. In the same vein, the underrepresentation of research from South contexts, where different pedagogical traditions and resource constraints exist, limits our understanding of how TEL-LA might function in diverse educational ecosystems. The geographic skew potentially creates a form of 'algorithmic colonialism' where learning analytics models developed in resource-rich contexts are exported without adequate consideration of local educational philosophies, cultural learning preferences, or infrastructural realities (Kohnke & Foung, 2024; Azeez & Adeate, 2024).

The implications of such geographic concentration are profound. First, it suggests that questions of learner agency and control may be answered differently across cultural contexts—what constitutes 'personalization' in individualistic educational cultures may differ from collectivist learning environments (Ma et al., 2025; Komisarof & Akaliyski, 2025). Second, the technological requirements and data practices embedded in current TEL-LA systems reflect the regulatory and ethical frameworks of their countries of origin, which creates potential barriers to adoption in regions with different privacy laws or data governance approaches. Third, the pedagogical assumptions built into these systems—such as the emphasis on individual progress tracking versus collaborative learning—may not align with educational goals in all contexts (Guitert Catasús et al., 2025).

Furthermore, the current TEL-LA landscape being shaped predominantly by certain educational systems also has implications for global educational equity (Iraj et al., 2020; Leite et al., 2022; Thomas et al., 2024). The algorithms and analytics models developed within specific cultural and educational contexts embed specific assumptions about learning, assessment, and student success (Baker & Hawn, 2022). As such, when these systems are being adopted in different contexts without critical adaptation, they risk perpetuating educational inequalities rather than addressing them. For instance, mindset interventions in K–12 sectors showed highly variable and heterogeneous effects depending on individuals and contexts, suggesting a growth mindset study may only predict achievement among privileged students and not those from disadvantaged groups (Vanacore et al., 2023). Conversely, predictive models trained on data from well-resourced institutions may perform poorly when applied to under-resourced educational settings, potentially mislabeling students as 'at-risk' based on contextual factors rather than actual learning needs (Günther, 2021). On the other hand, as a result of massification and standardization, the HE sector has experienced an increase in student numbers and expanded diversity. Nonetheless, diversity demands HE institutions strategize plans to provide all students with equal opportunities to get support and identify learning needs regardless of the learner's socio-economic background. However, massification with decreased resources has also led to large class sizes and reduced capacity in monitoring learning progress and providing personalized feedback, resulting in lower satisfaction and lower levels of student development (Iraj et al., 2020).

The concentration also raises questions about whose vision of 'personalized learning' is being realized through TEL-LA interventions. The dominance of certain geographic regions and institutional types in the research suggests that the field may be optimizing for specific educational outcomes valued in those contexts, such as individual achievement and standardized test performance, rather than exploring alternative conceptions of educational success that might include collaborative skills, cultural competence, or community engagement (Khalil et al., 2023b).

Moving forward, addressing these imbalances requires not just geographic diversification of research but also critical examination of how control and agency are conceptualized and operationalized in different educational contexts. Future research should explore how TEL-LA systems can be designed to respect and enhance learner agency while acknowledging the diverse ways that agency manifests across cultural and educational settings.

Our work addresses key research gaps identified in previous studies, including the shortage of intervention research (Li & Wong, 2020) and the need for comprehensive reviews of TEL-LA practices that are precisely utilized in STEM education (Li & Wong, 2023). The current study identifies critical characteristics of TEL-LA interventions across various ALPs, particularly ASSISTments, Canvas, and Moodle. Consistent with earlier findings (Li & Wong, 2020), we observed that descriptive analytics, statistical analysis, and regression techniques were predominant assessment approaches.

In addition, it makes an important contribution by expanding the focus to include K–12, addressing the scarcity of PSL research in these environments noted by recent works (Du Plooy et al., 2024; Khor & Mutthulakshmi, 2023). The analyzed interventions provided various personalization approaches: individualized instruction (Salehian Kia et al., 2021; Vanacore et al., 2023), customized learning pathways (Qushem et al., 2022), tailored practice opportunities (Fan et al., 2021), and self-regulation support (Lim et al., 2021b). These approaches enhanced student growth by improving both performance and engagement, with some interventions helping students achieve mastery in specific skills like arithmetic fluency (Qushem et al., 2022).

The effectiveness of TEL-LA interventions was further shaped by diverse learning strategies. Game-based Learning (GBL) through the ST Math instructional program successfully engaged previously disinterested students, with predictions of improved post-test performance influencing students' decisions to participate in elective replay activities (Zhang et al., 2022). Video-based learning in MOOCs provided concise, accessible content that facilitated easier review, saved time, and improved academic outcomes (Lang et al., 2020). Meanwhile, inquiry-driven learning environments like Crystal Island (Carpenter et al., 2021) offered flexibility that promoted active learning through a blend of online resources and classroom activities, resulting in heightened engagement and more interactive, immersive learning experiences.

Addressing the call for more adaptive, personalized learning approaches centered on learner needs (Xie et al., 2019), our findings reveal predominantly positive impact across key learning dimensions, including academic performance, student engagement, learning behaviors, cognitive development, and motivation. However, we also identified mixed or insignificant outcomes in four intervention studies (Garbers et al., 2023; Gurung et al., 2024; Moltudal et al., 2020; Thomas et al., 2024), highlighting the complexity of this research area.

Approximately two-thirds of the analyzed studies demonstrated improved learning performance (Cogliano et al., 2022; Suarez-Warden et al., 2023), with many reporting that increased student engagement directly contributed to positive learning outcomes in personalized learning environments (Hilpert et al., 2023; Lo & Tsai, 2022). As such, it suggests that TEL-LA interventions promote outcome-based learning in STEM education. The integration of these technologies also enhanced specific competencies, including mathematical proficiency (Moltudal et al., 2020), problem-solving capabilities (Vanacore et al., 2023), and quality judgment skills (Gyamfi et al., 2022).

From an educational perspective, HE students showed grade improvements when problem-based learning was integrated within VR platform-based instructional design (Suarez-Warden et al., 2023), aligning with previous research findings (Christopoulos et al., 2023; Xie et al., 2019). Technology-mediated feedback demonstrably enhanced self-regulated behaviors and academic achievement across multiple studies (Iraj et al., 2020; Lim et al., 2021b, 2021a).

The integration of TEL-LA through data-driven approaches benefits both students and instructors. The moment-by-moment learning curves dashboard within Adaptive Learning Technologies (Molenaar et al., 2021) visualized students' acquisition of specific math skills during the learning process, providing instructors with essential progress monitoring capabilities. Similarly, hybrid human-AI tutoring approaches increased student engagement while fostering improved learning outcomes (Thomas et al., 2024). Importantly, our findings indicate that intervention effectiveness varies based on instructional context and individual student characteristics (Lim et al., 2021a), underscoring the need for contextually sensitive implementation strategies.

Despite the potential improvement on PSL through TEL-LA interventions, several challenges and limitations across studies were found. In greater detail, we found issues associated with personalized learning, methodology, and data. Several studies highlighted that reduced sample sizes due to incomplete data, missing demographic information, and difficulties in generalizing findings across different contexts were a common phenomenon (Cho et al., 2024). Another pressing issue was about generalizability, which indicated that having a positive outcome from a single learning platform and time period may not ensure the effectiveness or efficiency compared to other TEL platforms or domains (Khalil & Prinsloo, 2025; Zambrano & Baker, 2024). Furthermore, data collection problems, self-selection bias, and the inherent complexity of human learning pose additional hurdles (Iraj et al., 2020). The reliance on self-reported data can introduce social desirability bias, affecting the accuracy of measurements (Cogliano et al., 2022; Salehian Kia et al., 2021). Addressing these limitations requires careful consideration of data quality, context-specificity, and the development of more personalized learning intervention (Hilpert et al., 2023; Qushem et al., 2022). Future research should focus on refining existing challenges and guiding educators to design and implement more personalized yet STEM-oriented interventions and solutions to support K–12 and HE learners.

5. Implications

The theoretical implications emerging from the present review extend beyond immediate practical applications. Our analysis reveals a fundamental tension between algorithmic personalization and learner agency—a tension that manifests differently across educational contexts and cultural settings. Even though adaptive learning platforms can provide tailored support that enhances learning efficiency, questions remain about how much control should be ceded to algorithms versus preserved for learners and educators. Therefore, maintaining such balance becomes even more critical when considering the potential for TEL-LA systems to either reduce or exacerbate educational inequities, depending on their design and implementation.

PSL, supported by TEL-LA interventions, carries significant implications for enhancing student engagement and outcomes through tailored approaches (Vanacore et al., 2023; Zambrano & Baker, 2024). These data-driven approaches and practices are transforming STEM education by facilitating personalized intervention. While PSL has the potential to create more effective, equitable, and interactive educational experiences for all students regardless of their capacity levels (Vanacore et al., 2023), educators and stakeholders must focus more deliberately on effect-based learning outcomes and validation of technology beyond simple measures of learning effectiveness and formative assessment. This broader perspective is essential if we aim to advance the PSL research sector and future TEL-LA-based interventions across diverse educational contexts (van Haastrecht et al., 2024). Based on our analysis, we present several implications for K–12 and HE stakeholders, including teachers:

Rather than viewing TEL-LA as targeted support for struggling learners, we distill from our scoping review that TEL-LA has further potential to restructure inequities in STEM education. By embedding LA into the educational fabric (curricula, teacher dashboards, institutional assessment systems), TEL-LA can enable early and large-scale identification of at-risk students and shift from reactive remediation to proactive equity-focused design (Thomas et al., 2024). Our implication for policymakers is thus to treat TEL-LA not as experimental add-ons but as part of future strategies for equity in STEM.

Our scoping review shows that the current interventions of TEL-LA are more Western-centric which might reflect that there are cultural biases when generalizing personalized learning best practices and recommendations. We implicate that there are risks of "algorithmic colonialism" in STEM education (Karumbaiah & Brooks, 2021). Future research and funding must invest in culturally adaptive learning models of TEL-LA that reflect different pedagogical traditions and resource environments. For the field, this means advancing design principles that integrate context-sensitive personalization rather than universalized solutions.

Multimodal TEL-LA systems should not be seen as optional data enhancements but as the next frontier for personalized STEM education (Cogliano et al., 2022). By combining cognitive, behavioral, and affective traces, multimodal data integration can power feedback loops that move from reactive correction to proactive, holistic learning orchestration (Prinsloo et al., 2023). This positions LMS and ITS platforms not just as delivery channels, but as equity-enabling infrastructures that systematically anticipate and address learner needs across diverse contexts (Qushem et al., 2022). Future research should focus on developing standards and ethical guidelines for multimodal integration to ensure that such personalized feedback mechanisms are more scalable and equitable.

For K–12 mathematics teachers, our review highlights that Intelligent Tutoring Systems (ITS) such as ASSISTments (Gurung et al., 2024; Vanacore et al., 2023; Zambrano & Baker, 2024) consistently improve performance when they provide adaptive difficulty levels and automated, immediate feedback. Teachers can use the system's dashboards not only to assign practice tasks but also to identify patterns of misconceptions and form small groups for targeted support. Embedding self-regulated learning prompts (e.g., encouraging students to review hints or set goals within the platform) has also been shown to strengthen problem-solving skills and persistence (Iraj et al., 2020; Molenaar et al., 2021).

For Higher Education instructors in engineering and sciences, immersive technologies offer promising avenues to address abstract or spatially complex concepts. For example, VR-based learning environments have been shown to improve students' ability to visualize and manipulate manufacturing processes (Suarez-Warden et al., 2023) and to enhance understanding of biological concepts such as genetics (Christopoulos et al., 2023). These tools are most effective when paired with structured activities such as guided inquiry or post-simulation reflection tasks (Lo & Tsai, 2022), ensuring that technology deepens rather than substitutes conceptual understanding.

6. Study limitations and recommendations for future reviews in TEL-LA research in STEM

As with all research works, the present review also comes with several limitations that must be acknowledged.

First, our search strategy focused exclusively on interventional studies that featured technological platforms or environments and LA practices. The methodological decision, while ensuring we captured studies with clear TEL-LA implementations, may have excluded relevant research that could inform our understanding of PSL. Precisely, we captured only 31 studies over five years, which might not represent the full breadth of work being conducted in such a rapidly evolving field.

Second, although we investigated well-known academic databases to identify relevant research on PSL and education, our search terms and database selection may have introduced biases. The STEM subjects are extremely diverse, and studies may have been omitted owing to variations in terminology or because they did not explicitly mention STEM-related educational outcomes in their abstracts or keywords. Some relevant work published in discipline-specific venues or in languages other than English would not have been captured by our search strategy.

Third, we reviewed studies based on their reported learning outcomes but did not conduct a quantitative synthesis or meta-analysis. We did not calculate effect sizes or assess the statistical significance of reported impact, which limits our ability to make comparative judgments about the relative effectiveness of different TEL-LA approaches or to determine which interventions yield practically meaningful improvements.

Fourth, our analysis relied on information reported in the published articles, which varied considerably in detail and scope. Some studies provided rich descriptions of their TEL-LA implementations, while others offered limited technical or pedagogical details, constraining our ability to identify specific features that contribute to successful interventions.

The following recommendations can be taken into consideration for future reviews in the TEL-LA domain:

First, expand search strategies beyond interventional studies to include observational, qualitative, and longitudinal research designs. This broader scope would enable a more comprehensive understanding of how TEL-LA systems function across varied educational contexts and how they influence learner autonomy outside controlled experimental settings.

Second, develop more inclusive search criteria to capture the full diversity of STEM-related research. Future reviews could employ dual search strategies: one targeting explicit STEM terminology and another identifying discipline-specific studies that may use different vocabulary to describe similar phenomena.

Third, conduct meta-analytic reviews that synthesize evidence through effect sizes (e.g., Cohen's *d*). This quantitative approach would deepen understanding of how varying levels of personalized support and TEL-LA implementation impact learning outcomes, while also facilitating rigorous evaluation of differential effects across student populations and educational contexts.

7. Conclusion

The present scoping review synthesized 31 empirical intervention studies from 2020–2024 to understand how TEL-LA interventions support PSL. Our findings reveal that TEL-LA interventions have yielded measurable improvements, with approximately two-thirds of studies reporting positive impact on academic performance, engagement, and cognitive development. Especially noteworthy was the consistent finding that SRL strategies, when embedded within ALP, produced improvements across multiple learning dimensions—from problem-solving capabilities to metacognitive accuracy.

Nevertheless, the review exposes significant challenges that temper enthusiasm for wholesale adoption. The geographic concentration of research in Western contexts raises fundamental questions about the generalizability and cultural appropriateness of current personalization models. The prevalence of small-scale interventions and methodological limitations (e.g., selection bias, missing data, limited longitudinal assessment) indicates that the evidence base, while promising, requires substantial strengthening before TEL-LA can be considered a mature educational approach.

A major limitation of current interventions is their short time horizon. Our findings imply the need to study TEL-LA not just for immediate grade improvements but for its impact on STEM career pathways, persistence in learning, and identity formation. A field-shaping implication is that future research must integrate longitudinal metrics and career relevance, positioning TEL-LA as a determinant of workforce readiness and STEM pipeline development.

CRediT authorship contribution statement

Umar Bin Qushem: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Athanasios Christopoulos:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Rogers Kaliisa:** Writing – review & editing, Validation, Methodology, Conceptualization. **Mohammad Khalil:** Writing – review & editing, Validation, Methodology. **Tapio Salakoski:** Validation, Supervision, Project administration, Conceptualization. **Mikko-Jussi Laakso:** Validation, Supervision, Resources, Funding acquisition, Conceptualization.

Declaration of competing interest

No potential conflict of interest was reported by the author(s).

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Appendices

Fig. A.1, Table B.1

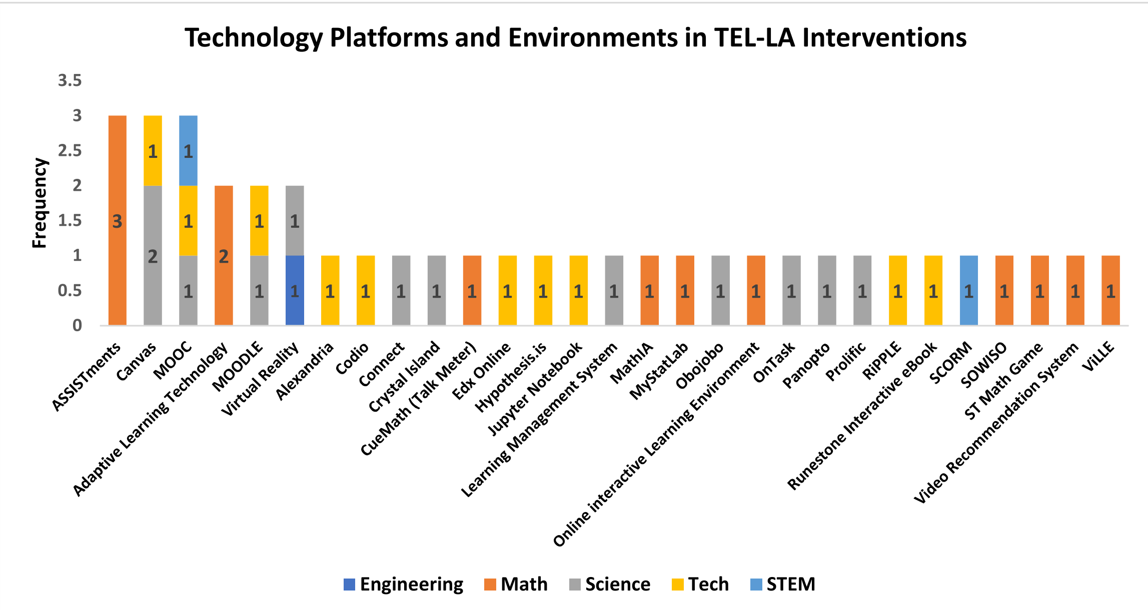

Fig. A.1. Technology platforms by Domain.

Table B.1
Technology platforms and environments used among TEL-LA intervention for PSL.

Categories	Specification	Frequency
Digital Learning Environments (DLEs)	Alexandria	1
	Canvas	3
	Connect	1
	Crystal Island	1

(continued on next page)

Table B.1 (*continued*)

Categories	Specification	Frequency
	Edx Online	1
	Hypothesis.is	1
	Learning Management System	1
	MOOC	3
	MOODLE	2
	Obojobo	1
	Online Interactive Learning Environment	1
	Panopto	1
	Prolific	1
	Runestone Interactive eBook	1
	SCORM	1
	ViLLE	1
Adaptive Learning Platforms (ALPs)	Adaptive Learning Technology	2
	ASSISTments	3
	CueMath	1
	MathIA	1
	MyStatLab	1
	RiPPLE	1
	SOWISO	1
	ST Math Game	1
	Video Recommendation System	1
Technology-mediated Learning Environments (TMLEs)	Codio	1
	Jupyter Notebook	1
	OnTask	1
	Virtual Reality	2

Fig. A.2, Table B.2

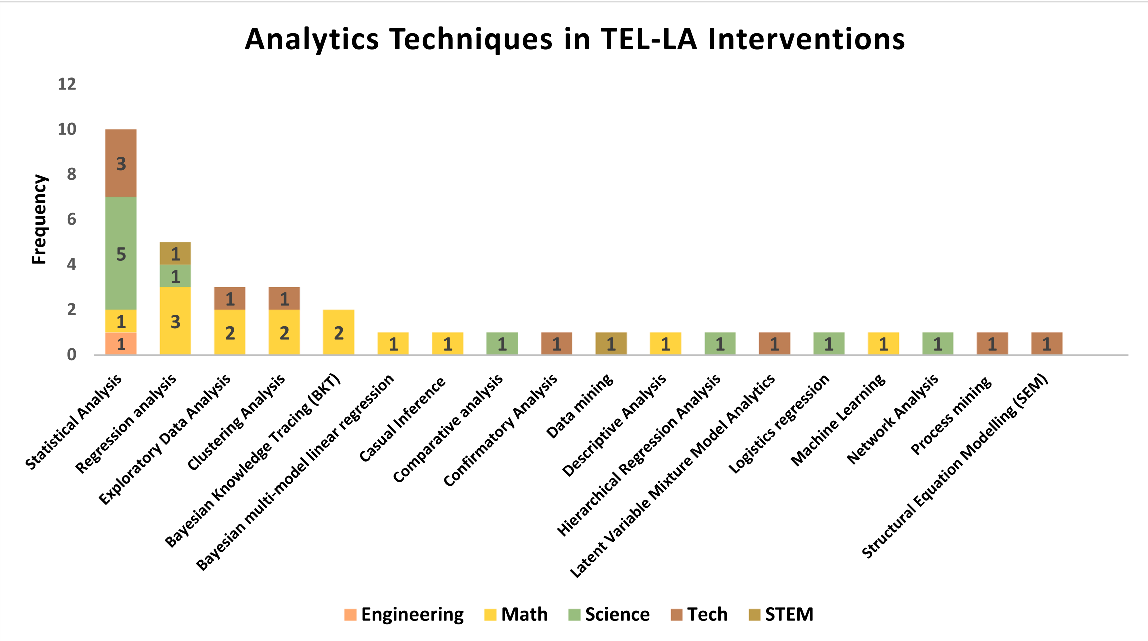

Fig. A.2. Analytics techniques by domain.

Table B.2
Learning analytics techniques applied among TEL-LA intervention studies for PSL.

Categories	Specification	Frequency
Statistical Analyses	Statistical Analysis	9
Inferential Analyses	Bayesian Multi-model Linear Regression	1
	Confirmatory Analysis	1
	Hierarchical Regression Analysis	1
	Regression Analysis	5
	Structural Equation Modelling	1
Machine Learning	Clustering Analysis	3

(continued on next page)

Table B.2 (*continued*)

Categories	**Specification**	**Frequency**
	Data Mining	1
	Machine Learning	1
	Network Analysis	1
	Process Mining	1
Descriptive Analyses	Descriptive Analytics	1
	Exploratory Data Analysis	4
Predictive Analyses	Bayesian Knowledge Tracing	2
	Logistic regression	1
Casual Analysis	Casual Inference	1
Statistical Modelling	Latent Variable Mixture Model Analytics	1
Decision-Based Analysis	Comparative Analysis	1

Fig. A.3, Table B.3

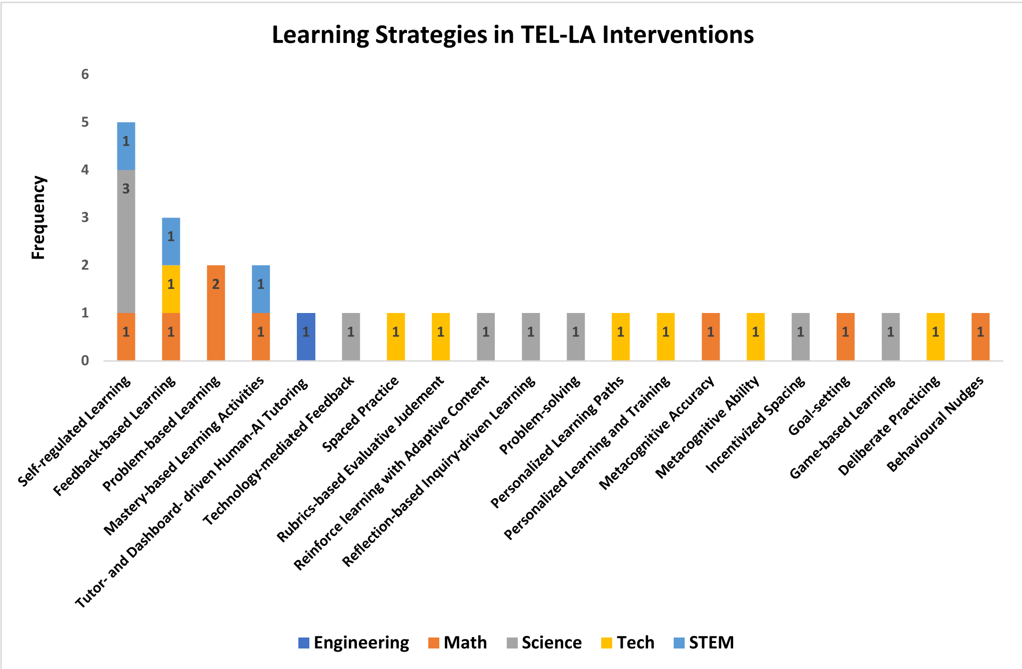

Fig. A.3. Learning strategies by domain.

Table B.3
Overview of the learning strategies utilized in TEL-LA interventions.

Categories	Specification	**Frequency**
Self-Regulated and Metacognitive Learning	Metacognitive Ability	1
	Metacognitive Accuracy	1
	Reflection-based Inquiry-driven Learning	1
	Self-regulated Learning	5
Feedback-Based Learning	Feedback-based Learning	3
	Personalized Feedback	1
	Rubrics-based Evaluative Judgment	1
	Technology-mediated Feedback	1
	Tutor- and Dashboard-driven Human-AI Tutoring	1
Motivation and Behavioral Strategies	Affective States-based Learning Enhancement	1
	Behavioral Nudges	1
	Goal-setting	1
	Incentivized Spacing	1
Problem-Based Learning	Problem-based Learning	2
	Problem-solving	1
Personalized and Adaptive Learning	Personalized Learning and Training	1
	Personalized Learning Paths	1
	Reinforce Learning with Adaptive Content	1
Mastery-Based Learning	Mastery-based Learning Activities	2
Practice-Based Learning	Deliberate Practicing	1

(*continued on next page*)

Table B.3 (*continued*)

Categories	Specification	Frequency
	Spaced Practice	1
Game-Based Learning	Game-based Learning	1

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