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REVIEW ARTICLE

A Meta-Analysis of Moderators of the Effects of Technology-Enhanced Adaptive Learning on Primary and Secondary Students' Learning Outcomes

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ABSTRACT

Background: Technology-enhanced adaptive learning, which includes Intelligent Tutoring Systems (ITSs), represents a significant research stream targeted at individualised learning. Although systematic review and meta-analysis studies have synthesised the evidence of technology-enhanced adaptive learning, most did not differentiate how this effect may promote different learning outcomes to varying degrees and especially did not shed much light on potential moderating effects.

Objectives: This comprehensive meta-analysis (CMA) is focused on the effects of technology-enhanced adaptive learning on cognitive, affective, and behavioural learning outcomes, considering a series of specific moderator variables.

Methods: This meta-analysis synthesised 69 studies from electronic databases and high-impact journals in educational technology published between 2012 and 2021, with a total of 9095 students.

Results and Conclusions: The findings indicate that technology-enhanced adaptive learning has a medium-positive effect on primary and secondary school students' learning in terms of cognitive, affective, and behavioural learning outcomes. Further moderator analyses revealed that factors in categories of research context, adaptive strategy, technology, and study quality significantly moderated the summary effect sizes for at least one learning outcome dimension. Twelve significant moderators for cognitive learning outcomes (e.g., subjects, adaptive targets, adaptive technology), two for affective learning outcomes (i.e., feedback type, data collection methods), and two for behavioural learning outcomes (i.e., learner characteristics, hardware used in experimental groups) were identified. The implications of the findings and directions for technology-enhanced adaptive learning practices are discussed.

Takeaway: Stakeholders need to be aware of what matters in technology-enhanced adaptive learning; it is not just the effectiveness of these adaptive learning systems but knowing how to develop, design, implement, and evaluate the effects that matter.

1 | Introduction

The increasing diversity of the student population in terms of their prior knowledge, learning styles, and working memory capacity (Siddique et al. 2019) and the integration of technology in education have promoted discussions about shifting from a *one-size-fits-all* approach to implementing adaptive learning around the world (Gurcan et al. 2021; Wang et al. 2020). The development of adaptive learning environments and the provision of adaptive content and instruction tailored to students' learning characteristics are increasingly prevalent (Tang et al. 2021). Specifically, technology-enhanced adaptive learning has

Practitioner Notes

- What is already known about the subject matter?
  - Technology-enhanced adaptive learning has become a critical concept.
  - The benefits of technology-enhanced adaptive learning were validated in meta-analyses.
  - More research is needed on the effects, particularly outside of higher education.
  - Moderators should be examined to improve our understanding of the effects.
- What does this paper add?
  - This study investigated the main effects on three types of learning outcomes.
  - Technology-enhanced adaptive learning model including four categories of moderator variables was developed.
  - 12 significant moderators for cognitive learning outcomes were identified.
- What are the implications of study findings for practitioners?
  - This paper provides evidence for effective adaptive learning.
  - Developers should prioritise the development of adaptive learning systems that consider and adapt to various learner characteristics.
  - Developers should prioritise the inclusion of elaborated feedback within adaptive learning systems.

become a critical paradigm in educational technology research (Xie et al. 2019), broadly emphasising content and instructional models together with learner models (Martin et al. 2020).

The goal of technology-enhanced adaptive learning is to provide high-quality education to all students regardless of their backgrounds, at any time, place, path, and pace. A qualitative synthesis study summarised the potential benefits of technology-enhanced adaptive learning to support individual learners (e.g., by increasing motivation and attitude and preparing for future careers), teachers (e.g., via learner feedback and learning analytics), and institutions (e.g., improving compulsory education) (FitzGerald et al. 2018). However, teachers may find it challenging to implement technology-enhanced adaptive learning in classes of approximately 30 students due to various barriers, such as equipment/technical infrastructure problems, and data privacy (Holmes et al. 2018).

The potential of technology-enhanced adaptive learning to facilitate various learning outcomes across cognitive, affective, and behavioural learning domains (Xie et al. 2019), underscores the need for a comprehensive examination of this field to address previous research limitations. In line with Bloom's Taxonomy (Bloom 1965) and empirical studies (e.g., Volk et al. 2017), the effectiveness of adaptive learning is evaluated in terms of its impact on cognitive, affective, and behavioural outcomes. Cognitive learning outcomes relate to academic results such as math and reading and are often assessed via standardised tests (Vanbecelaere et al. 2021). Affective learning outcomes reflect learners' emotions (e.g., anxiety, pleasure) and perceptions of experience and benefits from technology-enhanced adaptive learning, including motivation, attitude, usefulness, and satisfaction, which can be evaluated using self-report measures (Ritzhaupt et al. 2021). Behavioural learning outcomes relate to learners' actual behaviour and interactions in adaptive learning (e.g., time spent to gain mastery status, course completion) (Vanbecelaere et al. 2021; Wei et al. 2021).

Recently, researchers have further argued that more research is needed to figure out the conditions under which technology-enhanced adaptive learning is effective and relative to what learning conditions (Wang et al. 2020), especially on a global scale and outside the higher education field (Martin et al. 2020). To fill these gaps, this article presents robust evidence derived from a meta-analysis of experimental and quasi-experimental design studies. By specifically analysing the relative effectiveness of technology-enhanced adaptive learning in primary and secondary schools, this study provides valuable insights into its impact on students' cognitive, affective, and behavioural learning outcomes. This research surpasses the constraints of previous meta-analyses, which were limited by their focus on specific populations, technologies, or outcomes, as well as a small number of experimental design studies. Through a comprehensive analysis incorporating various moderators, such as research context, adaptive strategy, technology, and study quality, this study significantly enhances our understanding of the factors that shape the effectiveness of technology-enhanced adaptive learning interventions. Additionally, by incorporating the latest advancements in artificial intelligence and newer adaptive learning technologies, this meta-analysis offers a contemporary perspective on the field, providing a solid foundation for informed decision-making and future advancements in educational practice.

Furthermore, this study bridges knowledge gaps and offers a comprehensive overview of the current state of technology-enhanced adaptive learning in primary and secondary education. These educational sectors possess distinct characteristics and pedagogical considerations that differ significantly from postsecondary education. Prior research, for example Schmid et al. (2014), has underscored the importance of tailored pedagogical strategies that address the diverse learning needs and motivations across different age groups. By focusing specifically on primary and secondary education, this study aims to investigate the effectiveness of technology-enhanced adaptive learning within the context of compulsory education. The exclusion of older learners and postsecondary education allows for an exploration of the unique challenges and opportunities specific to compulsory education. Ultimately, this research sheds light on how technology-enhanced adaptive learning interventions effectively meet the distinctive requirements and developmental stages of students at the primary and secondary levels, fostering their academic growth and personal development.

1.1 | Technology-Enhanced Adaptive Learning

The various definitions of adaptive learning in the scientific literature indicate that a more common understanding is needed. Furthermore, adaptive learning has been associated with other concepts, mostly with personalised learning, without clearly demarcating their boundaries (Shemshack and Spector 2020). Peng et al. (2019) conclude that adaptive learning and personalised learning both emphasise individual differences, individual performance, and adaptive adjustment. However, it is challenging to implement personalised learning without technology (Patrick et al. 2013). Therefore, boundaries between *personalised learning* and *adaptive learning* become vague if restricted to the context of *technology-enhanced learning* (Xie et al. 2019).

In a review of personalised learning terms, Shemshack and Spector (2020) found that adaptive learning is mainly used in technology-enhanced learning contexts, even though personalised learning is becoming more integrated with technology and taking advantage of what it offers. In this study, by adopting the term *technology-enhanced adaptive learning*, we aimed to highlight both *technology-enhanced learning* and *adaptive learning*, which refers to *an emerging learning technology that dynamically adjusts instructional content to provide interactive and personalised learning paths to the individual to facilitate learning* (Martin et al. 2020). This definition has been used in the most recent systematic review on adaptive learning and we acknowledge that the term will evolve with time.

Previous narrative reviews describe several central issues in technology-enhanced adaptive learning research, bringing diverse perspectives on research context, adaptive strategy, and technology, study quality, and learning outcomes. Regarding research context, systematic reviews have been conducted across various educational levels and subject domains over the last 4 years, with the majority of included studies focusing on higher education settings and employing computer science and sciences (Martin et al. 2020; Mousavinasab et al. 2021; Xie et al. 2019).

The adaptive strategy used in the adaptation of instructional content has received much attention in various review studies. Considering the important role of both adaptive sources based on the learner model and adaptive targets based on the content and instructional model (Martin et al. 2020), researchers have shifted their attention from the learner model (e.g., learning styles, Afini Normadhi et al. 2019; Özyurt and Özyurt 2015; Truong 2016) to the technology-enhanced adaptive learning model, which incorporates both source and target (Slavuj et al. 2017). Moreover, feedback is one of the key characteristics of technology-enhanced adaptive learning. A recent review revealed that the majority of systems provided immediate feedback based on student behaviours, or after the task completion; however, only a few systems provided feedback upon request (Deeva et al. 2021).

In addition to adaptive strategy, recent studies examined various types of adaptive technology, such as adaptive learning systems, adaptive learning applications, adaptive teaching approaches, and adaptive designs (see Martin et al. 2020), and narrative reviews into intelligent tutoring systems (ITSs) (Mousavinasab et al. 2021) or adaptive educational hypermedia (Özyurt and Özyurt 2015) are available. Despite the rapid growth of mobile technologies, still traditional computers or devices are most often adopted for running adaptive learning systems (Xie et al. 2019), and systems designed for web user interfaces increase over time (Deeva et al. 2021; Mousavinasab et al. 2021).

Furthermore, study quality is increasingly recognised as a critical factor influencing learning outcomes, as studies with weaker designs, smaller sample sizes, or non-independent measures often report inflated effect sizes (Cheung and Slavin 2016; Wang et al. 2023). Therefore, in this study, we included study quality as a moderator to systematically examine its role in technology-enhanced adaptive learning. Experimental designs are mostly employed in technology-enhanced adaptive learning (Martin et al. 2020; Zhang et al. 2020). Frequent evaluation methods are tests and surveys (see e.g., Deeva et al. 2021; Martin et al. 2020; Truong 2016). Regarding learning outcomes, despite many positive findings, including cognitive, affective, and behavioural learning outcomes, there are few negative or neutral findings (Özyurt and Özyurt 2015; Xie et al. 2019).

Although existing studies provide helpful insights and efforts have been made to construct search strings (Afini Normadhi et al. 2019), most of the aforementioned narrative reviews employed only one or two keywords pertaining to adaptive learning and restricted access to specific databases, hence limiting the number of articles being retrieved. More importantly, without statistical methods to calculate an overall effect and identify potential moderators, it remains unclear to what extent technology-enhanced adaptive learning works compared with which groups.

1.2 | Potential Moderators Considered

Scholars have extensively explored the benefits of technology-enhanced adaptive learning by emphasising its heightened levels of interactivity and adaptability when compared to teacher-led instruction and traditional technology-enhanced learning approaches (i.e., multimedia PowerPoint presentations). Specifically, previous empirical studies have attributed the effectiveness of technology-enhanced adaptive learning to engaging and appealing to students (Baker et al. 2017), the effects of feedback directed to students rather than teachers (Faber et al. 2017), the importance of timely, situation-aware and personalised affective feedback (Daradoumis and Arguedas 2020), and the adaptivity feature that caters to individual needs and facilitates monitoring of solutions (Hooshyar, Malva, et al. 2021).

The superiority of technology-enhanced adaptive learning over other modes of instruction in relation to various learning outcomes has been consistently substantiated by previous meta-analyses. In Appendix A, we provide a comprehensive overview of nine meta-analyses that have examined the effects of technology-enhanced adaptive learning on learning outcomes. These collective findings form the basis for our proposition that the effects of technology-enhanced adaptive learning on learning outcomes are subject to moderation by multiple variables, thereby enabling its proficiency across each of the aforementioned advantages when contrasted with other instructional approaches.

In order to provide a robust justification for exploring these moderators, we have categorised them into two main categories: adaptive strategy and adaptive technology, drawing upon the Adaptive Learning Framework proposed by Martin et al. (2020). Additionally, we have included research context and study quality as important categories derived from both contextual and methodological perspectives. Through this categorisation, we aim to comprehensively address the factors that may moderate the relationship between technology-enhanced adaptive learning and learning outcomes. By considering these different categories of moderators, we seek to deepen our understanding of the underlying mechanisms and identify the specific conditions under which technology-enhanced adaptive learning is most effective.

Firstly, research context plays a crucial role in moderating the effects of technology-enhanced adaptive learning, as indicated by several meta-analyses. Educational levels (e.g., Kulik and Fletcher 2016), subjects (e.g., Ma et al. 2014) and prior domain knowledge (e.g., Ma et al. 2014) have been identified as significant moderators in influencing the outcomes of adaptive learning interventions. For example, Ma et al. (2014) found that ITS was particularly beneficial for students with low prior domain knowledge compared to those with medium prior domain knowledge. However, a different meta-analysis by Steenbergen-Hu and Cooper (2013) focusing on the impact of ITS on mathematical learning among K-12 students revealed that general students benefited more than low achievers from using ITS. These inconsistent findings suggest that the effects of technology-enhanced adaptive learning can vary depending on the research context. To further explore this, Major et al. (2021) proposed considering additional population characteristics, for example, community type (rural vs. urban) and socioeconomic status, to support the development of personalised technology that is contextually appropriate.

Secondly, adaptive strategy factors encompass various dimensions, including the instructional role of adaptive instruction, learner characteristics, content and instructional characteristics (i.e., adaptive targets), and feedback provided. Meta-analyses by Ma et al. (2014) and Steenbergen-Hu and Cooper (2014) examined the instructional role of adaptive instruction, such as integrated class instruction, separate in-class activities, and homework. However, their findings differed, highlighting the need for further investigation. In terms of learner characteristics and adaptive targets, Major et al. (2021) observed that highly personalised approaches that adapt to students' difficulty level and learning pace tended to yield larger effect sizes compared to approaches that primarily match learners' interests or experiences and provide personalised feedback. Furthermore, in relation to adaptive targets, the use of software with tailored prompts and personalised guidance showed promising results (Zheng et al. 2022). While previous research demonstrated the effectiveness of ITS in improving learning outcomes regardless of feedback provision (Ma et al. 2014), the significance of feedback in adaptive learning should not be underestimated. Shute's (2008) comprehensive review study emphasised the importance of distinguishing between feedback type and feedback timing. Feedback types include elaborated feedback, knowledge of results, knowledge of correct results, and no feedback. Feedback timing encompasses immediate or action-based feedback, upon-request feedback, and end-of-task feedback (Deeva et al. 2021). It is important to note that feedback types and feedback timing have not been explored as potential moderators in previous meta-analyses. By incorporating these factors into our analysis, we aim to gain a deeper understanding of their influence on the effectiveness of technology-enhanced adaptive learning.

Third, technology factors include adaptive technology, hardware used in experimental groups, comparison treatments, and degree of technology use in control groups. Regarding adaptive technology, previous research highlighted the significant moderating effects of specific types of ITSs (Ma et al. 2014). However, our study aims to expand the scope of the investigation to encompass a wider range of adaptive technology, including adaptive learning systems/applications and adaptive teaching approaches or adaptive design solutions proposed by Martin et al. (2020). By incorporating these elements, a comprehensive understanding of how adaptive technology enhances learning outcomes will be achieved. Notably, previous meta-analyses on technology-enhanced adaptive learning did not specifically examine the hardware used in experimental groups. However, a review study on technology-enhanced adaptive learning from 2007 to 2017 revealed the utilisation of various hardware types to support adaptive/personalised learning (Xie et al. 2019). Traditional hardware systems were predominantly used, while personalised/adaptive systems in wearable devices were lacking. Investigating the specific hardware used in experimental groups is crucial to understanding its role, particularly in relation to recent studies and the emerging trend of wearable learning technologies. Furthermore, comparison treatments in previous meta-analyses on ITSs, such as large-group human instruction, small-group human instruction, individual human instruction, individual computer-based instruction (CBI), or individual textbook/workbook instruction, were identified as significant moderators (Ma et al. 2014; Xu et al. 2019). Expanding on this insight, a hypothesis is proposed that the advantage observed in technology-enhanced adaptive learning, compared to other instructional modes, may be attributed to its shared characteristics with other forms of individual instruction and CBI. Additionally, the degree of technology use in control groups, including pen-and-paper or traditional technology, was recognised as a moderator influencing the overall effect sizes for learning outcomes in the context of mobile learning (e.g., Wang et al. 2023). Expanding on this finding, it is proposed that the intervention groups, employing technology-enhanced adaptive learning, outperform control groups, regardless of the degree of technology use within the control groups.

Fourth, many study quality factors, including research design (Liu et al. 2020; Ma et al. 2014), intervention duration (Steenbergen-Hu and Cooper 2013), data collection methods (e.g., test type; Kulik and Fletcher 2016), group assignment (Kulik and Fletcher 2016), and instructor effects (Kulik and Fletcher 2016) have been widely considered as moderators in previous meta-analyses. Given the focus on primary and secondary education in this study, it is crucial to examine these variables and elucidate their roles in influencing technology-enhanced adaptive learning within this specific educational context. Furthermore, the effects of the procedure of ES Extraction and learning content/topic equivalence, which are important quality features (Abrami and Bernard 2012), have not been adequately explored in previous meta-analyses. Additional investigation is required to explore the potential moderating effects of the procedure of ES Extraction and learning content/topic equivalence in technology-enhanced adaptive learning. Moreover, concerns have been raised about the level of rigour in experimental designs of mobile-learning studies, with a majority demonstrating low or medium-low levels of rigour (Sung et al. 2019). Therefore, we propose employing the Checklist for the Rigour of Education-Experiment Designs as a tool to evaluate the level of rigour in experimental designs and assess its potential significance as a moderator.

Although previous meta-analyses analysed the status of technology-enhanced adaptive learning, these studies also had limitations. One limitation is the small number of experimental design studies. These studies could not conduct a comprehensive moderator analysis with a limited sample. Furthermore, additional moderators, such as populations, specific features of adaptive learning systems (Major et al. 2021; Martin et al. 2020; Xu et al. 2019), and study quality (Abrami and Bernard 2012; Sung et al. 2019) should be examined in a more exploratory fashion. Second, previous meta-analyses had a limited scope, either only synthesising cognitive learning outcomes (e.g., Liu et al. 2020; Ma et al. 2014; Steenbergen-Hu and Cooper 2014) or only focusing on health professionals and students (e.g., Fontaine et al. 2019) or educational games (e.g., Liu et al. 2020). Although Zheng et al. (2022) investigated the effects of various adaptive learning approaches on learning achievements and learning perception, the contrasts in the categories of adaptive strategy were very small, and moderator analyses did not include affective effects, which limits the generalisation of moderating effects. The third limitation is that previous meta-analyses narrow adaptive learning systems to ITS (e.g., Ma et al. 2014; Steenbergen-Hu and Cooper 2014; Xu et al. 2019), thus ignoring that many newer systems grounded in artificial intelligence have meanwhile been developed and implemented in schools. This meta-analysis, therefore, aims to provide new knowledge regarding the effectiveness of technology-enhanced adaptive learning and to increase our understanding of the various moderators that may influence learning outcomes in primary and secondary schools.

1.3 | The Present Study

The present study aims to make a significant contribution to the field of technology-enhanced adaptive learning by addressing limitations identified in previous meta-analyses. These earlier studies have exhibited certain shortcomings, including a limited exploration of moderator variables and a narrow focus on specific dimensions of learning outcomes (see Appendix A for detailed information). Moreover, the inclusion of relatively outdated adaptive learning technologies has restricted the generalizability of their findings. In contrast, our study expands its scope by adopting a systematic and meticulous approach to overcome these limitations. Additionally, our study endeavours to address the lack of consensus and the need for further investigation in primary and secondary education settings, as highlighted by the systematic review conducted by Martin et al. (2020). That review sheds light on the accelerated growth of technology adoption and online learning in higher education, suggesting contextual disparities in the utilisation of technology between primary/secondary education and higher education. By specifically focusing on primary and secondary education, our study enables us to explore the effectiveness of technology-enhanced adaptive learning within these distinctive contexts and provide valuable insights specific to these age groups.

The primary objective of this work was to systematically review and meta-analyse peer-reviewed true experiments and quasi-experiments that focused on students' learning in primary and secondary education. The effectiveness of adaptive learning is investigated in terms of cognitive, affective, and behavioural outcomes, in line with existing educational theory (Bloom 1965) and empirical evidence (e.g., Volk et al. 2017). Based on the existing narrative reviews and meta-analyses, and drawing on the four categories of potential moderators, we developed the research model that guided our study (see Figure 1). The purpose of this meta-analysis is to address two research questions specifically:

RQ1. Compared with other modes of instruction, what is the overall effectiveness of technology-enhanced adaptive learning in primary and secondary education on student learning outcomes in terms of cognitive, affective, and behavioural dimensions?

RQ2. What, if any factors, that is research context factors, adaptive strategy factors, technology factors, and study quality factors, moderate the relationship between technology-enhanced adaptive learning and student learning outcomes?

2 | Method

2.1 | Inclusion and Exclusion Criteria

Inclusion criteria including conceptual relevance, and exclusion criteria were established before coding the studies (Cooper 2017).

2.1.1 | Inclusion Criteria

1. Participants: studies had to focus on students in general primary and secondary education. Specifically, primary education encompassed participant samples within the age range of 5–11 years, while secondary education included ages ranging from 12 to 18 years. These age brackets align with the recommendation provided by Van Schoors et al. (2021).
2. Research articles: the effects of technology-enhanced adaptive learning on student learning outcomes had to be investigated empirically.
3. Study design: studies had to employ an experimental or quasi-experimental research design.
4. Intervention and comparison: studies had to employ an independent comparison condition. The results of the technology-enhanced adaptive learning experimental group were compared with control group students using other modes of instruction. Each article must specifically address the use of adaptive learning systems, such as digital formative assessment (e.g., Snappet; Faber et al. 2017;

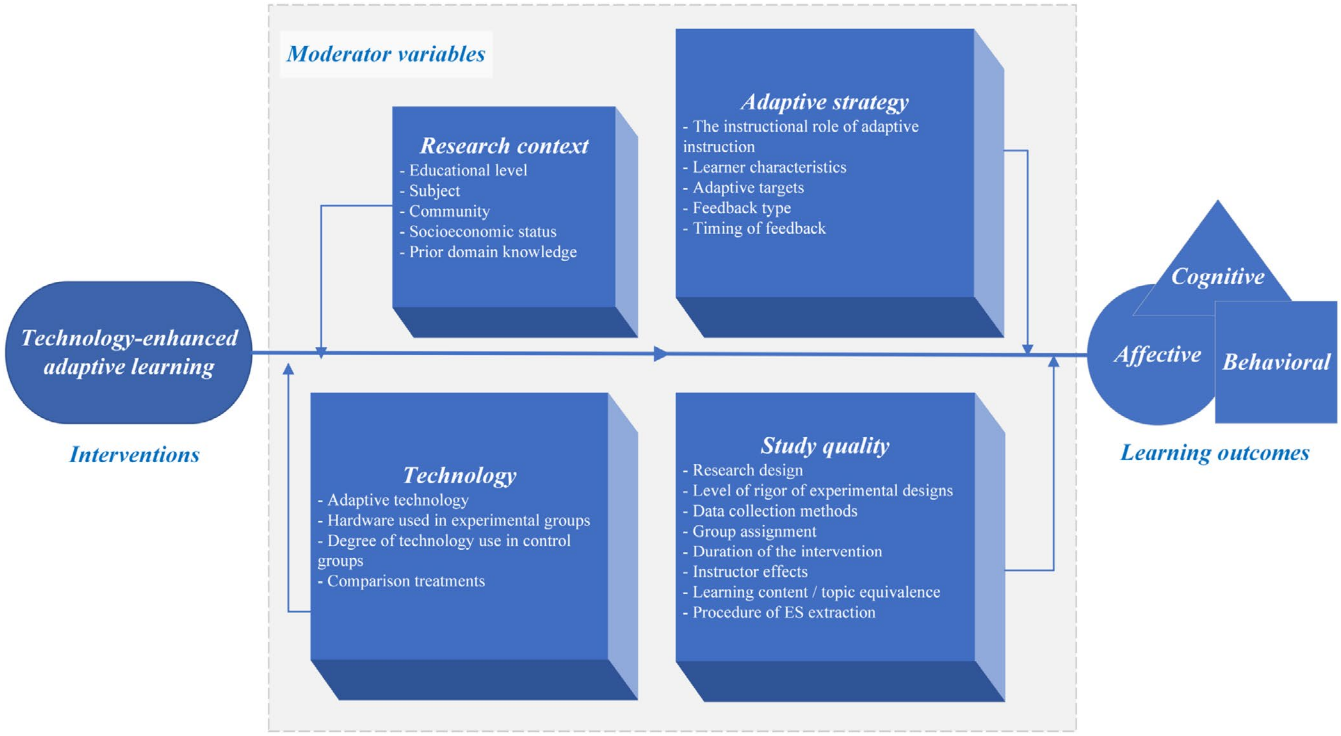

FIGURE 1 | Technology-enhanced adaptive learning model including four categories of moderator variables considered and three types of learning outcomes.

Faber and Visscher 2018), and computer-based assessment (e.g., Got it Language; Admiraal et al. 2020), to support student learning. As we are interested in variations in technology-enhanced adaptive learning, we have incorporated four types of moderators from the perspective of technology. Importantly, our classification of control conditions (i.e., degree of technology use in control groups, comparison treatments), is informed by established frameworks observed in prior research (e.g., Ma et al. 2014; Major et al. 2021).

5. Measures of learning outcomes: studies had to measure the effectiveness of the technology-enhanced adaptive learning on at least one learning outcome, such as post-test score, learning motivation, and time on task.
6. Data: studies had to provide the necessary quantitative information (e.g., means, standard deviations, the sample size in each group) for the computation or estimation of ESs.
7. Publication status: articles must be published in peer-reviewed publications with access to the complete version. Although unpublished literature (such as dissertations and reports) may contain valuable data, it often lacks the quality assurance provided by peer review. To address concerns about publication bias, we conducted several analyses to evaluate the robustness of our findings (see Section 3.2 for details).
8. Timing: English-language articles were published between 2012 and 2021. Choosing 2012 as the beginning year was because the number and functionality of adaptive learning systems have been developed and implemented since then (see e.g., Chu et al. 2014). Moreover, several prior meta-analyses (e.g., Kulik and Fletcher 2016; Ma et al. 2014; Steenbergen-Hu and Cooper 2013; VanLehn 2011) have examined the effectiveness of ITS on student learning outcomes in primary and secondary education, including published studies in 2012 or before.

2.1.2 | Exclusion Criteria

The subsequent exclusion criteria were applied. Firstly, secondary data analyses, reviews, qualitative research, non-experimental research, and non-empirical research were excluded. Furthermore, we excluded research that focuses on gifted and special education students.

2.2 | Literature Search and Study Selection

Studies were identified from two different sources, enabling us to include more potential publications. First, after consultation with a librarian, a database search was performed at the library of University of Leiden. The search was conducted using the University Libraries catalogue, which utilises the Central Discovery Index (CDI) containing academic material and links to over 800 subscribed databases. Examples of major databases included in the search are EBSCOhost, ERIC (Educational Resources Information Center), Google Scholar, JSTOR, Sage journals online, ScienceDirect, Taylor & Francis online, Web of Science, and Wiley Online Library. Five groups of keywords were connected by the Boolean operator AND: (1) participant (i.e., student); (2) adaptive learning related terms (i.e., adaptive learning, adaptive feedback, adaptive gam*, adaptive computer, adaptive assignment, adaptive difficulty adjustment, intelligent adaptation, adaptive testing, adaptive assessment, individualise, personalise, formative assessment, tailored); (3) technology-related terms (i.e., technology, tool, game, computer, system, program, application); (4) learning outcomes related keywords (i.e., assessment, evaluation, post-test, learning outcome, learning result, performance, achievement, gain); and (5) research designs (i.e., experimental and quasi-experimental). The inclusion of the keyword "student" was necessitated by limitations imposed by the library, as we had already utilised a significant number of search terms for interventions and learning outcomes, making it the most optimal choice to ensure comprehensive coverage within the given constraints. Within each group, similar terms were combined by the Boolean operator OR.

Concurrently, we did an advanced search using the following restrictions to filter our results, incorporating the aforementioned keywords: (1) the retrieval scope of the group of terms, specifically adaptive learning, is limited to the title, while other keywords can be retrieved in any field; (2) the publication must be an online, peer-reviewed journal article; (3) the publication date has to fall between January 1, 2012 and December 31, 2021; and (4) the publication must be in English. The search date was May 26, 2021. A total of 1007 documents were collected and imported into Mendeley using this procedure. Because no duplicate was identified, the 1007 publications remained for consideration. Next, according to the criteria, one author (JW) carefully read each paper's title and abstract to evaluate if the studies were 'yes', 'maybe', or 'no' (Liberati et al. 2009; Wang et al. 2023) and assigned the papers in the 'maybe' group to the other two authors (DT and WA) for the final decision. At this step, 56 eligible papers were obtained.

Moreover, to expand our search results without limiting the adaptive learning-related keywords to the title, in June 2021, we purposefully selected six influential journals and browsed them online, including the *British Journal of Educational Technology*, *Computers & Education*, *Educational Technology Research and Development*, *Educational Technology & Society*, *Journal of Computer Assisted Learning*, and *Interactive Learning Environments*. *Adapt** was searched anywhere within the journals' websites, since we focus on adaptive learning systems. This constraint narrows our search to systems that specifically address adaptive learning. However, it was not possible to type *adapt* to search within all articles in the journal website of *Educational Technology & Society*, so we decided to include all articles published since 2012 for further screening. The last search date was June 8, 2021. From this journal search, we initially identified 4086 articles. After removing 48 duplicates within this set, two reviewers screened the titles and abstracts of the remaining articles. This process yielded 91 additional eligible studies. These were then combined with the 56 studies identified through the database search, resulting in a total of 147 studies selected for full-text review.

At the last full-text screening step, article eligibility was evaluated by three independent reviewers. Through paired discussions, disagreements were resolved until consensus was obtained. At this stage, 69 studies from 55 journal articles met the criteria and were added to this meta-analysis. In our meta-analysis, the term *studies* refers to individual investigations with a defined group of participants and one or more interventions and outcomes, as defined by the PRISMA guidelines. The study selection procedure according to The PRISMA 2020 guidelines (Page et al. 2021) is illustrated in Figure 2.

2.3 | Coding Procedures

All coding was conducted by two independent authors (JW and TY). To ensure that the remaining papers could be coded, and data extracted systematically, we carefully read each one thoroughly. Initially, a codebook describing the coding procedure for included studies was developed, and the categories of each variable were derived from previous systematic reviews or meta-analysis literatures (e.g., Deeva et al. 2021; Kulik and Fletcher 2016; Ma et al. 2014; Martin et al. 2020; Shute 2008; Sung et al. 2019; Xie et al. 2019). This phase began with a training session on the code book. After coding 11 papers identified in the University library, reviewers attended another training session to address coding disagreements with other authors and resolve inconsistencies in coding. Following this round of pilot coding, the codebook was revised to enhance transparency in the coding process and remove unnecessary information (Cooper 2017).

The final codebook can be found in Appendix B. For example, based on the theory and empirical studies, the codebook categorised the dependent variables into three outcome types: cognitive learning outcomes, which encompassed measures related to knowledge and test performance; affective learning outcomes, which focused on emotional and attitudinal factors such as motivation and satisfaction; and behavioural learning outcomes, which examined aspects such as interaction and completion time. This comprehensive approach allowed us to effectively cluster and analyze the three dimensions of learning outcomes.

The resulting Cohen's Kappa for all variables was from 0.374 (95% CI = 0.162, 0.586) to 1 (95% CI = 1, 1), and the overall inter-rater reliability between the two coders was 0.894 (95% CI = 0.876, 0.812). The disagreements between the two coders for each variable were then identified and discussed. In the event of a disagreement, the two coders and a third researcher discussed it together to reach a consensus.

2.4 | Effect Size Calculation

The dependent variable in this meta-analysis was the standard difference from the mean between the intervention group and the control group. *Effect sizes* represent the quantification of treatment effects observed within each study. We used Hedges' g since it is suitable for small sample sizes (Borenstein et al. 2009). A positive ES indicates that the intervention group outperformed the control group. According to Cohen (1992), the Hedges' g values of any set are as follows: 0.2 is considered small, 0.5 is considered medium, and 0.8 is considered large.

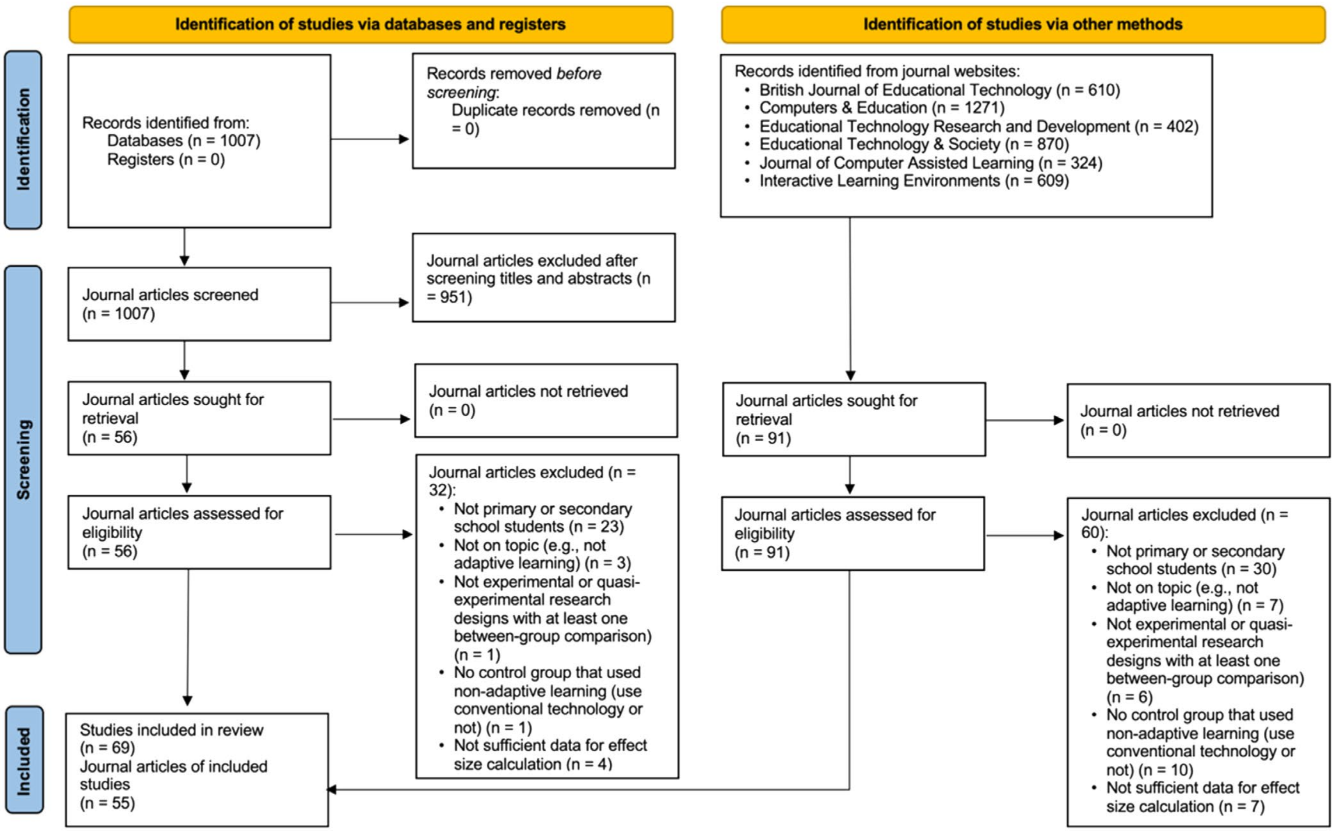

FIGURE 2 | Flowchart of the study selection process following the guidelines of The PRISMA 2020 (Page et al. 2021).

As scores showing changes from the baseline to subsequent ones are not independent, ESs were estimated using means and standard deviations from the post-baseline (Cuijpers et al. 2017). This methodological choice helps mitigate biases associated with pre-post comparisons, ensuring a more accurate assessment of treatment effects. When post-test data was unavailable, alternative inferential statistics were utilised as long as they could differentiate between the different conditions.

Using the software Comprehensive Meta-Analysis (CMA) Version 2, we independently calculated ESs for each contrast regarding cognitive, affective, and behavioural outcomes. An ES was calculated for each outcome when multiple outcomes from a study were extracted.

2.5 | Data Analysis

We employed the same strategies as the previous meta-analysis (Wang et al. 2023) to address statistical dependence arising from multiple effect sizes within individual studies and to ensure compatibility with the assumptions of the random-effects model. We identified 13 studies with multiple comparisons and conducted sensitivity analyses using only a single effect size per study (either the largest or the smallest). The results revealed no significant differences (see Section 3.3). In cases where there were multiple outcomes or time points within a study, we calculated a synthetic effect size by averaging across the reported outcomes, following a conservative approach to reduce the influence of within-study dependency (Borenstein et al. 2009). This method accounts for the dependent nature of the outcomes and ensures a more robust combination of the data. We also made sure to include the measurement closest to the end of the intervention to minimise confounding factors when multiple time points were available. Furthermore, for studies involving multiple independent experiments, we treated each experiment as an individual study and analyzed the effects within them as the primary unit of analysis. After addressing within-study dependencies, all resulting study-level effect sizes were pooled using a random-effects model to estimate the overall effects while allowing for heterogeneity across studies.

To answer RQ1, separate meta-analyses were conducted on cognitive, affective, and behavioural learning outcomes. Due to the wide variety of participants, interventions, and outcome measures across studies, we calculated the average ESs using the random-effects model (Borenstein et al. 2009). Also, we set the effect direction as Auto or Negative during the analysis (see Appendix B. Codebook). The choice between using "auto" or "negative" for effect size calculation depends on the outcome measure. For outcomes where a higher score is always desired, "auto" is used. However, when the outcome measure involves different directions, such as pleasure or anxiety, it is important to ensure a consistent direction for the effect size. In such cases, "auto" is used when the experimental group performs better with a higher score, and "negative" is used when a lower score indicates better performance, accurately reflecting the experimental group's learning outcomes. The examination of heterogeneity begins with a thorough examination of the forest plot, which is used to examine ES distributions and aid in detecting outliers. Viechtbauer and Cheung (2010) stated that outlier tests should not be used to justify the removal of studies; instead, they should be utilised to identify studies that need further investigation. Also, Q-statistics and the I^2-statistic were used to assess the heterogeneity. According to Higgins et al. (2003), the levels of heterogeneity at 25%, 50%, and 75% are low, moderate, and high, respectively.

To answer RQ2, we examined the effects of potential moderators employing a random effects model (see Section 1.2 for explanations, and Figure 1 and Appendix C for the summary of potential moderators considered). Only categorical moderator variables with at least four contrasts per category were employed (Bakermans-Kranenburg et al. 2003). Subgroup analysis was chosen as the analytical approach in the meta-analysis to assess categorical moderators separately, aligning with the recommendation of Rubio-Aparicio et al. (2017), which allowed for a focused examination of specific characteristics of interest. Considering the limited number of studies within certain moderator categories and the uneven distribution of covariates, the use of meta-regression was deemed unreliable, as emphasised in the guidance provided by Higgins et al. (2019). Furthermore, given the comprehensive exploration of diverse moderators across distinct studies, employing correction techniques for multiple comparisons was not considered appropriate (Sormani and Bruzzi 2012). Given the exploratory nature of our subgroup analyses in this study, we present results with point estimates and confidence intervals, while acknowledging that p-values are reported without correction (Wang et al. 2021). Moreover, we did not include these factors (i.e., community and socioeconomic status) in moderator analyses due to the small number of research studies in particular categories. Whenever categories could be merged to meet the criteria for four contrasts, we included these variables in moderator analyses. This process allowed us to merge some categories of three potential moderators, namely, duration of the intervention (1– $<$ 1 day, 2– $\geq$ 1 day), hardware used in experimental groups (1-mobile devices, e.g., wearable devices, smartphones, tablet computers, 2-traditional computers, or devices), level of rigour of experimental designs (1-not low, 2-low). For example, the coding of experimental design rigour was based on the Checklist for the Rigour of Education-Experiment Designs, developed by Sung et al. (2019). This checklist includes five distinct levels: 1 = high, 2 = medium-high, 3 = medium, 4 = medium-low, and 5 = low. To ensure sufficient statistical power for moderator analysis, we grouped levels 1 to 3 into a "not low" category and levels 4 and 5 into a "low" category.

In each set of studies, publication bias was assessed. Rosenthal's fail-safe N was calculated to reflect the number of missing studies with a z-value of zero that must be added for the overall effect size to be statistically insignificant (Rosenthal 1979). Using Egger's test of the intercept, the statistical significance of the bias revealed by the funnel plot was determined (Egger et al. 1997). The trim-and-fill method (Duval and Tweedie 2000) was also applied to look for asymmetry resulting from publication bias.

3 | Results

3.1 | Characteristics of Included Studies

A total of 69 studies from 55 papers were included, for a total sample size of N = 9095. The term *total sample size* represents the total number of participants included across all the studies included in our analysis. In the reference list, studies included in this meta-analysis are indicated with an asterisk (*). Appendix D summarises these studies. The 55 articles are from 13 international journals, including 14 articles from *Computers and Education* and 10 articles from *Interactive Learning Environments*. The trend of research on adaptive learning started to rise in 2017 and peaked in 2019, with 17 publications in 1 year.

3.2 | Evaluation of Publication Bias

The fail-safe N was 5017, 501, and 330, with cognitive, affective, and behavioural learning outcomes, respectively, which were far greater than the tolerable numbers (i.e., 380, 130, and 110, respectively). Results of Egger's regression tests showed that there was no indication of publication bias for behavioural learning (intercept = 2.026, 95% CI [−0.570, 4.622], $t(18) = 1.640$, $p = 0.118$). However, the intercept for cognitive learning (intercept = 2.649, 95% CI [1.943, 3.356], $t(72) = 7.479$, $p < 0.001$) and affective learning (intercept = 1.988, 95% CI [0.274, 3.702], $t(22) = 2.406$, $p = 0.025$) was significant, suggesting the funnel plots were non-symmetric.

The trim-and-fill method may calculate missing effect sizes on the assumption that ESs have a normal distribution (Duval and Tweedie 2000). Six imputed ESs for cognitive learning outcomes were shown on the left using the trim-and-fill method. This suggests that the estimated ES might become 0.432 with a 95% CI [0.320, 0.544] if six missing studies were included in the random effects category. Additional trim and fill tests on non-cognitive learning outcomes revealed that no additional studies were required, leading to adjusted point estimates and confidence intervals for affective and behavioural learning outcomes, respectively, that were the same as the primary findings ($g = 0.448$, 95% CI [0.253, 0.644]) and ($g = 0.380$, 95% CI [0.176, 0.585]). All of this suggests that our study's validity was not at risk from publication bias.

3.3 | Overall Effects of Technology-Enhanced Adaptive Learning

To address RQ1, we compared the effects of technology-enhanced adaptive learning with other modes of instruction on learning outcomes in 74 cognitive comparisons, 24 affective comparisons, and 20 behavioural comparisons. Figures 3, 4, and 5 display each study's ESs and 95% confidence intervals. The overall effect showed that technology-enhanced adaptive learning had moderately beneficial and statistically significant effects on cognitive learning ($g = 0.486$, 95% CI [0.380, 0.593]), affective learning ($g = 0.448$, 95% CI [0.253, 0.644]), and behavioural learning ($g = 0.380$, 95% CI [0.176, 0.585]). Heterogeneity was large and significant for the effects on all three learning

Study name	Statistics for each study		
	Hedges's g	Lower limit	Upper limit
Baker et al. (2017)	-0.153	-0.000	0.288
Basu, Biewas, and Kinnebrew (2017)	1.896	0.861	1.611
Bhagat, Laui, Sposter, and Chang (2018)	1.917	1.366	3.479
Chen and Chen (2021)	0.551	-0.270	0.973
Chen, Chen, and Horng (2021)	0.540	0.008	1.670
Chen, Yu, and Chiang (2017)	1.023	0.486	1.550
Cho, Yang, Teeng, and Yang (2019)	0.403	0.049	0.796
Daradourhis and Arguedas (2020)	0.522	-0.095	1.119
Faber, Luyten, and Weacher (2017)	0.103	0.090	0.196
Furie, Gensidez-Gancedo, Juan, Segıź. and Rando (2015)	-0.484	-0.914	-0.654
Ghyseis and Haelermans (2019)	0.100	-0.030	0.390
Gustalson, Hordshorn, Andersson, Frfith, and Ingvar (2016) Comp 1	-0.044	-0.284	0.146
Gustalson, Hordshorn, Andersson, Frfith, and Ingvor (2015) Comp 2	-0.068	-0.287	0.165
Haclermans and Ghyseis (2017) Comp 1	0.301	-0.029	0.431
Haclermans and Ghyseis (2017) Comp 2	-0.045	-0.274	0.164
Hooley and Thorpe (2017)	0.321	-0.086	0.706
Hooshyar et al. (2021)	0.468	0.020	0.842
Hooshyar, Maive, Yeng, Pedaste, Wang, and Lim (2021)	0.488	0.031	0.915
Hau, Hwang, and Chang (2012) Comp 1	0.880	0.483	1.447
Hau, Hwang, and Chang (2013) Comp 2	1.096	0.011	1.280
Hoang, Liu, Chang (2012)	1.192	0.396	1.348
Hwang, Sung, Hung, Hang, and Tsai (2012)	0.094	0.096	1.289
Jia, Chen, Diug, and Nush (2012)	0.337	-0.083	0.737
Leonoers, Joolingen, Øylers, and Bellen (2014)	0.088	-0.612	0.649
Lin and Chen (2019)	0.603	0.010	1.737
Lin et at (2013)	0.453	-0.045	0.851
Liorens, Cerdàn, and Vidal Abarca (2014) Comp 1	0.257	-0.239	0.753
Lierens, Cerdàn, and Vidal Abarca (2014) Camp 2	0.411	-0.105	0.627
Lierens, Vidal-Abarca, and Cerdàn (2016) Sample 1 Comp 1	0.901	-0.339	0.446
Lierens, Vidal-Abarca, and Cerdàn (2016) Sample 1 Comp 2	0.365	-0.168	0.717
Lierens, Vidal Abarca, and Cerdàn (2016) Sample 2 Comp 1	0.395	-0.198	0.738
Lierens, Vidal-Abarca, and Cerdàn (2016) Sample 2 Comp 2	0.667	0.197	1.027
Merch, Engeness, Cheng, Choung, and Wung (2017)	0.198	-0.360	0.764
Melenaar, Trade, Bastel, and Sleegers (2012)	-0.374	-0.718	0.001
Nadotski and Hummal (2017)	0.515	0.098	1.004
Nicou and Economious (2016)	0.014	0.231	0.899
Gzyurl. Dzyurt, Guven, and Baki (2014)	0.091	0.195	0.867
Sandberg, Maris, and Hoogendoom (2014)	0.004	0.068	0.621
Serrana, Vidal - Aborca, and Ferrer (2019)	-0.033	-0.200	0.448
Shih, Kue, and Lip (2012)	0.401	0.099	0.763
Shute et al. (2021) Comp 1	0.162	-0.183	0.587
Shute et al. (2021) Comp 2	0.188	-0.142	0.538
Shute et al. (2021) Comp 3	0.276	-0.688	0.619
Siddique, Durrani, and Naqvi (2019) Sample 1	2.134	0.827	3.342
Siddique, Durrani, and Naqvi (2019) Sample 10	6.760	-0.260	1.555
Siddique, Durrani, and Naqvi (2019) Sample 11	0.679	-0.360	1.631
Siddique, Durrani, and Naqvi (2019) Sample 12	2.216	0.576	2.881
Siddique, Durrani, and Naqvi (2019) Sample 2	1.985	0.617	3.893
Siddique, Durrani, and Naqvi (2019) Sample 3	2.134	0.627	2.342
Siddique, Durrani, and Naqvi (2019) Sample 4	1.914	0.448	2.890
Siddique, Durrani, and Naqvi (2018) Sample 5	1.514	0.448	3.890
Siddique, Durrani, and Naqvi (2018) Sample 6	2.383	1.648	3.477
Siddique, Durrani, and Naqvi (2018) Sample 7	3.307	1.624	4.789
Siddique, Durrani, and Naqvi (2018) Sample 8	2.112	0.929	3.295
Siddique, Durrani, and Naqvi (2018) Sample 9	4.648	2.718	6.379
Tapinglale, Pangiburee, Hwang, and Srisawaadi (2020)	0.341	-0.027	0.710
Teonder and Sawyer (2021)	1.142	0.460	1.794
Van Giıikal, Ruis, Monsnen, Karaman, Neijzer, and Sitthiwarschan (2020)	6.145	-0.080	0.692
Vanbscelsere, Conville, Sasanguie, Reynvoet, and Depaape (2021)	-0.088	-0.554	0.357
Wan and Yu (2020)	0.399	-0.118	0.635
Wang et al. (2020) Study 1	0.249	-0.098	0.598
Wang et al. (2020) Study 2	0.848	-0.007	1.085
Witxon and Cois (2019)	0.005	-0.519	0.329
Winkler, Seliner, and Leimeister (2021) Sample 1	0.883	-0.023	1.149
Winkler, Seliner, and Leimeister (2021) Sample 2	1.543	0.686	2.201
Wengwaret, Susawasdi, Hwang, and Panjaburee (2017)	0.910	-0.211	1.730
Wu and Chang (2023)	0.175	-0.355	6.565
Wu, Kuo. and Wang (2017) Comp 1	0.222	-0.291	0.695
Wu, Kuo. and Wang (2017) Comp 2	0.910	-0.436	6.455
Yı lmaz and Kıtıę ҫakmaк (2012)	2.037	1.468	2.607
Yang (2017) Comp 1	0.273	-0.324	0.771
Yang (2017) Comp 2	0.345	-0.286	0.684
Yang and Lı (2016)	0.911	0.198	1.122
Yang, Cheng, Hwang, and Zou (2020)	0.001	-0.537	6.544
	0.210	0.225	0.715

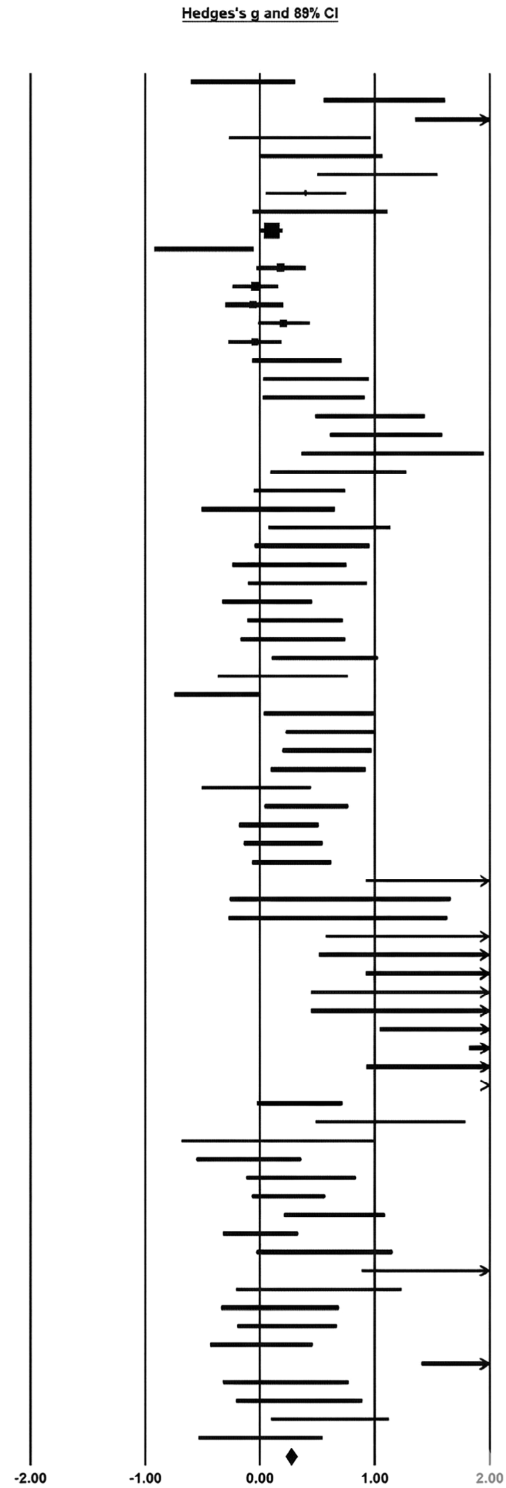

FIGURE 3 | Forest plot of the 74 effect sizes for cognitive outcomes. Within one article, when multiple sample or studies were presented, the figure reports the result of each sample (Sample 1, Sample 2, etc.) or study (Study 1, Study 2, etc.) separately. Similarly, when studies used multiple comparisons, the figure reports the result of each comparison (Comp 1, Comp 2, etc.) separately.

outcomes: $I^2 = 77.459$ for the cognitive aspect, $I^2 = 83.305$ for the affective aspect, $I^2 = 85.752$ for the behavioural aspect.

A total of 13 studies stood out due to their inclusion of multiple comparisons, which may violate the assumption of statistical independence due to shared control groups. As an alternative to the full meta-analysis, which includes all available comparisons, we conducted a sensitivity analysis to evaluate the robustness of our findings. Following commonly used strategies in meta-analysis research (e.g., Cuijpers et al. 2014),

Study name	Hedges's g	Lower limit	Upper limit
Bhagat, Liou, Spector, and Chang (2019)	0.972	0.478	1.465
Chen, Yu, and Chiang (2017)	0.688	0.178	1.198
Daradoumis and Arguedas (2020)	1.937	1.183	2.692
Faber, Luyten, and Visscher (2017)	0.150	0.050	0.249
Furió, González-Gancedo, Juan, Segui, and Rando (2013)	0.159	-0.285	0.563
Hooshyar et al. (2021)	0.675	0.208	1.143
Hooshyar, Malva, Yang, Pedaste, Wang, and Lim (2021)	0.396	-0.292	1.063
Hsu (2015)	0.399	0.087	0.710
Hsu, Hwang, and Chang (2013) Comp 1	0.371	-0.085	0.827
Hsu, Hwang, and Chang (2013) Comp 2	0.101	-0.351	0.552
Hwang, Sung, Hung, Hung, and Tsai (2012)	0.400	-0.175	0.374
Molenaar, Roda, Boxtel, and Sleegers (2012)	-0.036	-0.412	0.341
Nadolski and Hummel (2017)	0.086	-0.416	0.546
Nikou and Economides (2018)	0.736	0.349	1.124
Sampayo-Vargas, Cope, He, and Byme (2013) Comp 1	-0.309	-0.618	0.001
Sampayo-Vargas, Cope, He, and Byme (2013) Comp 2	-0.314	-0.629	0.001
Tapingkae, Panjaburee, Hwang, and Strisawasdi (2020)	0.406	0.037	0.776
Vanbecelaare, Comillie, Sasangule, Reynvoet, and Depaape (2021)	1.456	0.950	1.962
Wan and Yu (2020)	0.507	0.032	0.982
Wongwatkit, Srisawasdi, Hwang, and Panjaburee (2017)	1.425	0.968	1.983
Yılmaz and Kılıç-çakmak (2012)	1.620	1.026	2.214
Yang (2017) Comp 1	0.023	-0.523	0.569
Yang (2017) Comp 2	0.096	-0.450	0.642
Yang, Chang, Hwang, and Zou (2020)	-0.186	-0.735	0.363
	0.448	0.253	0.844

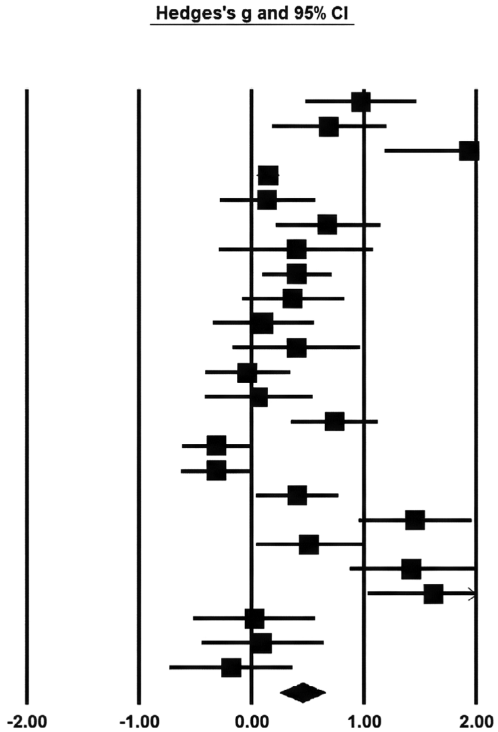

FIGURE 4 | Forest plot of the 24 effect sizes for affective outcomes.

Study name	Hedges's g	Lower limit	Upper limit
Ackermans, Rusman, Nadolski, Specht, and Brand-Gruwe (2021) Comp 1	0.957	0.538	1.377
Ackermans, Rusman, Nadolski, Specht, and Brand-Gruwe (2021) Comp 2	1.338	0.905	1.770
Basu, Biswas, and Kinnebrew (2017)	-0.216	-0.639	0.206
Chen, Chen, and Homg (2021)	0.648	0.113	1.183
Iterbeke, Witte, and Scheifhout (2021) Comp 1	0.665	0.411	0.800
Iterbeke, Witte, and Scheifhout (2021) Comp 2	-0.031	-0.177	0.115
Iterbeke, Witte, and Scheifhout (2021) Comp 3	0.092	-0.069	0.253
Llorens, Cerdán, and Vidal-Abarca (2014) Comp 1	0.300	-0.197	0.797
Llorens, Cerdán, and Vidal-Abarca (2014) Comp 2	0.776	0.247	1.305
Llorons, Vidal-Abarca, and Cerdán (2016) Sample 1 Comp 1	0.452	0.049	0.855
Llorens, Vidal-Abarca, and Cerdán (2016) Sample 1 Comp 2	1.296	0.823	1.769
Llorens, Vidal-Abarca, and Cerdán (2016) Sample 2 Comp 1	0.275	-0.180	0.730
Llorens, Vidal-Abarca, and Cerdán (2016) Sample 2 Comp 2	1.233	0.729	1.737
Molenaar, Roda, Bostel, and Sleegers (2012)	0.377	0.003	0.752
Sandberg, Maris, and Hoogendoorn (2014)	0.157	-0.252	0.567
Tapingkae, Panjaburee, Hwang, and Srisawasdi (2020)	0.242	-0.123	0.607
Van Ginkel, Ruiz, Mononen, Karaman, Keijzer, and Sitthiworachart (2020)	-0.177	-1.015	0.660
Vanbecelaere, Comillie, Sasanguie, Reynvoet, and Depaepe (2021)	-0.303	-0.747	0.142
Walkington (2013)	-0.385	-0.712	-0.058
Wu and Chang (2023)	0.095	-0.444	0.633
	0.380	0.176	0.585

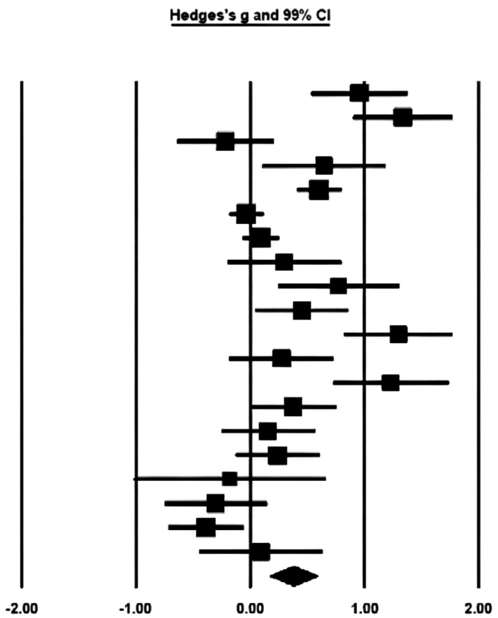

FIGURE 5 | Forest plot of the 20 effect sizes for behavioural outcomes.

we ran two separate analyses, with one retaining the largest effect size per study and the other retaining the smallest. This approach was used to avoid possible overestimation or underestimation of effect sizes that can occur when multiple comparisons share the same control group. In addition, we conducted a second sensitivity analysis by removing possible statistical outliers to further assess the stability of the results. The overall pooled effects are presented in Table 1, while the detailed results of these sensitivity checks are reported in Appendix E. Heterogeneity tests in the sensitivity analyses were insignificant across all three learning outcomes, suggesting that the observed differences may not reflect meaningful variation.

3.4 | Moderator Analyses

To address RQ2, moderator analyses were employed. The effects of these variables are summarised in Appendix C, and weighted mean ESs and 95% CI for cognitive, affective, and

TABLE 1 | Overall effect sizes of technology-enhanced adaptive learning.

			ES and 95% confidence interval			Heterogeneity			
Dependent variable	***N***	***K***	***g***	**SE**	**95% CI**	***Q* (*p*)**	**df (*Q*)**	**τ^2 (SE)**	**I^2 (%)**
Cognitive learning outcome	7170	74	0.486	0.054	(0.380, 0.593)	323.851 (<0.001)	73	0.141 (0.051)	77.459
Affective learning outcome	3280	24	0.448	0.100	(0.253, 0.644)	137.765 (<0.001)	23	0.180 (0.102)	83.305
Behavioural learning outcome	2509	20	0.380	0.104	(0.176, 0.585)	133.352 (<0.001)	19	0.171 (0.090)	85.752

Abbreviation: CI, confidence interval.

behavioural learning outcomes are presented in Tables F1–F3, respectively, in Appendix F, together with between-study heterogeneity.

A total of 12 moderators were identified for cognitive learning outcomes from 20 examined variables. First, regarding research context, studies conducted in secondary education ($g = 0.607$) produced larger ESs than primary education ($g = 0.330$) and adopted language arts ($g = 1.006$) had the largest ESs among subjects. These between-level variances were statistically significant under a random-effects model, indicating significant differences across educational levels ($Q_B = 6.689$, $p = 0.010$) and subjects ($Q_B = 30.546$, $p < 0.001$).

Second, regarding adaptive strategy, studies examining multiple learner characteristics in adaptive learning ($g = 1.901$), investigating content as adaptive targets ($g = 0.985$), and adopting elaborated feedback ($g = 0.670$) had higher ESs than others. These between-level variances were statistically significant under a random-effects model, indicating significant differences across learner characteristics ($Q_B = 38.096$, $p < 0.001$), adaptive targets ($Q_B = 21.558$, $p < 0.001$), and feedback types ($Q_B = 15.555$, $p < 0.001$).

Third, regarding technology, studies examining the effects of adaptive learning systems or applications ($g = 0.547$) produced larger effect sizes than those using adaptive teaching approaches or design solutions ($g = 0.113$). In terms of comparison treatments, studies comparing adaptive learning interventions with regular teaching, defined as traditional teacher-led instruction without adaptive technology ($g = 0.621$) yielded larger effect sizes than those comparing with individual CBI ($g = 0.378$) or with individual textbook or workbook use ($g = 0.209$). These between-levels variances were statistically significant under a random-effects model, indicating significant differences across adaptive technologies ($Q_B = 21.870$, $p < 0.001$) and comparison treatments ($Q_B = 10.521$, $p = 0.005$).

Fourth, regarding study quality, studies adopting quasi-experimental designs ($g = 0.535$), studies with medium/high rigour of experimental designs ($g = 0.631$), and intervention duration less than 1 day ($g = 0.697$), having different instructors teaching treatment and control groups ($g = 0.735$), and equivalent learning content/topic between comparison groups ($g = 0.531$) resulted in a higher ESs than others. These between-levels variances were statistically significant under a random-effects model, indicating significant differences across research designs ($Q_B = 7.167$, $p = 0.007$), level of rigour of experimental designs ($Q_B = 12.159$, $p < 0.001$), duration of the intervention ($Q_B = 5.665$, $p = 0.017$), instructor effects ($Q_B = 12.962$, $p = 0.002$), and learning content/topic equivalence ($Q_B = 33.403$, $p < 0.001$).

Regarding affective learning outcomes, we only found indications that ESs differed significantly ($Q_B = 15.086$, $p < 0.001$) between elaborated feedback ($g = 0.686$) and knowledge of results ($g = -0.113$). In addition, the ES was larger when data was collected through test data ($g = 0.922$), indicating significant differences across data collection methods ($Q_B = 4.704$, $p = 0.030$).

Regarding behavioural learning outcomes, only studies adopting behavioural learner characteristics ($g = 0.752$) had a greater significant ES than studies applying cognitive learning characteristics ($g = 0.260$), and studies using traditional computers or devices in experimental groups ($g = 0.438$) were significantly more effective than those using mobile devices ($g = -0.033$). These between-level variances were statistically significant under a random-effects model, indicating significant differences across learner characteristics ($Q_B = 4.531$, $p = 0.033$) and hardware used in experimental groups ($Q_B = 6.829$, $p = 0.009$).

4 | Discussion

The purpose of this meta-analysis was to investigate whether or not technology-enhanced adaptive learning improves learning outcomes for students in primary and secondary schools. Compared with previous relevant meta-analyses (see Appendix G), our analysis included a total of 69 studies, out of which at least 55 studies were newly added. Notably, when comparing our study to Liu et al.'s (2020) meta-analysis, only 2 studies were found to overlap, indicating a substantial difference in the remaining 67 studies, which were novel additions to our analysis. This difference arises because Liu et al. (2020) focused on educational games, game-based learning, and gamification, while our meta-analysis covered a broader range of adaptive learning technologies. For Zheng et al.'s (2022) meta-analysis, the exact number of overlapping studies could not be ascertained due to insufficient information and unsuccessful attempts to contact the authors. However, given that their study comprised only 12 studies focusing on primary and secondary education, it suggests that at least 57 studies in our analysis were not present in their research. Zheng et al. (2022) focused on personalised learning and excluded adaptive learning from their keywords. In contrast, our study specifically targeted adaptive learning technologies with a comprehensive set of keywords, leading to a distinct set of studies in our analysis. It is important to highlight that our analysis stands out in comparison to the other 7 meta-analyses, as all the studies included in our investigation were newly introduced and had not been previously considered in those earlier meta-analyses. For example, Fontaine et al. (2019) focused on health professionals and students, which differs significantly from our target group of primary and secondary education students. Studies like Major et al. (2021) only considered keywords related to adaptive learning or personalised learning, while our search included a broader range of terms. Other meta-analyses, such as Xu et al. (2019) and Kulik and Fletcher (2016), focused narrowly on specific keywords like "intelligent tutoring systems," potentially excluding many newer adaptive learning systems. Overall, the present study provides an interesting portrait of the state of technology-enhanced adaptive learning in primary and secondary education over about a decade.

To the best of our knowledge, this is the first study to investigate the main effects of technology-enhanced adaptive learning on three types of learning outcomes—cognitive, affective, and behavioural—and to specifically test several potential moderator variables. We were able to examine 20 potential moderator variables relating to the research context, adaptive strategy, technology, and study quality due to our attempts to include as many possibly relevant studies as possible. Based on 69 studies with a total of 9095 students, this meta-analysis revealed that technology-enhanced adaptive learning had medium-positive and statistically significant effects on primary and secondary students' cognitive, affective, and behavioural learning outcomes. Below, we first discuss the significant moderators identified that provide additional insight into how the effects of technology-enhanced adaptive learning vary.

4.1 | Research Context

In line with earlier meta-analyses on the effects of ITSs, our study acknowledges the significant role of educational levels and subjects as moderators (Kulik and Fletcher 2016; Ma et al. 2014). Notably, our research distinguishes itself by incorporating a distinct and non-overlapping set of data, therefore offering fresh insights into the topic. Specifically, when analyzing cognitive learning outcomes, our mean ES for secondary education ($g = 0.607$) was slightly larger than the mean ES for middle school ($g = 0.41$) and high school ($g = 0.4$) reported by Ma et al. (2014). Unlike prior reviews, we coded secondary education as a separate category, allowing for a more nuanced analysis. We directly compared ESs at two levels of schooling and found that secondary school students benefit more from technology-enhanced adaptive learning than their primary school counterparts. This discrepancy may be attributed to the greater familiarity and ease of use of technology among secondary school students today.

Additionally, our findings differ from Ma et al. (2014), who reported that ITSs had a medium effect ($g = 0.34$) on language and literacy learning across the 14 studies in their meta-analysis. In contrast, we found that technology-enhanced adaptive learning had a large effect ($g = 1.006$) in 24 primary and secondary school language arts studies. It is noteworthy that our study stands apart from Ma et al. (2014) as there is no overlap between the two meta-analyses, highlighting the inclusion of a distinct set of studies. This counterintuitive result may be due to the increased development and use of adaptive language learning systems in recent years. Besides, the layered spiral of interleaved practice forms a learning path in adaptive learning systems for language subjects, for example, in Duolingo's lessons, which have been shown to produce better mastery (Munday 2016). In contrast, the learning path has clear dependencies in a subject like math.

Furthermore, unlike Ma et al. (2014) and Steenbergen-Hu and Cooper (2014), this meta-analysis showed that although cognitive learning outcomes for students with high domain knowledge were larger than for students with low domain knowledge, the difference was not significant. It is important to emphasise that our study distinguishes itself from Ma et al. (2014) and Steenbergen-Hu and Cooper (2014) as there is no overlap in the studies included in our respective meta-analyses. However, it is crucial to interpret these findings with caution since only 17 studies reported prior domain knowledge of the sample. Future research needs more research context information to understand the effects better.

4.2 | Adaptive Strategy

For adaptive strategy, as seen in Appendix C, of all five variables tested, three moderators, that is, learner characteristics, adaptive targets, and feedback type, were found. Positive mean ESs were observed for both in-class and out-of-class applications of technology-enhanced adaptive learning, consistent with Ma et al. (2014), who reported significant ESs across various instructional contexts. However, due to difficulties in obtaining relevant data, our meta-analysis categorised in-class instruction as a distinct category of treatment instruction, and we observed a nonsignificant mean ES. This suggests that technology-enhanced adaptive learning can be beneficial across different instructional contexts in primary and secondary education.

Previous meta-analyses of adaptive learning failed to identify learner characteristics as moderators (e.g., Liu et al. 2020; Zheng et al. 2022), but our analysis did. In total, our analysis included at least 55 newly conducted studies, providing an updated and comprehensive perspective compared to the previous meta-analyses (see Appendix A). Specifically, we directly compared technology-enhanced adaptive learning ESs for four categories of learner characteristics coded by cognitive, affective, behavioural, and multiple learner characteristics based on the work of Martin et al. (2020). The ES ($g = 1.901$) on cognitive learning outcomes was notably large mainly when multiple learning characteristics were adapted, as compared to the ES for cognitive learner characteristics ($g = 0.256$), affective learner characteristics ($g = 0.517$), and behavioural learner characteristics ($g = 0.221$). These findings are in accordance with the theoretical underpinnings of adaptivity, for example, Vygotsky's Zone of Proximal Development (Vygotsky 1978) and Csikszentmihalyi's Flow Theory (Csikszentmihalyi 1990).

In line with Zheng et al.'s (2022) meta-analysis of technology-facilitated personalised learning, our analysis extends the research by including at least 57 newly conducted studies. This extension of research provides additional evidence supporting the moderating role of adaptive targets. However, most of our mean ESs for adaptive targets were markedly smaller than those reported in Zheng et al. (2022) meta-analysis of technology-facilitated personalised learning. This discrepancy might be related to the small sample size in their study, which can produce larger ESs compared to larger studies. Notably, all the contrasts per category for personalised learning support-software in Zheng et al.'s (2022) research consisted of only one or two studies. Our finding that feedback type was a significant moderator is in accordance with Shute (2008). Our findings confirm the importance of elaborated feedback in improving affective learning outcomes. This finding is important as few previous meta-analyses have examined the moderating role of feedback type on non-cognitive learning outcomes.

Lastly, research has revealed the significance of various learner characteristics (Martin et al. 2020). However, this effect on non-cognitive learning outcomes has not been investigated in prior meta-analyses of technology-enhanced adaptive learning. According to subgroup analysis, students whose behavioural learner characteristics were adapted had better behavioural learning outcomes than those whose cognitive learner characteristics were adapted. This may be because big data and learning analytics techniques can monitor each learner's progress and behaviour by capturing their learning profiles to explore factors influencing learning efficiency.

4.3 | Technology

From the perspective of technology, the findings revealed two moderators (i.e., adaptive technology and comparison treatments) on cognitive learning outcomes. Nonetheless, no significant moderators of affective learning outcomes were found, and only hardware used in experimental groups was a significant moderator on behavioural learning outcomes. While previous meta-analyses, such as those by Ma et al. (2014) and Steenbergen-Hu and Cooper (2014), have focused on various types of ITS, our study emphasises the need to broaden the scope of technology-enhanced adaptive learning systems. This requires studies to move beyond the examination of the affordances offered by ITS to explore different types of adaptive technology (Shemshack and Spector 2020). Therefore, based on Martin et al. (2020) classifications, we examined how ES varied with adaptive technology and found that students who learned using adaptive learning system/application had higher cognitive learning outcomes than those who learned with an adaptive teaching approach or an adaptive design. This finding gives insights into the development of adaptive learning system functions and provides evidence for increasing the accessibility and capabilities of technology-enhanced adaptive learning as a new learning technology initiative to facilitate personalised education.

In terms of comparison treatments, unlike the previous study (Ma et al. 2014), we combined large-group instruction and small-group instruction as a separate category, that is, regular teaching, for which we found the difference between technology-enhanced adaptive learning and learning from regular teaching had the largest ES ($g = 0.621$), followed by individual CBI ($g = 0.378$), and individual textbook or workbook ($g = 0.209$). It is important to note that there is no overlap in studies between our meta-analysis and the meta-analysis conducted by Ma et al. (2014). These findings suggest that, given the diversity in the classroom, adopting technology-enhanced adaptive learning is an effective way to improve school students' cognitive learning, as one way of teaching will not reach all students.

Finally, significant differences appeared when the type of hardware used in the experimental groups differed. Specifically, technology-enhanced adaptive learning had a significant positive effect on behavioural learning outcomes when experimental group students used traditional computers or devices for learning ($g = 0.438$). However, when experimental group students used mobile devices for learning, technology-enhanced adaptive learning appeared to have a nonsignificant negative impact ($g = -0.033$) on students' behavioural learning outcomes. Although previous research has indicated that traditional computers or devices were more often used in studies of adaptive learning than mobile devices (Xie et al. 2019), no meta-analysis has directly examined the moderating role of hardware used in experimental groups from mobile vs. non-mobile perspectives. Given the small sample size in our meta-analysis and the increasing popularity of mobile devices in schools, the specific hardware used in experimental groups could be extended in future research.

4.4 | Study Quality

Many prior meta-analyses have found that the strength of ESs is affected by study quality, including research design (Ma et al. 2014) and duration of the intervention (Kulik and Fletcher 2016; Steenbergen-Hu and Cooper 2013). Our analysis confirms these findings for cognitive learning outcomes. Another finding was that when different instructors taught treatment and control groups, the average ES was slightly but significantly larger than when the same instructor taught both groups. In contrast to Kulik and Fletcher (2016), who found that instructor effects were not a significant moderator, our study revealed a slightly larger ES when different instructors were involved, with a median ES of 0.55 in 16 studies with different instructors and a median ES of 0.63 in 30 studies with the same instructor in their study. These findings imply that technology-enhanced adaptive learning may still lie in supporting teaching. Besides, previous meta-analyses have not considered the potential moderating effects of other study quality characteristics. However, this study indicated that the level of rigour of experimental designs and learning topic/content equivalence were important moderators of cognitive learning outcomes, with higher ES observed when the rigour of experimental designs was medium/high, and when the same subject or material was adopted. Overall, the quality of the studies affected the effects on cognitive learning, which supports the suggestion that studies of technology-enhanced adaptive learning need to be more rigorous in their methods. Additionally, although our meta-analysis does not overlap with Kulik and Fletcher's (2016) meta-analysis, our findings align with theirs regarding the significance of data collection methods as a moderator. This suggests that alignment of measures and instructional objectives plays a crucial role in determining the evaluation results. The range of learning outcomes for our study was not restricted to cognitive learning outcomes and test type. We also included other outcome measurements such as survey and clickstream data for a broader overview in the data collection methods. We found a very large ES ($g = 0.922$) in test data, which produced significantly higher ES than the survey on affective learning outcomes. However, because the study number in test data was small, this finding was not sufficient to lead to a firm conclusion.

4.5 | Limitations and Future Research

Firstly, while current research mainly focuses on cognitive learning outcomes, future studies could delve deeper into affective and behavioural outcomes within the framework of technology-enhanced adaptive learning. For instance, gaining insight into whether and how technology-enhanced adaptive learning influences affective and behavioural aspects of learning, such as reducing the cognitive load (Wan and Yu 2020) or enhancing students' digital citizenship behaviuor (Tapingkae et al. 2020), can provide a more holistic understanding of adaptive learning interventions, guiding the development of more effective educational technologies and practices.

Secondly, two potential moderators, that is, community type and SES, were excluded from the moderator analyses due to the lack of supported data. This means these results cannot be interpreted to have any significance beyond the immediate learning context. Therefore, future research is needed to discern important contextual factors related to the effects of technology-enhanced adaptive learning that might contribute to an explanation for those effects, such as how technology-enhanced adaptive learning may best benefit learning with which student groups and under what local and cultural contexts.

Thirdly, it is simply too soon to say technology-enhanced adaptive learning is effective if ignoring the significant heterogeneity in the overall result. Researchers need to acknowledge the diversity of adaptive strategies, technology features, and study quality, including moderation analysis, to understand why interventions are ineffective for particular learners and how to prevent and prepare for adverse effects. In addition, the identification of seven previously untested moderators (e.g., feedback type, level of rigour of experimental designs) in Appendix A suggests that future research could focus on examining these variables more closely to determine how they interact with technology-enhanced adaptive learning. For instance, future research could examine the differential impact of various feedback types on learner motivation, self-efficacy, and attitudes towards technology-enhanced adaptive learning.

Fourthly, specific features of adaptive technology, could be considered in future studies. While our current analysis assessed the moderating role of adaptive technology on cognitive learning outcomes, we were limited in exploring non-cognitive learning outcomes due to insufficient studies employing adaptive teaching approaches or design solutions as interventions. Despite this limitation, the inclusion of one study (Faber et al. 2017) utilising such an approach for non-cognitive learning outcomes highlights the potential for future research in this area. As more studies become available on the effectiveness of both adaptive learning systems/applications and adaptive teaching approaches or design solutions on non-cognitive learning outcomes, future researchers could conduct a more CMA, offering a holistic understanding of the role of adaptive technology in education.

Finally, because of low variability in the outcomes, in many subgroup analyses, only two categories were identified. For example, more than half the studies that reported intervention duration indicated the intervention duration was less than one day, and we could only compare the effects between less than one day and greater than or equal to one day. However, technology-enhanced adaptive learning environments may be better designed if both technology's intensity and duration (Xu et al. 2019) are considered to find out the optimal conditions. Therefore, we urge that a greater emphasis be placed on various conditions in research designs in order to successfully reveal variation in the diversity of study quality.

4.6 | Contributions and Implications for Developers

4.6.1 | Contributions

Our meta-analysis offers several significant contributions to the domain of technology-enhanced adaptive learning, effectively addressing some of the key limitations identified in prior research. Firstly, we have expanded the exploration of moderator variables, moving beyond the narrow set typically considered in previous meta-analyses. This broader examination allows us to present a more nuanced view of the various factors that can influence learning outcomes. Secondly, our study includes recent advancements in adaptive learning systems, diverging from earlier studies that may have only considered outdated technologies. This inclusion ensures that our findings are applicable to the current educational technologies in use, providing insights that are pertinent to contemporary educational settings. Lastly, we have chosen to concentrate specifically on primary and secondary education. This focus is deliberate, aimed at addressing the existing gap in consensus and the recognised need for more research in these educational stages. By doing so, our study is able to delve into the distinctive effectiveness of adaptive learning technologies within these age groups. This exploration is crucial for understanding how these systems can be tailored and optimised to meet the specific needs of different educational levels and contexts.

4.6.2 | Implications for Developers

Our findings underscore the critical role of adaptive strategies in enhancing the effectiveness of learning systems. Adaptive strategies are essential because our research identified that at least one moderator within this category significantly influences cognitive, affective, and behavioural learning outcomes. The following recommendations focus on adaptive strategies and are specifically tailored to guide developers in creating more effective adaptive learning systems:

- Design adaptive learning systems that incorporate multiple learner characteristics.
- Integrate content as adaptive targets.
- Emphasise the importance of elaborated feedback.
- Ensure the usability and user experience of adaptive learning systems.
- Stay updated with emerging technologies.

With respect to the recommendation to design adaptive learning systems that incorporate multiple characteristics, our findings indicate that learner characteristics significantly moderate the effectiveness of adaptive learning systems, particularly influencing cognitive outcomes. Developers could prioritise the development of adaptive learning systems that consider and adapt to various learner characteristics, such as prior knowledge, learner interest, and learner profile. For instance, systems that adjust content difficulty based on prior knowledge can better support individual learning needs.

With respect to the recommendation to integrate content as adaptive targets, our study shows that adaptive content strategies can significantly enhance cognitive learning outcomes. Developers could explore the integration of adaptive strategies that target the content itself, such as dynamically adjusting the difficulty level, sequencing of learning materials, or providing adaptive content recommendations based on learners' progress and performance. This approach can optimise learning by ensuring that content is appropriately challenging and supportive.

In terms of recommendation to emphasise the importance of elaborated feedback, our research has identified feedback type as a critical factor that moderates cognitive and affective learning outcomes. Elaborated feedback helps students process information more deeply and correct errors, thereby enhancing the learning process. Developers could prioritise the inclusion of elaborated feedback within adaptive learning systems. This feedback should provide explanations, guidance, and corrective suggestions to learners, understand their mistakes, and improve continuously, particularly enhancing cognitive and affective learning outcomes.

When it comes to ensuring the usability and user experience of adaptive learning systems, our findings suggest that the effectiveness of these systems is partly dependent on how easily students can navigate with them, affecting both cognitive and behavioural learning outcomes. Developers could focus on designing user-friendly systems that are easy to navigate, visually appealing, and provide a seamless learning experience, ensuring that technical aspects do not hinder learning.

Regarding the recommendation to stay updated with emerging technologies, this is important because emerging technologies can offer new ways to implement adaptive strategies, making them more effective and engaging. Technologies like AI, VR, gamification, and learner analytics can significantly enhance adaptivity and the overall learning experience. Developers could actively explore the integration of emerging technologies into adaptive learning systems. By leveraging these innovative technologies, developers can provide more personalised and engaging learning environments.

Author Contributions

Jingxian Wang: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, visualization, writing – original draft, writing – review and editing. **Dineke E. H. Tigelaar:** conceptualization, formal analysis, methodology, project administration, supervision, writing – review and editing. **Tong Ye:** data curation, formal analysis, visualization. **Wilfried Admiraal:** conceptualization, formal analysis, methodology, project administration, supervision, writing – review and editing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Peer Review

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Appendix A

Overview of Selected Meta-Analyses Synthesising Technology-Enhanced Adaptive Learning Research

No.	Study information: Meta-analyses (year)	Study information: Inclusive dates	ESs on learning outcomes: *K*	ESs on learning outcomes: Average ES	Moderators explored: Research context	Moderators explored: Adaptive strategy	Moderators explored: Technology	Moderators explored: Study quality
1	Zheng et al. (2022)	2001–2020	• 34 for learning achievement • 7 for learning perceptions	• 0.673 for learning achievement • 0.259 for learning perceptions	• Sample level • Learning domains	• Research settings • Learning methods[a] • User-oriented personalised parameters • Personalised learning support-software[a]	• Personalised learning support-hardware	• Sample size • Research design • Intervention duration
2	Major et al. (2021)	2007–2020	15 for mathematics and literacy outcomes	0.18 for mathematics and literacy outcomes	Learning domain	• Personalization level[a] • Personalization delivery type		• Intervention intensity and duration
3	Liu et al. (2020)	1993–2018	• 14 for learning • 16 for game performance • 6 for engagement	• 0.393 for learning • −0.273 for game performance • 0.405 for engagement		• What to adapt: learner variable • What to adapt: instructional variable • How to adapt	• Game genres[a]	• Randomization[a] • Gameplay length[a]
4	Fontaine et al. (2019)	2003–2018	• 6 for knowledge • 7 for skills	• 0.70 for knowledge • 1.19 for skills	• Population			• Comparator
5	Xu et al. (2019)	2000–2017	19 for reading comprehension	0.60 for reading comprehension				• Comparison group[a] • The interaction between program intensity and duration[a] • Research design
6	Kulik and Fletcher (2016)	1985–2013	50 for posttest	0.66 for posttest	• Grade level[a] • Subject[a] • Country	Tutoring steps		• Test type[a] • Sample size[a] • Cognitive tutor study[a] • Publication bias • Publication year • Pretreatment differences • Group assignment • Study duration[a] • Instructor effects • Study type

No.	Study information: Meta-analyses (year)	Study information: Inclusive dates	ESs on learning outcomes: K	ESs on learning outcomes: Average ES	Moderators explored: Research context	Moderators explored: Adaptive strategy	Moderators explored: Technology	Moderators explored: Study quality
7	Ma et al. (2014)	1990–2012	107 for cognitive outcomes	0.41 for cognitive outcomes	• Grade levels[a] • Subject domains[a] • Prior domain knowledge[a] • Continent[a]	• Setting[a] • ITS intervention[a] • Feedback provided[a] • Model misconception	• Type of ITS[a]	• Comparison treatments[a] • Treatment duration • Study duration • Random assignment[a] • Source[a] • Attrition of participants[a]
8	Steenbergen-Hu and Cooper (2014)	1990–2011	• 26 studies measured with adjusted ESs for academic learning • 37 studies measured with unadjusted ESs for academic learning	• 0.37 for adjusted ESs • 0.32 for unadjusted ESs	• Subject matter • Study time[a]	• Intervention condition	• Different ITS	• Original comparisons[a] • Broader comparisons[a] • Teacher involvement on unadjusted ESs[a] • ES reporting
9	Steenbergen-Hu and Cooper (2013)	1997–2010	• 17 studies measured with adjusted ESs for mathematical learning • 26 studies measured with unadjusted ESs for mathematical learning	• 0.01 for adjusted ESs • 0.09 for unadjusted ESs	• Subject • Sample achievement level • Schooling level • Year of data collection			• ITS duration[a] • Sample size • Research design • Counterbalanced testing • Report type[a] • Measurement timing

Note: k = Nutmber of studies.
[a] Significant moderator.

Appendix B

Codebook

Categories and details of the codebook

Study information

Study ID number

Journal name

Article title

Author(s)

Years of publication

Outcome information

Comparison

A short description of the experimental and control conditions (open-ended entry)

Outcome measure

A short description of the dependent variables (open-ended entry)

Outcome type

1. Cognitive outcomes (Cognitive focused on thought, e.g., knowledge, post-test, retention test, transfer test, success rate)
2. Affective outcomes (affective focused on feeling, e.g., motivation, satisfaction, relevance, confidence, behaviour intention to use)
3. Behavioural outcomes (behavioural focused on interaction, e.g., time taken to learn, completion time)
4. 999 (Not mentioned)

Data extraction

Experimental group: mean (M), standard deviation (SD), sample size (N).

Control group: mean (M), standard deviation (SD), sample size (N).

T, P, F, MD, Cohen's d.

Effect direction

1. Auto
2. Negative

Research context

Region

A short description of the location where the study was conducted (open-ended entry).

Community

1. Urban
2. Rural
3. Semi-urban
4. 999 (Not mentioned)

Educational level

1. Primary education
2. Secondary education
3. 999 (Not mentioned)

Subject

1. Language arts
2. Social studies
3. Mathematics
4. Science
5. Professional subjects
6. Engineering
7. Digital citizenship
8. Multiple
9. 999 (Not mentioned)

Socioeconomic status

1. Low SES
2. Not low SES
3. 999 (Not mentioned)

Prior domain knowledge

1. Low
2. High
3. Varied
4. 999 (Not mentioned)

Adaptive strategy

The instructional role of adaptive instruction

1. In class (the adaptive learning systems was used for classroom instruction, separate laboratory or other exercises that took place during class time)
2. Outside class (the adaptive learning system was used as part of homework assignments)
3. 999 (Not mentioned)

Learner characteristics

1. Cognitive learner characteristics (e.g., cognitive styles and thinking styles, learner prior knowledge and background knowledge, and learner knowledge and metacognitive knowledge)
2. Affective learner characteristics (e.g., learner self-efficacy, and learner interest)
3. Behavioural leaner characteristics (e.g., learner profile)
4. Multiple
5. 999 (Not mentioned)

Adaptive targets (content and instructional characteristics)

1. Content (e.g., adaptive content)
2. Assessment (e.g., adaptive feedback, adaptive course topics and question difficulty)
3. Navigation (e.g., adaptive learning paths, adaptive learning sequences, adaptive navigation, adaptive pacing)
4. Presentation (e.g., adaptive formatting and presentation of materials, adaptive header filtering)
5. Multiple
6. 999 (Not mentioned)

Feedback type

1. Knowledge of results (Also known as *outcome knowledge* or *knowledge of results*, it tells learners that their answers are correct)
2. Knowledge of correct response (Also known as *knowledge of correct responses*, it tells the learner the correct answer to a particular question without providing additional information)
3. Elaborated feedback (A general term that refers to an explanation of the correctness or incorrectness of a particular response and allows the learner to review part of the instruction. It may or may not provide the correct answer)

4. No feedback (Refers to a situation where the learner is asked to answer a question, but there is no indication of the correctness of the learner's response)
5. Multiple feedback
6. 999 (Not mentioned)

Timing of feedback

1. Immediate or action-based feedback (Providing feedback after some action or a set of actions, or immediately after the system detects an error in a student's answer)
2. On request feedback (the student requests the feedback, which means that the student must make some effort to get the feedback (e.g., clicking a prompt button)).
3. End-of-task feedback (Feedback is provided after the learning task is completed and submitted.)
4. 999 (Not mentioned)

Technology

Adaptive technology

1. Adaptive learning system/application
2. Adaptive teaching approach or adaptive design solution

Hardware used in experimental groups

1. Mobile devices (e.g., wearable devices, smart phones, tablet computers)
2. Traditional computers or devices
3. Multiple
4. 999 (Not mentioned)

Degree of technology use in control groups

1. Without technology
2. With technology
3. 999 (Not mentioned)

Comparison treatments

1. Regular teaching
2. Individual human instruction
3. Individual computer-based instruction (CBI)
4. Individual textbook or workbook
5. 999 (Not mentioned)

Study quality

Research design

1. Quasi-experimental
2. True experimental design
3. 999 (Not mentioned)

Level of rigour of experimental designs

1. Not low
2. Low
3. 999 (Not mentioned)

Data collection methods

1. Test data
2. Survey
3. Extant data (email, recording, discussion data)
4. Observation
5. Clickstream data/log file
6. 999 (Not mentioned)

Group assignment

1. Intact groups: existing classes or groups assigned to treatment and control conditions
2. Random: participants assigned randomly to conditions
3. 999 (Not mentioned)

Duration of the intervention

1. < 1 day
2. ≥ 1 day
3. 999 (Not mentioned)

Instructor effects

1. Different instructors: different teachers taught treatment and control groups
2. Same instructor: same teacher or teachers taught treatment and comparison groups
3. Without instructor
4. 999 (Not mentioned)

Learning content/topic equivalence

1. Different
2. Same
3. 999 (Not mentioned)

Procedure of ES extraction

1. Calculated from exact descriptive (Means, standard deviations, sample sizes are provided)
2. Calculated from inferential statistics (Only T/P/F values are provided)

Appendix C

Summary of Significance of Potential Moderators on Different Learning Outcome

Potential moderators considered	Learning outcomes: Cognitive — Intervention favoured for[a]	Cognitive — Significance[b]	Affective — Intervention favoured for[a]	Affective — Significance[b]	Behavioural — Intervention favoured for[a]	Behavioural — Significance[b]
Research context						
Educational level	Secondary education	*	Primary education	n.s.	N/A	N/A
Subject	Language arts	***	Professional subjects	n.s.	N/A	N/A
Prior domain knowledge	High	n.s.	N/A	N/A	N/A	N/A
Adaptive strategy						
The instructional role of adaptive instruction	In class	n.s.	N/A	N/A	N/A	N/A
Learner characteristics	Multiple	***	Affective learner characteristics	n.s.	Behavioural leaner characteristics	*
Adaptive targets	Content	***	Navigation	n.s.	Navigation	n.s.
Feedback type[c]	Elaborated feedback	***	Elaborated feedback	***	N/A	N/A
Timing of feedback[c]	Immediate or action-based feedback	n.s.	N/A	N/A	N/A	N/A
Technology						
Adaptive technology	Adaptive learning system/application	***	N/A	N/A	N/A	N/A
Hardware used in experimental groups[c]	Mobile devices	n.s.	Mobile devices	n.s.	Traditional computers or devices	**
Degree of technology use in control groups[c]	Without technology	n.s.	Without technology	n.s.	Without technology	n.s.
Comparison treatments	Regular teaching	**	Regular teaching	n.s.	Individual computer-based instruction (CBI)	n.s.
Study quality						
Research design	Quasi-experimental design	**	N/A	N/A	True experimental design	n.s.
Level of rigour of experimental designs[c]	Not low	***	Not low	n.s.	Not low	n.s.
Data collection methods	Test data	n.s.	Test data	*	Survey	n.s.

Potential moderators considered	Learning outcomes					
	Cognitive		Affective		Behavioural	
	Intervention favoured for[a]	Significance[b]	Intervention favoured for[a]	Significance[b]	Intervention favoured for[a]	Significance[b]
Group assignment	Intact groups	n.s.	Random	n.s.	Random	n.s.
Duration of the intervention	<1 day	*	≥ 1 day	n.s.	<1 day	n.s.
Instructor effects	Different instructors	**	Different instructors	n.s.	Different instructors	n.s.
Learning content/topic equivalence[c]	Same	***	N/A	N/A	N/A	N/A
Procedure of ES extraction[c]	Calculated from exact descriptive	n.s.	Calculated from exact descriptive	n.s.	N/A	N/A

Note: N/A denotes not applicable. n.s. denotes not significant.
[a] Denotes that the subcategory appears to be favoured over the other subcategory or subcategories of that variable.
[b] Denotes whether the effects of technology-enhanced adaptive learning on the favoured subcategory were statistically significantly larger than those on the other subcategories.
[c] Denotes that this potential moderator has not been tested in previous meta-analyses identified in Appendix A, and the categories of the variable were adopted from other systematic review studies or based on real situations in conducting this meta-analysis. For example, categories of feedback were adopted from Shute's (2008) review study, and categories of procedure of ES extraction were based on the real situation of calculating ES.
* $p<0.05$.
** $p<0.01$.
*** $p<0.001$.

Appendix D

Overview of Studies Included in the Meta-Analysis

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Ackermans et al. (2021)	[1]The Netherlands [2]Not reported [3]Secondary education [4]Multiple [5]Not reported [6]Not reported	[7]Not reported [8]Behavior learner characteristics [9]Navigation [10]Not reported [11]Not reported	[12]Adaptive learning system/application [13]Not reported [14]Without technology [15]Not reported	[16]Quasi-experimental [17]Low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Different [23]Calculated from exact descriptive	Behavioural learning outcomes
Baker et al. (2017)	[1]USA [2]Urban [3]Primary education [4]Language arts [5]Low SES [6]Mix	[7]In class [8]Not reported [9]Assessment [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/application [13]Traditional computers and devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Different [23]Calculated from exact descriptive	Cognitive learning outcomes
Basu et al. (2017)	[1]USA [2]Urban [3]Secondary education [4]Science [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Clickstream data/log file [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Basu et al. (2017)	[1]USA [2]Urban [3]Secondary education [4]Science [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Clickstream data/log file [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Behavioural learning outcomes
Bhagat et al. (2019)	[1]Taiwan [2]Not reported [3]Primary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Elaborated feedback [11]End-of-task feedback	[12]Adaptive learning system/application [13]Mobile devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Bhagat et al. (2019)	[1]Taiwan [2]Not reported [3]Primary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Elaborated feedback [11]End-of-task feedback	[12]Adaptive learning system/ application [13]Mobile devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Chen et al. (2017)	[1]China [2]Not reported [3]Secondary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Multiple [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Not low [18 b] Test data/survey [19]Random: participants assigned randomly to conditions [20]> 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Chen et al. (2017)	[1]China [2]Not reported [3]Secondary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Multiple [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Not low [18]Survey [19]Random: participants assigned randomly to conditions [20]> 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Chen et al. (2021)	[1]Taiwan [2]Not reported [3]Primary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Not reported [11]On request feedback	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Chen et al. (2021)	[1]Taiwan [2]Not reported [3]Primary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Not reported [11]On request feedback	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Behavioural learning outcomes
Chen and Chen (2021)	[1]Taiwan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Affective learner characteristics [9]Presentation [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Chu et al. (2014)	[1]Taiwan [2]Not reported [3]Primary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Elaborated feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Daradoumis and Arguedas (2020)	[1]Spain [2]Not reported [3]Secondary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Affective learner characteristics [9]Assessment [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]Without technology [15]Regular teaching	[16]True experimental design [17]Not low [18]Survey [19]Random: participants assigned randomly to conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Daradoumis and Arguedas (2020)	[1]Spain [2]Not reported [3]Secondary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Affective learner characteristics [9]Assessment [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]Without technology [15]Regular teaching	[16]True experimental design [17]Not low [18]Survey [19]Random: participants assigned randomly to conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Faber et al. (2017)	[1]The Netherlands [2]Not reported [3]Primary education [4]Mathematics [5]Low SES [6]Not reported	[7]In class [8]Affective learner characteristics [9]Assessment [10]Knowledge of results [11]Immediate or action-based feedback	[12]Adaptive teaching approach or adaptive design solution [13]Mobile devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Faber et al. (2017)	[1]The Netherlands [2]Not reported [3]Primary education [4]Mathematics [5]Low SES [6]Not reported	[7]In class [8]Affective learner characteristics [9]Assessment [10]Knowledge of results [11]Immediate or action-based feedback	[12]Adaptive teaching approach or adaptive design solution [13]Mobile devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Affective learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Furió et al. (2013)	[1]Spain [2]Not reported [3]Primary education [4]Social studies [5]Not reported [6]Not reported	[7]Outside class [8]Not reported [9]Navigation [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Survey [19]Random: participants assigned randomly to conditions [20]Not reported [21]Without instructor [22]Same [23]Calculated from inferential statistics	Cognitive learning outcomes
Furió et al. (2013)	[1]Spain [2]Not reported [3]Primary education [4]Social studies [5]Not reported [6]Not reported	[7]Outside class [8]Not reported [9]Navigation [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Survey [19]Random: participants assigned randomly to conditions [20]Not reported [21]Without instructor [22]Same [23]Calculated from inferential statistics	Affective learning outcomes
Ghysels and Haelermans (2018)	[1]The Netherlands [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Not reported	[7]Outside class [8]Cognitive learner characteristics [9]Content [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]True experimental design [17]Not low [18]Test data [19]Random: participants assigned randomly to conditions [20] > 1 day [21]Without instructor [22]Different [23]Calculated from exact descriptive	Cognitive learning outcomes
Van Ginkel et al. (2020)	[1]The Netherlands [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Behaviour learner characteristics [9]Navigation [10]Not reported [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]True experimental design [17]Not low [18]Survey [19]Random: participants assigned randomly to conditions [20] > 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Van Ginkel et al. (2020)	[1]The Netherlands [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Behaviour learner characteristics [9]Navigation [10]Not reported [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]True experimental design [17]Not low [18]Survey [19]Random: participants assigned randomly to conditions [20] > 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Behavioural learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Gustafson et al. (2019)	[1]Swedish [2]Not reported [3]Primary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Not reported [11]Not reported	[12]Adaptive teaching approach or adaptive design solution [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Different [23]Calculated from exact descriptive	Cognitive learning outcomes
Haelermans and Ghysels (2017)	[1]The Netherlands [2]Urban [3]Secondary education [4]Mathematics [5]Not reported [6]Not reported	[7]Outside class [8]Cognitive learner characteristics [9]Assessment [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Individual textbook or workbook	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Hooley and Thorpe (2017)	[1]USA [2]Semi urban [3]Secondary education [4]Social studies [5]Low SES [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Multiple feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Hooshyar, Malva, et al. (2021)	[1]Estonia [2]Not reported [3]Primary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Content [10]Elaborated feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Hooshyar, Malva, et al. (2021)	[1]Estonia [2]Not reported [3]Primary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Content [10]Elaborated feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Affective learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Hooshyar, Pedaste, et al. (2021)	[1]Estonia [2]Not reported [3]Primary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Content [10]Elaborated feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Hooshyar, Pedaste, et al. (2021)	[1]Estonia [2]Not reported [3]Primary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Content [10]Elaborated feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Hsu (2015)	[1]Taiwan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Presentation [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Not reported [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Hsu et al. (2013)	[1]Taiwan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Affective learner characteristics [9]Content [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Hsu et al. (2013)	[1]Taiwan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Affective learner characteristics [9]Content [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Affective learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Huang et al. (2012)	[1]Taiwan [2]Not reported [3]Primary education [4]Mathematics [5]Not reported [6]Low	[7]In class [8]Cognitive learner characteristics [9]Navigation [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]Not reported [15]Not reported	[16]Quasi-experimental [17]Low [18]Test data [19]Random: participants assigned randomly to conditions [20]Not reported [21]Not reported [22]Same [23]Calculated from inferential statistics	Cognitive learning outcomes
Hwang et al. (2012)	[1]Taiwan [2]Not reported [3]Primary education [4]Science [5]Not reported [6]Not reported	[7]In class [8]Affective learner characteristics [9]Presentation [10]Elaborated feedback [11]Not reported	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Hwang et al. (2012)	[1]Taiwan [2]Not reported [3]Primary education [4]Science [5]Not reported [6]Not reported	[7]In class [8]Affective learner characteristics [9]Presentation [10]Elaborated feedback [11]Not reported	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Not low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Iterbeke et al. (2021)	[1]Belgium [2]Not reported [3]Secondary education [4]Professional subject [5]Not low [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Elaborated feedback/ Knowledge of results[a] [11]Not reported	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Behavioural learning outcomes
Jia et al. (2012)	[1]China [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Knowledge of results [11]End-of-task feedback	[12]Adaptive teaching approach or adaptive design solution [13]Traditional computers and devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Leenaars et al. (2014)	[1]The Netherlands [2]Not reported [3]Primary education [4]Engineering [5]Not reported [6]Not reported	[7]Not reported [8]Cognitive learner characteristics [9]Assessment [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Individual textbook or workbook	[16]True experimental design [17]Low [18]Test data [19]Random: participants assigned randomly to conditions [20]Not reported [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from inferential statistics	Cognitive learning outcomes
Lin et al. (2013)	[1]Taiwan [2]Not reported [3]Primary education [4]Mathematics [5]Not reported [6]Low	[7]In class [8]Not reported [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Test data [19]Random: participants assigned randomly to conditions [20]< 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Lin and Chen (2019)	[1]Taiwan [2]Urban [3]Primary education [4]Science [5]Not low [6]Not reported	[7]In class [8]Affective learner characteristics [9]Navigation [10]Not reported [11]Not reported	[12]Adaptive teaching approach or adaptive design solution [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Llorens et al. (2014)	[1]Spain [2]Not reported [3]Secondary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]True experimental design [17]Not low [18]Clickstream data/log file [19]Random: participants assigned randomly to conditions [20]< 1 day [21]Not reported [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Llorens et al. (2014)	[1]Spain [2]Not reported [3]Secondary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]True experimental design [17]Not low [18]Clickstream data/log file [19]Random: participants assigned randomly to conditions [20]< 1 day [21]Not reported [22]Same [23]Calculated from exact descriptive	Behavioural learning outcomes
Llorens et al. (2016) sample 1	[1]Spain [2]Not reported [3]Secondary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Behaviour learner characteristics [9]Assessment [10]Elaborated feedback [11]Immediate or action-based feedback/End-of-task feedback[a]	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]True experimental design [17]Not low [18]Clickstream data/log file [19]Random: participants assigned randomly to conditions [20]< 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Llorens et al. (2016) sample 2	[1]Spain [2]Not reported [3]Secondary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Behaviour learner characteristics [9]Assessment [10]Elaborated feedback [11]Immediate or action-based feedback/End-of-task feedback[a]	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]True experimental design [17]Not low [18]Clickstream data/log file [19]Random: participants assigned randomly to conditions [20]< 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Behavioural learning outcomes
Molenaar et al. (2012)	[1]Czech [2]Not reported [3]Secondary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Behaviour learner characteristics [9]Navigation [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Without instructor [22]Same [23]Calculated from inferential statistics	Cognitive learning outcomes
Molenaar et al. (2012)	[1]Czech [2]Not reported [3]Secondary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Behaviour learner characteristics [9]Navigation [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Without instructor [22]Same [23]Calculated from inferential statistics	Affective learning outcomes
Molenaar et al. (2012)	[1]Czech [2]Not reported [3]Secondary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Behaviour learner characteristics [9]Navigation [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Without instructor [22]Same [23]Calculated from inferential statistics	Behavioural learning outcomes
Mørch et al. (2017)	[1]Norway [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Elaborated feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Nadolski and Hummel (2017)	[1]The Netherlands [2]Not reported [3]Secondary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Individual computer-based instruction (CBI)	[16]True experimental design [17]Not low [18]Survey [19]Random: participants assigned randomly to conditions [20]Not reported [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Nadolski and Hummel (2017)	[1]The Netherlands [2]Not reported [3]Secondary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Individual computer-based instruction (CBI)	[16]True experimental design [17]Not low [18]Survey [19]Random: participants assigned randomly to conditions [20]Not reported [21]Without instructor [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Nikou and Economides (2018)	[1]Europe [2]Not reported [3]Secondary education [4]Social studies [5]Not reported [6]Not reported	[7]Outside class [8]Not reported [9]Content [10]Elaborated feedback [11]End-of-task feedback	[12]Adaptive learning system/ application [13]Multiple [14]Without technology [15]Individual textbook or workbook	[16]True experimental design [17]Not low [18]Test data [19]Random: participants assigned randomly to conditions [20]> 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Nikou and Economides (2018)	[1]Europe [2]Not reported [3]Secondary education [4]Social studies [5]Not reported [6]Not reported	[7]Outside class [8]Not reported [9]Content [10]Elaborated feedback [11]End-of-task feedback	[12]Adaptive learning system/ application [13]Multiple [14]Without technology [15]Individual textbook or workbook	[16]True experimental design [17]Not low [18]Survey [19]Random: participants assigned randomly to conditions [20]> 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Özyurt et al. (2014)	[1]Turkey [2]Not reported [3]Secondary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Behaviour learner characteristics [9]Content [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from inferential statistics	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Sampayo-Vargas et al. (2013)	[1]Australia [2]Not reported [3]Secondary education [4]Language arts [5]Not low [6]Not reported	[7]In class [8]Affective learner characteristics [9]Assessment [10]Knowledge of results [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14] With technology/ Without technology[a] [15] Individual computer-based instruction (CBI)/Individual textbook or workbook[a]	[16]Quasi-experimental [17]Low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] <1 day [21]Without instructor [22]Same [23]Calculated from inferential statistics	Affective learning outcomes
Sandberg et al. (2014)	[1]The Netherlands [2]Not reported [3]Primary education [4]Language arts [5]Not reported [6]Not reported	[7]Outside class [8]Not reported [9]Assessment [10]Not reported [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] >1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Sandberg et al. (2014)	[1]The Netherlands [2]Not reported [3]Primary education [4]Language arts [5]Not reported [6]Not reported	[7]Outside class [8]Not reported [9]Assessment [10]Not reported [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] >1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Behavioural learning outcomes
Serrano et al. (2018)	[1]Spain [2]Not reported [3]Primary education [4]Social studies [5]Not reported [6]Low	[7]In class [8]Cognitive learner characteristics [9]Content [10]Elaborated feedback [11]End-of-task feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]Without technology [15]Individual textbook or workbook	[16]Quasi-experimental [17]Low [18]Test data [19]Random: participants assigned randomly to conditions [20] >1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Shih et al. (2012)	[1]Taiwan [2]Not reported [3]Primary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Navigation [10]Elaborated feedback [11]End-of-task feedback	[12]Adaptive teaching approach or adaptive design solution [13]Mobile devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]Not reported [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from inferential statistics	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Shute et al. (2021)	[1]USA [2]Not reported [3]Secondary education [4]Science [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Not reported [11]On request feedback	[12]Adaptive learning system/ application [13]Multiple [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Siddique et al. (2019) sample 1	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Low	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Siddique et al. (2019) sample 2	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Low	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Siddique et al. (2019) sample 3	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Low	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Siddique et al. (2019) sample 4	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Low	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Siddique et al. (2019) sample 5	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Low	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Siddique et al. (2019) sample 6	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Low	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Siddique et al. (2019) sample 7	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]High	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Siddique et al. (2019) sample 8	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]High	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Siddique et al. (2019) sample 9	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]High	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]< 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Siddique et al. (2019) sample 10	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]High	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Siddique et al. (2019) sample 11	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]High	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Siddique et al. (2019) sample 12	[1]Pakistan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]High	[7]In class [8]Multiple [9]Content [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Tapingkae et al. (2020)	[1]Thailand [2]Not reported [3]Secondary education [4]Digital citizenship [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Navigation [10]Multiple feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Behavioural learning outcomes
Tapingkae et al. (2020)	[1]Thailand [2]Not reported [3]Secondary education [4]Digital citizenship [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Navigation [10]Multiple feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Affective learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Tapingkae et al. (2020)	[1]Thailand [2]Not reported [3]Secondary education [4]Digital citizenship [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Navigation [10]Multiple feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Toonder and Sawyer (2021)	[1]USA [2]Urban [3]Primary education [4]Mathematics [5]Low SES [6]Low	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Multiple feedback [11]Not reported	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Random: participants assigned randomly to conditions [20] > 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Vanbecelaere et al. (2021)	[1]The Netherlands [2]Not reported [3]Primary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Affective learner characteristics [9]Assessment [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Clickstream data/log file [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Vanbecelaere et al. (2021)	[1]The Netherlands [2]Not reported [3]Primary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Affective learner characteristics [9]Assessment [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Clickstream data/log file [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Vanbecelaere et al. (2021)	[1]The Netherlands [2]Not reported [3]Primary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Affective learner characteristics [9]Assessment [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Mobile devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Clickstream data/log file [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Behavioural learning outcomes
Walkington (2013)	[1]USA [2]Rural [3]Secondary education [4]Mathematics [5]Not low [6]Not reported	[7]In class [8]Affective learner characteristics [9]Not reported [10]Not reported [11]Not reported	[12]Adaptive learning system/ application [13]Not reported [14]Without technology [15]Not reported	[16]True experimental design [17]Not low [18]Clickstream data/log file [19]Random: participants assigned randomly to conditions [20] < 1 day [21]Not reported [22]Same [23]Calculated from inferential statistics	Behavioural learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Wan and Yu (2020)	[1]China [2]Not reported [3]Primary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Multiple [10]Not reported [11]End-of-task feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Wan and Yu (2020)	[1]China [2]Not reported [3]Primary education [4]Professional subject [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Multiple [10]Not reported [11]End-of-task feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Same instructor: same teacher or teachers taught treatment and comparison groups [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Wang et al. (2020) study 1	[1]China [2]Not reported [3]Secondary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Elaborated feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Random: participants assigned randomly to conditions [20]> 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Wang et al. (2020) study 2	[1]China [2]Not reported [3]Secondary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Elaborated feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Random: participants assigned randomly to conditions [20]> 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Wilson and Czik (2016)	[1]USA [2]Urban [3]Secondary education [4]Language arts [5]Low SES [6]Not reported	[7]In class [8]Not reported [9]Assessment [10]Elaborated feedback [11]End-of-task feedback	[12]Adaptive teaching approach or adaptive design solution [13]Traditional computers and devices [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Clickstream data/log file [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Winkler et al. (2021) sample 1	[1]Switzerland [2]Urban [3]Secondary education [4]Professional subject [5]Not reported [6]Not reported	[7]Outside class [8]Not reported [9]Navigation [10]Multiple feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Multiple [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Winkler et al. (2021) sample 2	[1]Switzerland [2]Urban [3]Secondary education [4]Professional subject [5]Not reported [6]Not reported	[7]Outside class [8]Not reported [9]Navigation [10]Multiple feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Multiple [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Wongwatkit et al. (2017)	[1]Thailand [2]Not reported [3]Primary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Multiple [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Not reported [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Wongwatkit et al. (2017)	[1]Thailand [2]Not reported [3]Primary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Multiple [10]Elaborated feedback [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Not reported [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Wu et al. (2017)	[1]Taiwan [2]Not reported [3]Primary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Multiple [10]Elaborated feedback/No feedback[a] [11]Immediate or action-based feedback/Not reported[a]	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]Without technology [15]Regular teaching	[16]Quasi-experimental [17]Low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Wu and Chang (2023)	[1]Taiwan [2]Not reported [3]Secondary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Multiple feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Mobile devices [14]Without technology [15]Individual textbook or workbook	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Wu and Chang (2023)	[1]Taiwan [2]Not reported [3]Secondary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Multiple feedback [11]On request feedback	[12]Adaptive learning system/ application [13]Mobile devices [14]Without technology [15]Individual textbook or workbook	[16]Quasi-experimental [17]Not low [18]Clickstream data/log file [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Behavioural learning outcomes
Yang (2017)	[1]Taiwan [2]Not reported [3]Primary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Content [10]Knowledge of results/Elaborated feedback[a] [11]Not reported	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Not reported [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Yang (2017)	[1]Taiwan [2]Not reported [3]Primary education [4]Social studies [5]Not reported [6]Not reported	[7]In class [8]Not reported [9]Content [10]Knowledge of results/Elaborated feedback[a] [11]Not reported	[12]Adaptive learning system/ application [13]Not reported [14]With technology [15]Regular teaching	[16]Quasi-experimental [17]Not low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Not reported [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Yang et al. (2020)	[1]Taiwan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Knowledge of results [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Not low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes
Yang et al. (2020)	[1]Taiwan [2]Not reported [3]Secondary education [4]Language arts [5]Not reported [6]Not reported	[7]In class [8]Cognitive learner characteristics [9]Assessment [10]Knowledge of results [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Not low [18]Survey [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] < 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Affective learning outcomes
Yang and Li (2013)	[1]Taiwan [2]Not reported [3]Primary education [4]Mathematics [5]Not reported [6]Not reported	[7]In class [8]Affective learner characteristics [9]Presentation [10]Knowledge of results [11]Immediate or action-based feedback	[12]Adaptive learning system/ application [13]Traditional computers and devices [14]Without technology [15]Individual textbook or workbook	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20] > 1 day [21]Without instructor [22]Same [23]Calculated from exact descriptive	Cognitive learning outcomes

Study	Research context	Adaptive strategy	Technology	Study quality	Outcome
Yılmaz and Kılıç-Çakmak (2012)	[1]Turkey [2]Rural [3]Secondary education [4]Science [5]Low SES [6]Not reported	[7]In class [8]Not reported [9]Navigation [10]Not reported [11]Not reported	[12]Adaptive learning system/application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from inferential statistics	Cognitive learning outcomes
Yılmaz and Kılıç-Çakmak (2012)	[1]Turkey [2]Rural [3]Secondary education [4]Science [5]Low SES [6]Not reported	[7]In class [8]Not reported [9]Navigation [10]Not reported [11]Not reported	[12]Adaptive learning system/application [13]Traditional computers and devices [14]With technology [15]Individual computer-based instruction (CBI)	[16]Quasi-experimental [17]Not low [18]Test data [19]Intact groups: existing classes or groups assigned to treatment and control conditions [20]> 1 day [21]Different instructors: different teachers taught treatment and control groups [22]Same [23]Calculated from inferential statistics	Affective learning outcomes

[a] Variables were different in the comparison groups for the same outcome variable.
[b] Both variables were presented in one comparison group for the same outcome variable.
[1] Country/region.
[2] Community type.
[3] Educational level.
[4] Subject.
[5] Socioeconomic status.
[6] Prior domain knowledge.
[7] The instructional role of adaptive instruction.
[8] Learner characteristics.
[9] Adaptive targets.
[10] Feedback type.
[11] Timing of feedback.
[12] Adaptive technology.
[13] Hardware used in experimental groups.
[14] Degree of technology use in control groups.
[15] Comparison treatments.
[16] Research design.
[17] Level of rigour of experimental designs.
[18] Data collection methods.
[19] Group assignment.
[20] Duration of the intervention.
[21] Instructor effects.
[22] Learning content/topic equivalence.
[23] Procedure of ES extraction.

Appendix E

In-Depth Effect Size Analysis of Technology-Enhanced Adaptive Learning

Dependent variable	N	K	ES and 95% confidence interval			Heterogeneity			
			g	SE	95% CI	Q (p)	df (Q)	τ^2 (SE)	I^2 (%)
Cognitive learning outcome									
All ESs	7170	74	0.486	0.054	(0.380, 0.593)	323.851 (< 0.001)	73	0.141 (0.051)	77.459
Possible outliers removed	4154	55	0.413	0.039	(0.335, 0.490)	79.029 (0.015)	54	0.025 (0.015)	31.670
One ES per study (largest)	6735	64	0.553	0.062	(0.431, 0.675)	297.601 (< 0.001)	63	0.162 (0.065)	78.831
One ES per study (smallest)	6609	64	0.528	0.063	(0.404, 0.651)	299.463 (< 0.001)	63	0.168 (0.067)	78.962
Affective learning outcome									
All ESs	3280	24	0.448	0.100	(0.253, 0.644)	137.765 (< 0.001)	23	0.180 (0.102)	83.305
Possible outliers removed	1243	17	0.344	0.075	(0.197, 0.491)	27.486 (0.036)	16	0.039 (0.033)	41.790
One ES per study (largest)	3149	21	0.527	0.108	(0.315, 0.739)	122.841 (< 0.001)	20	0.187 (0.112)	83.719
One ES per study (smallest)	3144	21	0.511	0.109	(0.298, 0.724)	123.608 (< 0.001)	20	0.188 (0.113)	83.820
Behavioural learning outcome									
All ESs	2509	20	0.380	0.104	(0.176, 0.585)	133.352 (< 0.001)	19	0.171 (0.090)	85.752
Possible outliers removed	1725	14	0.341	0.089	(0.166, 0.515)	38.619 (< 0.001)	13	0.064 (0.046)	66.338
One ES per study (largest)	1632	14	0.409	0.150	(0.114, 0.704)	94.414 (< 0.001)	13	0.262 (0.141)	86.231
One ES per study (smallest)	1906	14	0.168	0.098	(−0.025, 0.360)	44.200 (< 0.001)	13	0.086 (0.058)	70.588

Abbreviation: CI, confidence interval.

Appendix F

Moderator Analyses and Weighted Mean Effect Sizes for Learning Outcomes

TABLE F1 | Moderator analyses and weighted mean effect sizes for cognitive outcome variables.

Moderator variables	K	ES g	ES SE	95% CI	Q_B	p
Research context						
Educational level					6.689	0.010
Primary education	27	0.330	0.074	(0.185, 0.475)		
Secondary education	47	0.607	0.077	(0.455, 0.759)		
Subject					30.546	< 0.001
Language arts	24	1.006	0.162	(0.688, 1.323)		
Social studies	16	0.157	0.079	(0.002, 0.312)		
Mathematics	17	0.309	0.068	(0.175, 0.444)		
Science	7	0.675	0.211	(0.261, 1.089)		
Professional subjects	8	0.647	0.123	(0.405, 0.888)		
Prior domain knowledge					1.434	0.231
Low	11	1.359	0.269	(0.832, 1.886)		
High	6	2.115	0.571	(0.996, 3.233)		
Adaptive strategy						
The instructional role of adaptive instruction					1.769	0.184
In class	65	0.523	0.060	(0.405, 0.641)		
Outside class	8	0.318	0.141	(0.041, 0.596)		
Learner characteristics					38.096	< 0.001
Cognitive learner characteristics	18	0.256	0.060	(0.139, 0.374)		
Affective learner characteristics	9	0.517	0.153	(0.217, 0.816)		
Behavioural leaner characteristics	7	0.221	0.140	(−0.054, 0.496)		
Multiple	12	1.901	0.267	(1.377, 2.425)		
Adaptive targets					21.558	< 0.001
Content	23	0.985	0.143	(0.705, 1.265)		
Assessment	33	0.285	0.055	(0.178, 0.392)		
Navigation	10	0.563	0.235	(0.101, 1.024)		
Multiple	5	0.401	0.173	(0.063, 0.740)		
Feedback type					15.555	< 0.001
Knowledge of results	5	0.186	0.086	(0.019, 0.354)		
Elaborated feedback	37	0.670	0.095	(0.484, 0.856)		
Multiple feedback	6	0.625	0.191	(0.251, 0.999)		
Timing of feedback					5.307	0.070
Immediate or action-based feedback	28	0.714	0.115	(0.487, 0.940)		
On request feedback	13	0.396	0.077	(0.246, 0.547)		
End-of-task feedback	10	0.453	0.142	(0.175, 0.731)		
Technology						
Adaptive technology					21.870	< 0.001
Adaptive learning system/application	67	0.547	0.063	(0.423, 0.67)		

(Continues)

Moderator variables	K	ES		95% CI	Q_B	p
		g	SE			
Adaptive teaching approach or adaptive design solution	7	0.113	0.068	(−0.020, 0.246)		
Hardware used in experimental groups					1.285	0.526
Mobile devices	12	0.516	0.162	(0.199, 0.832)		
Traditional computers or devices	29	0.351	0.070	(0.215, 0.488)		
Multiple	6	0.487	0.159	(0.176, 0.798)		
Degree of technology use in control groups					2.545	0.111
Without technology	39	0.571	0.080	(0.415, 0.727)		
With technology	34	0.398	0.074	(0.253, 0.542)		
Comparison treatments					10.521	0.005
Regular teaching	42	0.621	0.080	(0.464, 0.778)		
Individual computer-based instruction (CBI)	24	0.378	0.093	(0.195, 0.561)		
Individual textbook or workbook	7	0.209	0.104	(0.005, 0.413)		
Study quality						
Research design					7.167	0.007
Quasi-experimental	62	0.535	0.064	(0.409, 0.660)		
True experimental design	12	0.299	0.061	(0.180, 0.418)		
Level of rigour of experimental designs					12.159	< 0.001
Not low	49	0.631	0.077	(0.481, 0.781)		
Low	25	0.269	0.070	(0.132, 0.406)		
Data collection methods						
Test data	53	0.572	0.068	(0.438, 0.706)	4.553	0.103
Survey	14	0.339	0.128	(0.089, 0.589)		
Clickstream data/log file	8	0.339	0.115	(0.114, 0.564)		
Group assignment					2.902	0.088
Intact groups: existing classes or groups assigned to treatment and control conditions	54	0.546	0.069	(0.411, 0.680)		
Random: participants assigned randomly to conditions	20	0.366	0.080	(0.210, 0.522)		
Duration of the intervention					5.665	0.017
< 1 day	35	0.697	0.109	(0.483, 0.911)		
≥ 1 day	34	0.397	0.063	(0.273, 0.521)		
Instructor effects					12.962	0.002
Different instructors: different teachers taught treatment and control groups	32	0.735	0.106	(0.527, 0.944)		
Same instructor: same teacher or teachers taught treatment and comparison groups	9	0.552	0.099	(0.359, 0.746)		
Without instructor	27			(0.161, 0.435)		
Learning content/topic equivalence					33.403	< 0.001
Different	4	0.015	0.068	(−0.118, 0.148)		
Same	70	0.531	0.058	(0.417, 0.645)		
Procedure of ES extraction					0.017	0.895
Calculated from exact descriptive	67	0.486	0.054	(0.380, 0.592)		
Calculated from inferential statistics	7	0.447	0.290	(−0.121, 1.014)		

Abbreviation: CI, confidence interval.

TABLE F2 | Moderator analyses and weighted mean effect sizes for affective outcome variables.

Moderator variables	*K*	ES		95% CI	Q_B	*p*
		g	SE			
Research context						
Educational level					0.700	0.403
Primary education	11	0.556	0.152	(0.258, 0.853)		
Secondary education	13	0.375	0.154	(0.073, 0.676)		
Subjects					4.209	0.122
Language arts	7	0.134	0.173	(−0.205, 0.472)		
Social studies	5	0.207	0.157	(−0.100, 0.514)		
Professional subjects	6	0.665	0.213	(0.248, 1.082)		
Adaptive strategy						
Learner characteristics					0.084	0.772
Cognitive learner characteristics	6	0.330	0.119	(0.096, 0.564)		
Affective learner characteristics	8	0.395	0.189	(0.024, 0.766)		
Adaptive targets					0.163	0.922
Content	7	0.370	0.116	(0.143, 0.596)		
Assessment	8	0.406	0.205	(0.004, 0.809)		
Navigation	4	0.496	0.300	(−0.092, 1.085)		
Feedback type					15.086	< 0.001
Knowledge of results	5	−0.113	0.136	(−0.379, 0.154)		
Elaborated feedback	7	0.686	0.154	(0.384, 0.987)		
Technology						
Hardware used in experimental groups					0.119	0.731
Mobile devices	8	0.501	0.148	(0.211, 0.791)		
Traditional computers or devices	8	0.401	0.250	(−0.090, 0.891)		
Degree of technology use in control groups					0.311	0.577
Without technology	6	0.556	0.213	(0.139, 0.973)		
With technology	18	0.418	0.126	(0.171, 0.665)		
Comparison treatments					0.368	0.544
Regular teaching	11	0.548	0.147	(0.261, 0.835)		
Individual computer-based instruction (CBI)	11	0.410	0.173	(0.071, 0.750)		
Study quality						
Level of rigour of experimental designs					1.031	0.310
Not low	14	0.537	0.135	(0.272, 0.802)		
Low	10	0.335	0.147	(0.047, 0.622)		
Data collection methods					4.704	0.030
Test data	4	0.922	0.239	(0.453, 1.391)		
Survey	20	0.359	0.101	(0.161, 0.556)		
Group assignment					0.829	0.362
Intact groups: existing classes or groups assigned to treatment and control conditions	19	0.399	0.109	(0.186, 0.613)		

(Continues)

Moderator variables	K	ES		95% CI	Q_B	p
		g	SE			
Random: participants assigned randomly to conditions	5	0.656	0.260	(0.146, 1.165)		
Duration of the intervention					1.167	0.280
< 1 day	13	0.383	0.166	(0.058, 0.709)		
≥ 1 day	9	0.636	0.165	(0.313, 0.959)		
Instructor effects					4.934	0.085
Different instructors: different teachers taught treatment and control groups	6	0.896	0.264	(0.379, 1.413)		
Same instructor: same teacher or teachers taught treatment and comparison groups	6	0.442	0.100	(0.246, 0.639)		
Without instructor	8	0.168	0.194	(−0.213, 0.549)		
Procedure of ES extraction					1.571	0.210
Calculated from exact descriptive	19	0.530	0.105	[0.324, 0.736)		
Calculated from inferential statistics	5	0.174	0.264	(−0.345, 0.692)		

Abbreviation: CI, confidence interval.

TABLE F3 | Moderator analyses and weighted mean effect sizes for behavioural outcome variables.

Moderator variables	*K*	ES *g*	ES SE	95% CI	Q_B	*p*
Adaptive strategy						
Learner characteristics					4.531	0.033
Cognitive learner characteristics	5	0.260	0.149	(−0.032, 0.551)		
Behavioural leaner characteristics	8	0.752	0.177	(0.405, 1.099)		
Adaptive targets						
Assessment	14	0.363	0.113	(0.141, 0.584)	0.746	0.388
Navigation	5	0.592	0.241	(0.121, 1.064)		
Technology						
Hardware used in experimental groups					6.829	0.009
Mobile devices	4	−0.033	0.128	(−0.283, 0.218)		
Traditional computers or devices	11	0.438	0.127	(0.190, 0.686)		
Degree of technology use in control groups					0.065	0.798
Without technology	5	0.445	0.323	(−0.188, 1.079)		
With technology	15	0.358	0.108	(0.146, 0.571)		
Comparison treatments					0.785	0.376
Regular teaching	4	0.221	0.151	(−0.074, 0.516)		
Individual computer-based instruction (CBI)	12	0.407	0.146	(0.121, 0.693)		
Study quality						
Research design					0.369	0.544
Quasi-experimental	12	0.321	0.120	(0.087, 0.555)		
True experimental design	8	0.478	0.230	(0.028, 0.928)		
Level of rigour of experimental designs					0.087	0.768
Not low	10	0.416	0.180	(0.062, 0.769)		
Low	10	0.349	0.137	(0.081, 0.617)		
Data collection methods					1.373	0.503
Test data	5	0.264	0.144	(−0.018, 0.546)		
Survey	5	0.592	0.241	(0.121, 1.064)		
Clickstream data/log file	10	0.341	0.193	(−0.037, 0.719)		
Group assignment					0.369	0.544
Intact groups: existing classes or groups assigned to treatment and control conditions	12	0.321	0.120	(0.087, 0.555)		
Random: participants assigned randomly to conditions	8	0.478	0.230	(0.028, 0.928)		
Duration of the intervention					0.162	0.687
< 1 day	13	0.411	0.12	(0.176, 0.646)		
≥ 1 day	7	0.303	0.238	(−0.164, 0.771)		
Instructor effects					0.041	0.839
Different instructors: different teachers taught treatment and control groups	7	0.441	0.169	(0.111, 0.772)		
Same instructor: same teacher or teachers taught treatment and comparison groups	10	0.393	0.163	(0.073, 0.714)		

Abbreviation: CI, confidence interval.

Appendix G

Comparison Between the Present Study and Previous Meta-Analysis Presented in Appendix A

	Previous meta-analyses			The present study (total included studies = 69)
No.	**Study information**	**Number of studies included**	**Overlap**	**Newly included studies**
1	Zheng et al. (2022)	34 (Table 2 in their study showed that only 12 studies were on primary and secondary education.)	Unknown (Maximum = 12)	Unknown (Minimum = 57)
2	Major et al. (2021)	15	0	69 (all)
3	Liu et al. (2020)	12	2 (Sampayo-Vargas et al. 2013; Sandberg et al. 2014)	67
4	Fontaine et al. (2019)	13	0	69 (all)
5	Xu et al. (2019)	19	0	69 (all)
6	Kulik and Fletcher (2016)	50	0	69 (all)
7	Ma et al. (2014)	107	0	69 (all)
8	Steenbergen-Hu and Cooper (2014)	39	0	69 (all)
9	Steenbergen-Hu and Cooper (2013)	34	0	69 (all)