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Use of Learning Analytics in K–12 Mathematics Education: Systematic Scoping Review of the Impact on Teaching and Learning

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Abstract

The generation, use, and analysis of educational data comes with many promises and opportunities, especially where digital materials allow usage of learning analytics (LA) as a tool in data-based decision-making (DBDM). However, there are questions about the interplay between teachers, students, context, and technology. Therefore, this paper presents an exploratory systematic scoping review to investigate findings regarding LA usage in digital materials, teaching, and learning in K–12 mathematics education. In all, 3,654 records were identified, of which 19 studies met all the inclusion criteria. Results show that LA research in mathematics education is an emerging field where applications of LA are used in many contexts across many curricula content and standards of K–12 mathematics education, supporting a wide variety of teacher data use. Teaching with DBDM is mainly focused on supervision and guidance and LA usage had a generally positive effect on student learning with high-performing students benefiting most. We highlight a need for further research to develop knowledge of LA usage in classroom practice that considers both teacher and student perspectives in relation to design and affordances of digital learning systems. Finally, we propose a new class of LA, which we define as guiding analytics for learners, which harnesses the potential of LA for promoting achievement and independent learning.

Notes for Practice

- LA is mainly used as a tool when teachers provide classroom assessments and feedback. When teaching with DBDM, teachers use LA to supervise or guide students.
- LA has a positive effect on student learning, and high-achieving students benefit most. With support from both teachers and technology, usage should enhance active learner and student ownership of learning, focusing on the learner as a user of LA.
- Design of LA should take the content of different subjects into consideration. For example, *guiding analytics for learners* is *analytics based on the analysis of student (log) data according to learning theories or content-oriented structures, which immediately presents learners with appropriate learning options*.
- Guiding analytics for learners can be a way to support both teaching and learning since such analytics can provide a conceptual map for teaching and promote self-regulated learning, whether individually, for the entire class, or in student collaboration.
- Further research is needed on using LA and DBDM to support teachers and school leaders to meet today's demands of utilizing data. Teachers should not have to use tools they have not been fully introduced to, and it is important to be aware of possible unwanted consequences (such as extensive monitoring). LA implementation should be combined with a pedagogically matched teaching or learning model.

Keywords: K–12 education, learning analytics, data-based decision-making (DBDM), analytics for learners, teaching, learning

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1. Introduction

The generation and use of digital data and their analyses in education comes with many promises and opportunities, such as delivering effective learning (Cen et al., 2007; Hillmayr et al., 2020), promoting self-regulated learning (SRL; Barrus, 2013; Martins et al., 2019), reducing gender and socioeconomic inequalities (Aguerrebere et al., 2022), as well as developing skills needed for lifelong learning (van Laar et al., 2017; van Leeuwen et al., 2022). However, the research evidence on this subject is still modest (Mora et al., 2018), especially in K–12 education (Du et al., 2021; Masiello et al., 2024; Viberg et al., 2020), though it is more common in some school subjects, for example in mathematics (Hase & Kuhl, 2024). In mathematics education, data analysis tools have been shown to be successful in teaching and learning (Ramli et al., 2019). However, most of the research on educational use of data does not use empirical data from classroom contexts but instead merely discusses potential benefits and focuses on measuring learning rather than supporting learning (Viberg et al., 2020). Additionally, the studies that use analyses based on empirical data usually only have small data sets (Du et al., 2021). In this article, we want to explore how learning analytics (LA) is used to support mathematics teaching and learning with digital materials in classroom practice. Thus, LA is central to our research objectives and is defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens & Baker, 2012, pp. 252–253).

According to a recent review examining the application of LA in mathematics (Ramli et al., 2019), the adoption of LA can predict learning performance and improve the efficiency and quality of learning. Their results also showed that LA in mathematics can give teachers information to improve the quality of their teaching and provide accurate student feedback. However, questions remain about how teachers utilize LA for teaching and learning in mathematics and about teacher readiness to use LA in the classroom (Lang et al., 2022; van Leeuwen et al., 2022). We consider these questions regarding real-life classroom context and everyday usage as crucial to the application of LA in mathematics education, and they will be considered when developing our research questions.

In this review, we discuss LA as "a sophisticated form of data driven decision making" (Mandinach & Abrams, 2022, p. 196) for mathematics teachers, helping them to make pedagogical decisions based on student performance. Data-driven decision-making, or data-based decision-making (DBDM), has been defined by Schildkamp and Kuiper (2010, p. 482) as "systematically analyzing existing data sources within the school, applying outcomes of analyses to innovate teaching, curricula, and school performance, and, implementing (e.g., genuine improvement actions) and evaluating these innovations." As Hoogland and colleagues (2016) state, "DBDM can be considered a subset of formative assessment" (p. 377). Teachers commonly provide feedback from DBDM on a class level based on objective outcome data from standardized tests (van der Kleij et al., 2015), but they also use informal assessment data, such as homework and quizzes. DBDM is a key for the interpretation of LA, and can use any form of data, but *in this review, the term DBDM is restricted to digital data*.

Since complexity is added by technology and data use (Hoogland et al., 2016), working with DBDM in the classroom may create barriers (Datnow et al., 2013; Schildkamp et al., 2014). For example, accountability pressure (i.e., pressure on teachers to ensure that students perform well) can become low or high, and a teacher's decision-making can be affected by either a reluctance to implement DBDM or by shifting their focus from learning to assessment results (Hoogland et al., 2016). Using LA as a tool for DBDM could streamline data, making it more readily interpretable, but since much LA research has focused only on concepts or framework and on proof-of-concept rather than actual analysis (Du et al., 2021), questions remain about how this can translate into practice (Mandinach & Abrams, 2022). According to Utterberg Modén et al. (2021), "An intelligent tutoring system needs to adapt to both the students' learning and the teacher's activity" (p. 1546); otherwise teachers might stop using the system. Indicating that even for high quality LA, there is still a need to consider its design and compatibility for educational applications.

Studying the integration of LA in teaching also embraces content matter and pedagogy, as exemplified in the technical, pedagogical, and content knowledge framework developed by Koehler and Mishra (2009). This framework is well established in research about digitalization and education (Wohlfart & Wagner, 2023), where technology, content, and pedagogical considerations can be taken into focus simultaneously. It offers an understanding that the quality of technology integration is not merely about technology use but about pedagogical use (Ottestad & Guðmundsdottir, 2018) and about transformation and amplification of teaching and learning through the use of technology (Consoli et al., 2023).

Wise et al. (2014) have studied different approaches for LA from learner points of view and found it can be divided into two classes of analytics for learners:

1. *Embedded analytics* is a seamless part of the learning environment; for example, adaptive learning software used by learners
2. *Extracted analytics* separates the interpretation of LA from the learning activity itself; for example, dashboards for learners and/or teachers that provide a compiled assessment for the student(s) in relation to learning goals

LA research primarily uses traditional analytics methods (e.g., statistics, visualization; Du et al., 2021) integrated into digital learning material (DLM), but LA also includes sophisticated system design (e.g., intelligent tutoring systems, augmented educational technology), adapted and personalized to the users (Sahin & Ifenthaler, 2021). To discuss this range of LA, we use the term digital learning systems (DLS), which in our case need to be connected to mathematics and LA, excluding all technology focused on administrative decision making, predication, or any other type that deals, for example, with data such as attendants. This study is limited to mathematics and LA where both teaching and learning are present in each publication. A recent thesis analyzed the use of digital mathematics textbooks either 1) without analytics, 2) with embedded analytics, or 3) with extracted analytics through dashboards (Utterberg Modén, 2021). Results indicated that if digital materials are not combined with extracted analytics, teachers experience a loss of transparency about the learning process when students engage in learning activities. van Leeuwen et al. (2022) point out that transparency and symmetry are the main issues when teachers and students use LA in the classroom. This is, in a way, intuitive, given that teachers' work is about knowing how students are involved with specific content matter and how learning is progressing, and, with this knowledge as a base, giving relevant feedback to their students.

The role of the teacher in student learning is clearly of central importance (Hattie & Yates, 2014; Yackel & Cobb, 1996), and teachers have a key responsibility to make digital technology a recourse in teaching to support student learning (Scherer et al., 2019). Therefore, in this present review, we consider it important to examine how the use of LA impacts both teaching and learning.

In the present exploratory systematic *scoping review*, the aim is to identify and synthesize empirical research from a broad range of methods regarding the use of LA and DBDM in classroom practice in primary and secondary (K–12) mathematics education. The scoping review framework used in this review originates from the work by Arksey and O'Malley (2005), which provides "a technique to 'map' relevant literature in the field of interest" (p. 20) and can be performed even if there is limited relevant published primary research (Gough et al., 2017). A systematic scoping review — in contrast to aggregative meta-analyses — addresses broader questions and may include studies with various designs and methods (Munn et al., 2018; Gough et al., 2017). The range of evidence we seek is located at the interplay between learners, teachers, and digital tools, and therefore a scoping review is appropriate. To synthesize and summarize the evidence we use a configurative (Gough et al., 2017) approach that involves using open questions rather than clear hypotheses, and informal and interpretive procedures rather than statistical inference. In the next sections, we present the method used for this scoping review, thereafter our findings, followed by thematic summaries and analysis, to answer our research questions.

2. Methods

This scoping review followed the *Joanna Briggs Institute's Manual for Evidence Synthesis* (Peters et al., 2020), using Arksey and O'Malley's (2005) five-stage framework, which includes the following steps: 1) identifying the research question, 2) identifying relevant studies, 3) study selection, 4) charting the data, and 5) collating, summarizing, and reporting the results. This scoping review study has a commonly used exploratory approach in which the research process can move back and forth between different steps in an iterative way (Colquhoun et al., 2014).

2.1. Identifying Research Questions

In didactical traditions of mathematics, there is a strong emphasis on the mathematical content in relation to both teaching and learning (Blum et al., 2019). Within these traditions, teaching is operationalized through the design of instructions and processes, which defines *what* (mathematical content and standards) and *how* (setting, technology integration) students (grade) learn. The challenge for LA is the interpretation and translation into classroom practice; therefore, both teachers and students must be included as participants in order for the studies to be included in this review. The publications do not necessarily need to present results on both teaching and learning but should in some way relate to teaching and learning or be anchored in a real-life classroom context.

The following research questions were drawn to ensure a wide range of literature relevant to the topic and research methods:

RQ1: How are analyses of digital data from DLM used in mathematics education?

RQ2: How do analyses of digital data from DLM impact teaching and learning?

2.2. Identifying Relevant Studies

The databases ACM Digital Library, ERIC, PsycINFO, Scopus, and Web of Science were chosen since they cover a wide range of topics within technology and educational science. The search strategy used across the databases was developed iteratively, taking each database into consideration, and adjusted as the eligibility criteria were finalized (Table 1). The full electronic search strategy with search terms can be found in Appendix A. The search was updated on 7 March 2023 (see section 2.3). We considered publications that met the inclusion criteria listed in Table 1. Exclusion criteria (also Table 1) were developed to ensure consistency within the selection process. The key elements of the research questions — Participants, Phenomena of Interest, Outcome, Context, and Type of Source of Evidence (Arksey & O'Malley, 2005) — were used to create the eligibility criteria.

Table 1. Eligibility Criteria According to Key Elements

Inclusion criteria	Exclusion criteria
a) Publications that address the use of DLMs in mathematics education b) Publications that address the use of the analysis of digital data in mathematics education	Publications should not address technologies outside the domain of LA in mathematics. Technologies used only for registering attendance, for administering salaries, or for enabling communication are not relevant.
c) Publications that address the use or analysis of digital data in relation to teaching and learning	Publications that do not address any pedagogical intent with the use of the analysis of digital data (e.g., proof-of-concept studies)
d) Publications that focus on students (6–19 years old) and teachers in primary and secondary education	Publications that focus on students younger than 6 years old or older than 19 years old.
e) Publications include peer review articles, grey literature, and books	Publications that are primarily editorial, discussion, or personal opinion.
f) Publications that report quantitative and/or qualitative data	
g) Publications written in English, Swedish, or Norwegian	
h) Papers published from 2000 to March 2023	

2.3. Study Selection and Charting the Data

The selection process is presented in Figure 1 as a PRISMA flowchart diagram (Tricco et al., 2018). This started with 3,654 identified records (Web of Science 887, ProQuest [ERIC + PsycInfo] 914, ACM 265, Scopus 1,542, other 46) imported into a data management program (EndNote version X9), where 667 duplicates were removed. The remaining 2,987 articles were split into six batches and each reviewer was assigned two unique batches, thereby two reviewers screened each record. Initial screening excluded studies that were off topic or did not meet inclusion criteria d, g, or h (Table 1), streamlined by searching for exclusion words, e.g., "higher education," "medicine," "kindergarten," and so forth, and validated by exclusion analysis (see Appendix B). The remaining 773 records were qualitatively coded using a template (see Appendix C) constructed according to inclusion criteria a–c and e–f. Discussions with the entire review group were held continuously throughout the process, and as a result, the relevance coding template (Appendix C) was developed into a new template (Appendix D). The new template was constructed using inclusion criteria a–b, renamed C1 and C2, and by breaking down inclusion criterion c into the four core components of the criterion — i.e., C3a (use) or C3b (analysis), and C4 (learning) and C5 (teaching) — to more clearly assess whether the publications met the inclusion criteria.

A second screening excluded 634 records, leaving 139 records to be coded according to the new template, which helped exclude 80 records and resulted in 59 records being identified as eligible. Thereafter batches were swapped between reviewers and fully screened. This included relevance coding according to the new template (Appendix D) to perform an inter-rater reliability (IRR) test (see section 2.3.1), data extraction, and final selection assessments. For the data extraction, the 59 records were evenly and randomly divided amongst the reviewers to extract data according to Arksey and O'Malley's (2005) framework in order to 1) see if any subtopics/data items emerged, 2) detect possibilities for mapping, 3) further clarify whether the publication was eligible (Colquhoun et al., 2014), and 4) enhance the reliability of the relevance assessment of the publications. After reviewers read every record and data extraction was completed, a final selection of 19 articles was made by group discussion and consensus, rejecting 40 records for reasons presented in Figure 1. Only one rejection reason was stated, e.g., if C2 *and* C5 were not fulfilled, then the record belongs to C2 in Figure 1. Appraisal of each source evidence was an integral part of the qualitative discussion in the last step of the selection process, as inclusion criterion f (see Table 1) demanded some form of empirical evidence.

2.3.1. Inter-Rater Reliability

An independent researcher outside of the review group was consulted to design the IRR test and validate the results. An IRR score was calculated by comparing the coding of the template (Appendix D) from the two batch groups who had performed the coding. Records for the IRR test were randomly selected from the 59 that passed the three screening phases, and nine records were examined. Every publication had five relevance coding cells in the template (Appendix D), thereby 45 cells were examined. For each matched cell (i.e., both groups that had read article X had similar coding), 1 point was denoted, for a maximum total of 45 (5 × 9) points. Since the coding was qualitatively performed, the IRR index was equal to the sum of match points divided by the maximum points (Appendix E). The calculated IRR score was 0.822, greater than 0.8, indicating a strong level of agreement (McHugh, 2012). Possible reasons for discrepancies included no predetermined coding, and the full article had not been accessed during step three but had been accessed during step four.

2.4. Collating, Summarizing (Synthesizing), and Reporting the Results

The PRISMA Extension for Scoping Reviews (PRISMAScR; Tricco et al., 2018) was used as a guideline for reporting the results. Included studies are marked with an asterisk in the reference list, and Appendix F presents a condensed version of the data extraction showing authors, year of publication, location, digital technology, and method for each study. The heterogeneity in our sample demanded a configurative approach to the synthesis to combine several types of evidence (Gough et al., 2017). A thematic summary provided the analysis with a narrative approach to answer RQ1. To explore RQ2 more deeply, a thematic synthesis was performed (Gough et al., 2017), which requires a label for the theme, definition, description, characteristics, quote/example, and indicators (Boyatzis, 1998). We focused the coding on results and methods, but the entirety of the publication was also considered. The coding was done by hand because of the small sample size.

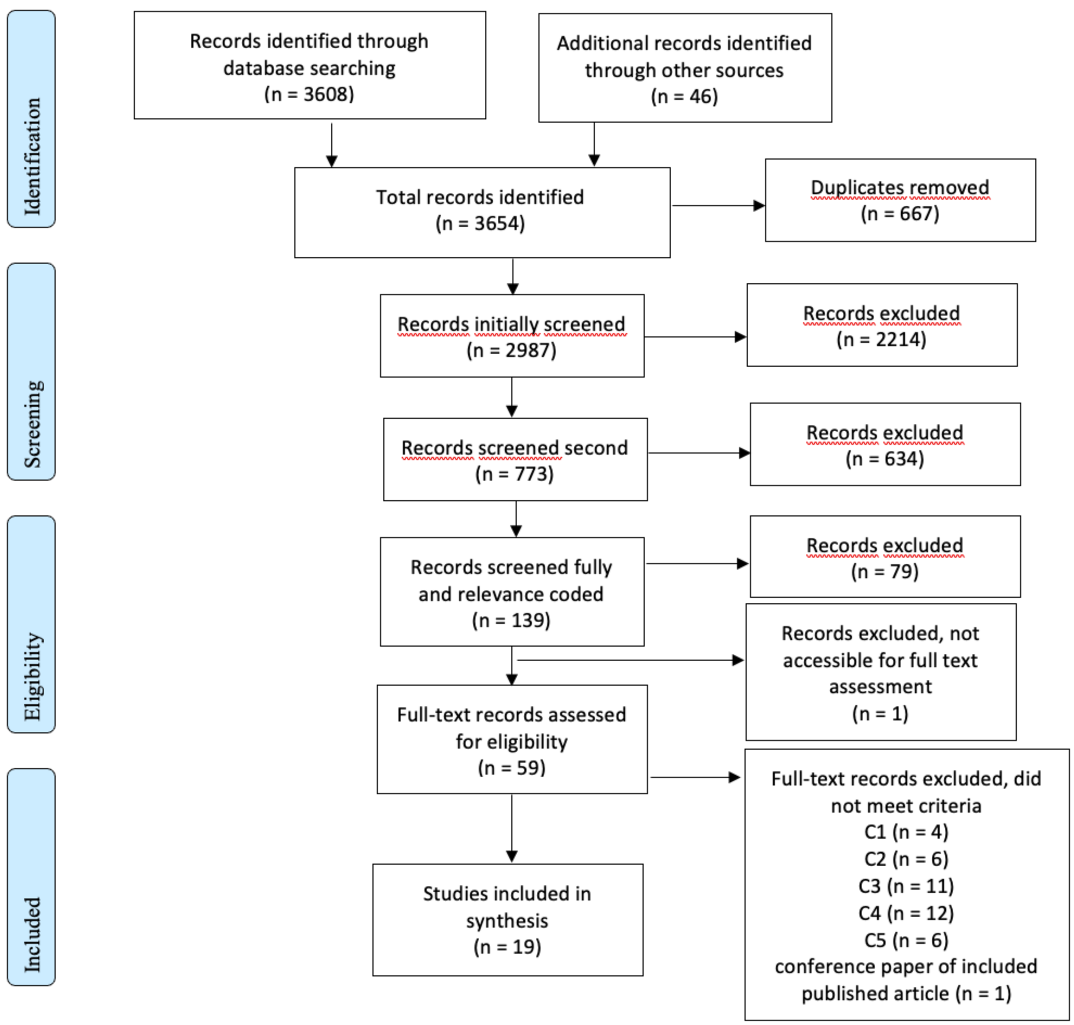

Figure 1. PRISMA flowchart diagram.

3. Results

The selection process, described in Figure 1, identified 3,654 records and resulted in 19 included studies (Campos et al., 2021; Chen & Chen, 2009; Confrey et al., 2019; Faber et al., 2017; Hawn, 2019a; Hawn, 2019b; Lin & Yang, 2021; Kalloo &

Mohan, 2011a; Kalloo & Mohan, 2011b; Molenaar et al., 2020; Molenaar & Knoop-van Campen, 2019; Moltudal et al., 2022; Qushem et al., 2022; Rodríguez-Martínez et al., 2023; Schwarz et al., 2018; Stecker & Foegen, 2022; Wang et al., 2022; Yang & Chen, 2023; Yang & Lu, 2021). See Appendix F for the full data extraction and the specifics of each study. The research in the included articles was conducted in the United States (n=5), Taiwan (n=4), Netherlands (n=3), Caribbean (n=2), and one each in China, Spain, Norway, Israel, and United Arab Emirates (see column *Location* in Table F.1). They used a variety of methods, with the first publication in 2009, two from 2011, and the remaining from 2017 and after. All four studies in Taiwan had an experimental design. Eleven studies used existing technology, and eight studies developed or improved digital technology as a part of the studies. The LA used in Confrey et al. (2019), Chen and Chen (2009), and Wang et al. (2022) underwent validation in connection to classroom practice as an initial part of the study; LA used in Schwarz et al. (2018) were still under development; Kalloo and Mohan (2011a, 2011b), Yang and Chen (2023), and Yang and Lu (2021) integrated LA with a game-based learning system.

3.1. RQ1: How Are Analyses of Digital Data from DLM Used in Mathematics?

Analysis of digital data was used in primary school (n=12), secondary school (n=4), or in both primary and secondary school (n=3) to teach/learn the following: mathematical ratio (n=5) by practising concepts, procedures, and basic problems; algebra (n=6) by focusing on core skills (procedural skills) and concepts; geometry (n=1) by students reasoning about quadrilateral relationships; arithmetic (n=3) by practising procedural skills or mathematical concepts; trigonometry (n=1); and/or non-specific content covered by mathematical curricula, i.e., mathematics in general (n=6). For identification of the particular articles in these groups, see the *Content* and *Setting* columns in Table F.1.

Fourteen of the studies used DLSs with direct feedback to students in a classroom setting (*blended learning*, commonly describes traditional classroom practice combined with digital tools for learning). For nine of these, the DLS was used as a *digital textbook*, and thereby as the main learning material (see *Setting* Table F.1). In Moltudal et al. (2022) the DLS was used for homework, the connection with classroom practice varied according to the teacher and ranged from being used as a textbook (integrated), to a supplement, or not being used at all by the students during lessons (separated). Whereas in Rodríguez-Martínez et al. (2023), the student homework was based on how they answered during lessons, and therefore was fully integrated into classroom practice. In Qushem et al. (2022) the DLS was used for homework and at least once a week in class during a 9-month period. The number of days during which the DLS was used varied. In school 1, the average number of days was 48 and 37 for the 4th- and 5th-grade students respectively (partly integrated). In school 3, the average number of days was 191 and 179 days for the 5th- and 6th-grade students respectively (integrated).

Instead of DLSs being used in a blended fashion, Hawn (2019a, 2019b) and Stecker and Foegen (2022) used *pen and paper* to collect data via tests and surveys that was converted into digital data by researchers, teachers, or admin personnel; and in Schwarz et al. (2018) all teaching and learning interactions occurred *digitally*. Schwarz et al. (2018) analyzed student interaction (log) data, collected from groups of 2–3 students. Campos et al. (2021) used student self-reported survey data on their understanding and experience of the mathematic lesson collected routinely from the students at the end of lessons. Wang et al. (2022) utilized student self-reported data regarding mathematics learning strategies. The remaining studies mainly based their LA on continuously collected individual student log data concerning student activity in relation to mathematical content and learning level, student answers to mathematical assignments, student usage time for different activities, or other forms of behavioural data.

The continuously collected data was used for embedded analytics for learners to adapt or personalize learning according to user performance. By using adaptive functions, analyses were used as a point of departure for mathematics lessons (e.g., Chen & Chen, 2009), as homework, or to support students on different levels (e.g., Moltudal et al., 2022). Twelve of the studies included embedded analytics (see *Digital technology used* in Table F.1). Individual student log data was also used for extracted analytics for learners, available in the DLS to be used as tools for formative assessment and visualized as alerts about online critical moments (Schwarz et al., 2018), presented through "teacher dashboards" (e.g., Faber et al., 2017), learning performance rules (Chen & Chen, 2009), and "learning ladders" (Confrey et al., 2019). All studies included extracted analytics (see *Digital technology used* in Table F.1), but accessibility varied for students and teachers. Analytics were available for both teachers and students (e.g., Chen & Chen, 2009), different analytics being available for teacher and student (e.g., Confrey et al., 2019), only available for teachers (e.g., Schwarz et al., 2018), or students had to ask the teacher to share extracted analytics, in which case the "teachers needed to determine which information to share with pupils and the extent to which they should contextualize the result" (Moltudal et al., 2022, p. 14). Overall, extracted analytics were mainly mentioned as a function for teacher usage where analytics need to be translated by teachers into some kind of pedagogical action (i.e., into teaching).

3.2. RQ2: How Do Analyses of Digital Data from DLM Impact Teaching and Learning?

In this section, the two aspects of teaching and learning are addressed and the included studies are analyzed for each aspect.

The terminology in the studies differs for teacher and student usage. Teacher data use refers to time or clicks spent using functions to view, analyze, or manage data within systems. Teacher actions relate to DBDM for various aspects of teaching, such as providing classroom assessment or feedback to students, or planning lessons. Student usage refers to time spent using systems. Student behaviour refers to sequences of student digital actions within a system.

3.2.1. Teaching

Data use varied a lot amongst teachers (Hawn, 2019a) and there were foundational differences across both school level and content area (Hawn, 2019b). Faber et al. (2017) found that mathematics teachers did not use data or feedback features to a great extent. In Hawn (2019a), mathematics teachers had higher usage than teachers of other subjects. The group that displayed both high variety and rate of use (8%) consisted almost exclusively of mathematics teachers. However, they mainly used the DLS to create and manage tests, as opposed to viewing and analyzing testing results. Mathematics teachers were also the only ones seen engaging in *Student-Centred Analysis*, a specialized use where they show a high rate of use based on multiple types of data for individual students. While teachers within other content areas spend more time interpreting data, mathematics teachers could utilize shorter, more frequent sessions as well as longer ones. According to Hawn (2019b), mathematics teachers when compared to other teachers, showed a positive attitude towards data use, had higher levels of usage, reported more actions based on data, higher usefulness for data activities or formalized testing, higher self-efficacy for DBDM but lower self-efficacy for teaching in general. Mathematics teachers reported a similar frequency of data-type use across middle and high school, though high school teachers perceived attendance and individualized student data in complex student profiles as more useful. Teachers in general valued their own data (assessments, observations, and grades) over data from DLSs.

Campos et al. (2021) explored and compared teachers' and coaches' sensemaking for instructional decisions by categorizing responses when viewing data as emotional, analytical, or intentional. Results suggest that teachers and coaches respond to data in diverse ways. In the analytical dimension, *Attribution of Cause* and *Recall* responses were significantly greater for teachers (47 and 21 recorded occurrences) than for coaches (21 and 4 occurrences), suggesting that teachers use their own experiences to make sense out of data. Having said that, *Attribution of Cause* co-occurred with no intentional response 62 times, meaning that although explanations were attributed to the data, planning or intended action did not often follow this. Additionally, emotional responses for teachers were common when viewing data. In Moltudal et al. (2022), teachers were concerned about student misuse, the amount of data (i.e., student activity) required to represent student knowledge accurately to place students at the right level, and they wondered if it was even possible for the dashboard to reflect student learning. This is exemplified by the interview finding for one of the teachers, Alex, who said, "The program maps out what the pupils can and cannot do, but not what the underlying problem is" (p. 12). Teachers were initially positive towards using the DLS but unsure how to use it in their own practice. Since the teachers did not receive any specific data training sessions during the intervention, they had to make sense out of data without quite knowing how to interpret it. Still the teachers reported using dashboard data to identify and support students who struggle, and to plan further classroom activities for the whole group and for specific pupils.

In Hawn (2019a), 62% of the teachers (of several subjects) displayed low use of data and the assessment platform. They mainly used data during in-person data training sessions. Communication of extracted analytics to teachers via email rarely led to any usage. Stecker and Foegen (2022) evaluated modules of professional development to support algebra progress monitoring by using a DLS. Teachers improved their scoring accuracy and knowledge significantly. Teachers reported spending 45 minutes on average viewing analytics each week. They mainly focused on individuals, where more teachers reported that use led to action when examining student errors than when examining student skills or progress graphs. Overall, teachers reported high levels of satisfaction, including "the clarity of the imbedded technological features" (p. 17). Wang et al. (2022) found that mathematics teachers show a positive attitude towards the personalization offered in DLSs. In Moltudal et al. (2022), mathematics teachers show a positive attitude for homework, volume training for students who struggle with writing skills, and variation through flipped classroom.

Table 2 contains studies (n=5) that observed and described how teacher actions were carried out in classroom practice. Studies with results on teachers self-reported actions are not presented in Table 2 since they do not go into detail about the various ways these actions can occur in a classroom context. Table 2 provides an overview of the themes and categories of teacher actions. The thematic synthesis yielded two themes: *Supervision*, containing variations of actions displayed in categories a–d, and *Guidance*, containing actions with different focuses in categories e and f.

The categories under the S*upervision* theme emerged from the use of DLS, where data and data analyses of student activities were made available to the teachers in a conventional teaching role. This role was exemplified by a peremptory communication style where students received summative feedback from their teacher, as teachers monitored student work and progress, managed groups and reprimanded or encouraged students.

Teaching within category a, the *Monitor* was either passive, i.e., the teacher observed without actions — a common response when teachers make sense out of data (Campos et al., 2021) — or active, and involved action connected to handling student learning activity by giving feedback. Feedback could refer to class or individual student behaviour, pace, or performance, to enforce or correct their learning. Some teachers focused on *Individual thinking and "correct" form of problem solving* (Moltudal et al., 2022), although actions were aimed equally at individuals or the entire class. Actions were often based on student mistakes to determine the cause of errors, or on previous agreements made with the class — e.g., "You are working as I suggested, well done!" (Molenaar & Knoop-van Campen, 2019, p. 6). In addition, when teachers emphasize monitoring students, they seem to use the DLS to a higher extent (Moltudal et al., 2022). Closely related to category a (*Monitor*), categories b (*Reprimand*) and c (*Encourage*) incorporate actions in which teachers gave either negative or positive personal summative feedback on student behaviour or performance. Category d (*Manage groupwork*) was similarly a form of supervision. Although social engagement was encouraged, the request for execution according to instructions was more visible than feedback on collaborative learning, thus emphasizing control over student learning activities (Schwarz et al., 2018). However, category d moves towards the next theme as the teachers explained how and in what way students could assess and use the analytics to address their personal needs. The intention being that grouping and awareness could benefit the students through creating settings for productive learning (Confrey et al., 2019), or the DLM could be used as a tool to adapt to a student's individual pace (Moltudal et al., 2022).

Table 2. Themes and Categories of Teacher Actions

Study	Supervision				Guidance	
	a) Monitor	b) Reprimand	c) Encourage	d) Manage groupwork	e) Formative focus	f) Conceptual focus
Chen & Chen, 2009	"Concentration degree 90%." "Accumulated Score of Q&A 4 points."	"Raise your hand before answering the question."	"Good job! Your solution is creative."			
Confrey et al., 2019				Productive use of tool: e.g., by dividing students according to their relative success on different levels and directing them to fix their mistakes in groups.	Extent of use of formative practices and growth mindset: e.g., by using analytics in a more class-oriented formative way oriented towards identifying student learning gaps.	The degree of learner-centred instructions: e.g., by adaptively using heatmaps to build teaching sequences with conceptual and procedural components that invite students to reach a solution while providing scaffolding.
Molenaar & Knoop-van Campen, 2019[a]	No action (19%). Process (40%). Teacher provides feedback on the way students handle their exercises. "Tim, you can move on to the next exercise."		Personal (4%). Actions in which the teacher comments on a student as a person. "You are doing well!"		Task (37%). Actions in which the teacher comments on how well exercises are understood or performed, related to content. "Please do not forget to add the numbers you have to keep in mind."	
Moltudal et al., 2022	Sam: Teacher observed and (re)directed pupils use of DLS when used. Emphasized that pupils set up calculations on paper.			Alex: Pupils who finished collaborative group tasks used DLS solo at the end of the lesson.		Kim: Referred to tasks, words, and concepts in DLS when guiding the pupils.
Schwarz et al., 2018	Monitoring and supervising (24%). Teacher made sure students undertook the execution of tasks as planned. "Please concentrate only on the first task! Stop dragging the diagonals of tasks 2 and 3."	Asking for justification (12%). "Please justify!"	Social validation (15%). "Excellent!"	Collaboration (6%). Consists of prompts for encouraging collaborative behaviours. "You need to reach an agreement about the right solution, all of you!!"		Scaffolding (43%). Teacher as a facilitator of knowledge construction. "Are the properties of the rhombus preserved after dragging the shape? Or might it be another kind of quadrilateral?"

Note. Actions are grouped within two themes and six categories. The cells display/reflect observed pedagogical actions of participating teacher(s), including frequency distribution (%) if present in the article, description, quote/example.
[a] Two categories in this study, Social and Metacognition, were omitted from Table 2 since no such observations were recorded.

The second theme involves actions of *Guidance*, with categories differentiated in terms of the focus as either formative or conceptual. Results indicate guidance to be a nuanced theme with complexity arising from the interplay of different pedagogical actions (Schwarz et al., 2018). The five studies (in Table 2) described a progression where actions of this kind were more desirable, e.g., "Some teachers transitioned […] This demonstrated movement toward *growth mindset*" (Confrey et al., 2019, p. 35), and pedagogical diversity was a mark for quality of teaching (Molenaar & Knoop-van Campen, 2019). Teachers who report a high frequency of actions derived from use were identified as having above average time spent using the system (Hawn, 2019b). No groups of teachers with a low use of the system but a high variety of use were identified (Hawn, 2019a). As the use of LA increased, so did the types of data being used and the variety of functions accessed, as well as the diversity in teacher actions (Confrey et al., 2019; Molenaar & Knoop-van Campen, 2019), thus permitting more actions with formative and conceptual focus.

When the DLS was used as a tool to support teaching with a *Formative focus* (category e), the teachers seemed to go beyond certain task or specific error analysis, to address student abilities in a more general way, or in relation to a wider content within the subject matter. Teachers used the DLS to assess student progression and guide students in their upcoming learning by identifying and informing them of their learning gaps, or what they should be aware of, and how planned classroom activities were related to these. Actions within category e dealt only with student mathematical assessment data, making the student (performance) the focus of the teaching (Confrey et al., 2019; Molenaar & Knoop-van Campen, 2019) by using previous knowledge about the students. Formative feedback on student learning could be communicated on an individual or class level but was more frequent for teaching aimed at individual students (Molenaar & Knoop-van Campen, 2019). When extracted analytics were used in a way that supported teaching and learning with a *Conceptual focus* (category f), the teaching was concerned with facilitating knowledge construction and to some degree contained learner-centred instructions. Between categories e and f, the focus of teaching shifted more directly onto mathematical content. Observed actions from which category f emerged involved a conceptual approach to teaching by targeted instructional design, discussions with students, or impromptu interventions during lessons where the teacher was very familiar with the mathematical content (Confrey et al., 2019; Moltudal et al., 2022; Schwarz et al., 2018). Besides using extracted analytics for guidance with a conceptual focus, having an overview of student interactions also permitted the teacher to intervene with pedagogical actions (Schwarz et al., 2018), and using the content provided by the DLM itself as a starting point, permitted discussions with students (Moltudal et al., 2022).

In summary, for all categories of both themes, student learning was planned, observed, and controlled by the teachers, as they corrected/steered students when they deviated from the planned course. Typically, actions for supervision were based on teacher appraisal of learning performance or behaviour, to give summative assessment feedback and were steered by teachers for students to accomplish productive learning, sometimes in a social setting. The frequency distribution of teachers' pedagogical actions suggests that extracted analytics are more commonly used for supervision than for guidance. When teachers emphasize the monitoring of students, they also use DLS to a higher extent. For teachers to provide guidance on the class level, interpretation of data needs to happen in advance, as only different variations of monitoring occurred on class level during lessons. Guidance actions were based on assessment of learning performance to give (in)formative assessment feedback, where the learning was characterized by collaborative student work as students engaged in self-regulated learning (SRL) or conceptual learning.

3.2.2. Learning

Looking at the articles regarding formative assessment and feedback, the studies show that:

1. Using a DLS with a formative assessment tool can have a positive effect on student mathematics achievement and motivation (Faber et al., 2017).
2. DLSs that contain functions that provide feedback to students based on formative assessment can lead to better learning performance, satisfaction, and confidence (Chen & Chen, 2009).
3. Personalized homework from an LA-based formative assessment tool can lead to a higher level of mathematical understanding compared to non-personalized homework (Rodríguez-Martínez et al., 2023).
4. Longer reading time of personalized feedback can have a positive effect on learning, while time spent reading general feedback does not seem to have an impact on learning (Yang & Lu, 2021).

Turning to the studies that use a tutoring system with personalized learning paths, the following main findings emerged. Qushem et al. (2022) found that when using the tutoring system as a complement to regular classroom activity, students needed to practise for at least 69 days for a minimum of three minutes a day in order to make substantial progress. For young students (Grade 4), use of the system supported the transfer of arithmetic fluency to more advanced domains, developing their conceptual understanding in mathematics. Molenaar et al. (2020) evaluated whether learning paths could be used as a tool in SRL by comparing two groups using a DLS with learning paths with three groups using the same DLS without learning paths. In the intervention conducted by the class teacher, the experimental group began their lessons by setting goals based on

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extracted analytics in the form of learning paths. Results indicated that using the learning paths for SRL did not increase student effort, but their accuracy improved, resulting in increased learning performance and transfer. It was found that students had difficulties estimating their abilities. Although students did not improve in their calibration of their abilities, they did show less overestimation but, at the same time, higher levels of underestimation.

Instead of examining formative assessments, Lin and Yang (2021) explored usage of a DLS and multiple scaffolds to support student SRL. An experimental design was used to compare three classes where two groups used the same DLS in various ways. The first class used a teaching strategy based on multiple scaffolds that contain SRL, computer supported collaborative learning, group presentation, and teacher scaffolding. The second class used a flipped classroom, and a third class used traditional teaching methods. The results show that using a DLS supported with multiple scaffolds can lead to better learning achievements and more student activity. Students also had a more positive attitude towards SRL as they scored higher on planning, self-monitoring, evaluation, reflection, and effort (Lin & Yang, 2021).

High-performing students profit more from using a DLS with embedded and extracted analytics without receiving adaptive teacher instruction (Faber et al., 2017; Kalloo & Mohan, 2011a; Lin & Yang, 2021). In fact, even when *Instruction to high-performing students* was rare, they still profited more than other students (Faber et al., 2017). Observations of high-achieving students using a DLS show young students engaging in high-level reasoning, indicating the *emergence of conceptual learning*, as students were working with mathematics way above their grade level (Schwarz et al., 2018). In Lin and Yang's study (2021), high-performing students used teaching material available in the DLS more than other students. High-achieving students who received multiple scaffolds performed significantly better than the high-achieving students who received traditional teaching, but there were no significant differences between the high-achieving students receiving multiple scaffolds compared to the flipped classroom.

Faber et al. (2017) found that using a DLS is more effective for learning if teachers use LA for DBDM. Kalloo and Mohan (2011a, 2011b) conducted three studies using a DLS with various levels of teacher support and classroom implementation. In study 1, nineteen students used a game-based DLS with personalized recommendations for three weeks. In study 2, twenty students used the DLS with teacher support, both via the application and in person. In study 1, 63% of the students improved their performance with an average increase of 8.8%. In study 2, 95% of the students improved their performance with an average increase of 10.2%. When usage was supported by the teacher, students used the DLS 67% more times and 300% longer (Kalloo & Mohan, 2011a). In the third study, the DLS was implemented in class as a learning tool for 18 students learning algebra for the first time (Kalloo & Mohan, 2011b). This group was compared with another group of 54 students who were not using the tool. The same teacher taught both groups. There was no difference between the control and experimental group, but evidence suggests that the students who passed the post-test (10/18) used the DLS 22% more and 63% longer than students who failed. Of the experimental group, 85% agreed that the DLS was useful and helpful and 83% agreed that they could learn from both the teacher and the DLS.

Familiarity with tools and tasks can lead to reducing such unwanted behaviour as *idleness* and *off-topic talk*, as well as increased collaboration (Schwarz et al., 2018). When teachers used LA to manage groupwork (category d, see section 3.2.1), students were observed engaging in self-regulated productive learning in a social setting as they directed their efforts appropriately (Confrey et al., 2019). The more students used the DLS to work collaboratively while reasoning, the less teachers had to intervene, suggesting the DLS afforded collaboration, which was also corroborated by student log data (Schwarz et al., 2018). In relation to guidance with a conceptual focus, the learning was partly self-generated/emerging when students were given room to reason with each other, allowing them to drive their learning forward while teachers scaffolded and supported their process solving mathematical tasks in which they previously had misconceptions, again suggesting that students were engaged in conceptual learning (Confrey et al., 2019; Schwarz et al., 2018).

Five studies included LA designed according to *mathematical concepts* (n=4, Lin & Yang, 2021; Rodríguez-Martínez et al., 2023; Wang et al., 2022; Yang & Lu, 2021) and/or *pedagogical* or *mathematical learning theories* (n=3, Lin & Yang, 2021; Wang et al., 2022; Yang & Chen, 2023). When basing LA on mathematical concepts, the analysis could, for example, be designed according to a taxonomy of error types, providing students with embedded analytics in the form of personalized homework (Rodríguez-Martínez et al., 2023). It could also be designed as knowledge structures of core skills for algebra visualized as a concept map, providing students with embedded and extracted analytics (Lin & Yang, 2021). For three of these five studies, the DLS provided students with an explicit interpreted output generated by the system according to learning theories or mathematical concepts and transformed into a form of *guiding analytics*. These, together with the system's instant feedback, present students with learning options referred to as "appropriate feedback" (Yang & Lu, 2021), "appropriate guidance and feedback" (Yang & Chen, 2023), or as an "improvement plan" (Wang et al., 2022). There is a connection between pedagogical or mathematical ideas or concepts and this type of analytics for learners, simply because the analytics is built according to ideas of learning mathematics. For example, in Yang and Chen (2023), the selected learning "strategy is structured as a guided learning process" (p. 13). From our synthesis of the included studies, we suggest the term *guiding* *analytics for learners*, which we define as *analytics based on the analysis of student (log) data according to learning theories or content-oriented structures which immediately presents learners with appropriate learning options*.

Two studies used guiding analytics by having a game-based learning system integrated with the "Prediction-Observation-Explanation" (POE) learning strategy (Yang & Chen, 2023), or with two-tier testing (Yang & Lu, 2021). A third study used an intelligent assessment of learning strategies as a form of guiding analytics (Wang et al., 2022). The POE teaching strategy consists of three stages: 1) the teacher first allows students to use the original knowledge concepts to predict an event and explain the reason for the prediction; 2) the teacher gives students time to observe, with the content for observation being as direct and specific as possible; and 3) the teacher allows the students to explain the difference between the observation and the prediction, hoping to achieve conceptual change in the process of explanation (Yang & Chen, 2023). Two-tier designed questions are based on knowledge statements related to a concept map. Like the POE strategy, the learner first assesses a mathematical scenario, followed by a second question asking the learner to explain the scenario. The design of the options for the second question are based on estimations of learner conceptions, misconceptions, or common errors. This design makes it harder for students to guess the answer (Yang & Lu, 2021). Instead of focusing on a preselected strategy, Wang et al. (2022) used improvement plans designed based on diagnosing aspects of a student's mathematical learning strategies. By measuring various aspects (cognitive, metacognitive, resource management) of the *mathematics learning strategy*, the system can identify shortcomings in student learning and construct a plan according to predetermined improvement strategies that address these. The teacher supports the student to understand the diagnostics, the strategies, and how to implement the strategies into daily learning activities by demonstrating, monitoring, correcting, rewarding, giving formative feedback, and guiding the students.

Usage of guiding analytics can lower math anxiety (Yang & Lu, 2021), prevent student misuse of DLS by random guessing (Yang & Chen, 2023; Yang & Lu, 2021) and help student development of learning strategies (Wang et al., 2022; Yang & Chen, 2023), thereby having a positive impact on student learning behaviour. "Appropriate feedback" does not necessarily lead to improved learning (Yang & Lu, 2021), but when the student receives analytics that include "appropriate guidance and feedback" they exhibit significantly better learning achievements and retention (Yang & Chen, 2023). When teachers support the use of guiding analytics, it can have a significant effect on student mathematics achievements and learning attitude, and significantly improve targeted learning strategies and an overall mathematics learning strategy (Wang et al., 2022). After working with guiding analytics for a longer time, students mentioned positive changes across the targeted aspects, the development of good learning habits, and improved learning efficiency. One student said that "my enthusiasm for mathematics learning has improved a lot" and another that their "learning burden has been greatly reduced" (Wang et al., 2022, p. 26). Likewise, the teachers expressed positive feelings towards the personalized improvement plans generated by the DLS and felt that the recommendations helped the students become aware of their problems and how to consciously address these, as well as helped the teachers support students according to their needs (Wang et al., 2022).

4. Discussion

Our main aim in this article was to conduct a systematic scoping review to investigate how analysis of data from digital learning materials (DLMs) is used in K–12 mathematics education. Our focus was on teaching and learning in school contexts. Our selection criteria specified not just that LA was used, but that teachers made use of that information in delivering teaching and, that student learning was examined. Compared to a previous review on LA in mathematics education (Ramli et al., 2019), this review has identified several additional studies on K–12 mathematics education, which shows a growing interest in this area. Studies identified in our sample showed variations in both intervention duration, from one week to one school year, and in data sets, from small sets (fewer than 100 students) to larger sets (over 1000 students). These significant differences in the field, in accordance with Du et al. (2021), indicate that LA research is still in an emerging state.

Together, the studies touch on many aspects of K–12 curricula in mathematics education, representing four of five process standards identified by the National Council of Teachers of Mathematics (2000). None of the studies deal with the process of making connections between different mathematical representations; most of the studies focus on a limited part of mathematics. The studies included in this review examine student digital learning behaviour by describing sequences of actions, learning outcomes, and student experiences. Hereby, we capture elements of the studying–learning process and how this may be affected by LA usage. We observed that studies focusing on learning often use an experimental design, as recommended by Ramli et al. (2019), but rarely include students' own voices (1/19), consistent with Hoogland et al. (2016).

One important finding concerned individual differences amongst learners. Typically, high-achieving students profit more from LA and can improve their learning by gaining access to learning material. They appear to have the capability to transfer their learning behaviours to working with these new technologies. Access to digital tools especially benefit those with a higher socioeconomic status and amplifies rather than diminishes discrepancies in education (Selwyn, 2016).

In terms of teacher use, the dominant behaviour seen in our studies concerned monitoring and supervision of behaviour, showing that supervision is an affordance of DLS design. Supervision encourages a passive, dependent learning role for students, thus limiting SRL; not allowing students to be intellectually autonomous in their mathematics learning (Yackel & Cobb, 1996). Monitoring can strain the teacher–student relationship (Utterberg Modén, 2021) and transfer values of "good," and "bad" ways of learning, which may exclude some students and demotivate them to engage in learning (Yackel & Cobb, 1996). Supervision is not in line with current views on learning, which emphasize student ownership of the learning process (Anderson et al., 2001; European Commission, 2019). Of course, supervision is hard to avoid, since much of the LA focus is on measuring (Viberg et al., 2020). As well, there is an expectation that effective/successful DBDM should lead to action (Schildkamp, 2019). Further, teachers are also exposed to accountability pressure (Hoogland et al., 2016) together with pressure to use technology (Webster, 2017).

LA provides a unique possibility for students to monitor their own learning and act accordingly (Wise et al., 2014). However, to use extracted analytics, students must actively access data, interpret them, and finally make decisions based on their interpretation. This is a challenge for learners (as well as for teachers), making the threshold for actively using extracted analytics (for learners) high. Embedded analytics for learners (Wise et al., 2014) is a more passive use of LA since the interpretation and decision making is built into the DLM. A downside to this is that embedded analytics can be hard for teachers to incorporate into their teaching, as they must accept that algorithms direct their teaching (Utterberg Modén, 2021). However, teachers mention that embedded analytics can increase classroom inclusion, as it adapts to the student's level without being visible to classmates. Another potential downside to embedded analytics is that it may limit the scaffolding and conceptual guidance that could be provided. Studies show that teachers with in-depth mathematical training show both higher levels of mathematical knowledge and pedagogical content knowledge (Krauss et al., 2008).

Our results show that teacher data use varies and that teachers do not rely on data from the DLS as much as they do on their own judgments and observations. As shown in Utterberg Modén (2021), teachers appreciate that data can inform them about student performance and which students might need support. However, teachers do not feel that they get access to rich information about student understanding.

To enhance teacher capacity to utilize data, professional development is needed. Filderman et al. (2022) state that teachers can increase their data literacy by daily practice in the classroom, whether the focus of their training is on data collection, interpretation, or decision-making. However, in relation to interpretation of data, and translation of that into action, data literacy training is rarely discussed (Ramli et al., 2019). Rather, van Leeuwen et al. (2022) suggest that for LA to be used effectively, it should suggest pedagogical actions to teachers for individual students.

SRL interventions seem to be especially effective in mathematics and can lead to increased overall academic performance (Dignath et al., 2008). Viberg et al. (2020) review how LA are used for SRL and show that most LA do not provide SRL support (59%). Those that do provide visualization (20%), feedback (19%), or recommendations (4%) as different types of SRL support (personalization). These can be classified as extracted analytics (Wise et al., 2014) based solely on student log/trace data. We have suggested the term *guiding analytics for learners*, which utilizes student log/trace data, but also integrates content knowledge of mathematics into the analysis. Here, LA can be supported by a conceptual map working in the background or as a base for deep machine learning mechanisms, producing LA in relation to both student and subject. Thus, guiding analytics do not require students or teachers to interpret the analytics. Instead, they provide learners with pre-structured explanations or guidance that matches the system's interpretation of the student's understanding. Therefore, we see guiding analytics as a promising new level of analytics where options are presented in the learning environment, thus providing a tool for learners, and summoning them to make active learning choices. Guiding analytics can offer students and teachers a learning map, due to its conceptual mathematical orientation, and can therefore also support teachers' pedagogical decision-making. Based on the studies included in our review, we suggest that extracted analytics (like dashboards) are insufficient for teachers to provide students with metacognitive feedback. Metacognitive feedback was only considered in two studies that both used guiding analytics. Combining strategies related to SRL shows a larger effect on learning achievements compared to using only one kind of strategy, and instructions based only on cognitive strategies can have a low or even negative effect on performance (Dignath et al., 2008).

The field of LA is growing rapidly (Masiello et al., 2024); a search for "learning analytics" in Web of Science reveals 400–500 publications annually between 2019 and 2023. With this in mind, we can ask why our review identified relatively few (19) studies. The answer to that, in large part, is because we were only interested in empirical studies that examined LA usage and its relation to teaching and learning. Du et al. (2021) suggest that a major part of LA-related research is either conceptual or focuses on proof-of-concepts, which this review can confirm by mapping some of the excluded articles. These were either theoretical (Dickinson & Hui, 2009), used simulated data (Wang et al., 2014), used student data but did not connect their results to learning (i.e., results could mean that students learnt how to use the system without necessarily reflecting their mathematics learning; e.g., Cen et al., 2007), or used data from teachers but without connecting their results to teaching

(Jormanainen & Sutinen, 2012), observing, for example, if and when teachers were provided with potentially useful LA, but without following up on whether it was indeed useful. Other studies utilized data to explore the hypothetical potential of a DLS (Cen et al., 2007), testing analytics, testing functionality in a classroom context, and showing possibilities of a DLS for learning and/or teaching (e.g., Jormanainen & Sutinen, 2012), or designing learning material (Taraghi et al., 2014). Our mapping is in alignment with Viberg et al. (2020), who argue that 70% of studies that focus on supporting learners or teachers do not provide empirical evidence on the topic, but instead only discuss potential support for teaching and learning.

It appears that new research in LA is often published stepwise. Based on reviews of LA research (e.g., Du et al., 2021; Viberg et al., 2020) combined with our mapping, we distinguish four steps of publication. Initially, papers that present and explain a DLS and mechanisms (technical aspects) of LA are published. Then, LA researchers publish papers containing proof that a concept or system could work, where they focus on measuring learning rather than supporting it (Du et al., 2021; Viberg et al., 2020). In the third stage, small-scale implementations or evaluations are performed, often related to certain educational aspects, and leaving out, for example, the teachers or students. In this stage, studies can mention empirical data collection without presenting related evidence. According to Larrabee Sønderlund et al. (2019) unpublished research should be made accessible in other forms as it can still be of value. An example is Aleven et al. (2022), who present results from several studies on useability in relation to teacher needs combined with results relevant for the design of educational technology. While some parts of Aleven et al.'s study would be relevant for this review, they do not present evidence from those research activities. Finally, publications on LA connect their research to the classroom context. Confrey et al. (2019) provide an example of this process because they do each of these steps as part of their validation study, though evidence on whether student learning was improved and for whom on an individual level will be provided in an upcoming study.

4.1. Limitations

Our inclusion criteria regarding mathematics, LA, teaching, and learning resulted in a small number of studies. We defend our criteria since we — in line with, for example, Lang et al. (2022), Ramli et al. (2019), and Utterberg Modén et al. (2021) — believe that for LA to be used successfully in K–12 education, tools need to be studied and evaluated in relation to the classroom context. In line with this focus, we limited our scope to only include interventions conducted by teachers. As interventions conducted by researchers tend to have a greater effect, they might not be representative in relation to everyday usage in the real-life classroom context (Dignath et al., 2008). All that said, it is possible that our method and search protocol meant that some relevant studies were missed and, of course, new studies are coming along all the time. Though our research group reflects many academic disciplines, designing the search protocol was a challenge since some search terms have different meanings depending on the field. We designed our search protocol according to components of LA, not by system design (e.g. "cognitive tutor*") nor classroom intervention design (e.g. "flipped classroom"). The inclusion criterion we struggled with most was the one regarding teaching and learning. In the end, we decided on teaching and/or learning and restrained the criteria to present evidence for at least one of them and to include both teachers and students as participants, or have a very clear description in the methods section about what went on in the classroom. Given the criteria used, it is not possible to generalize findings such that LA can be stated to have a positive effect on learning with all kinds of educational technology. Finally, the selection process for this review, by design, eliminated several papers claiming that the tools being used possess LA qualities when in fact they do not, or at least they are not accounted for.

5. Conclusion and Implications for Research and Practice

We conclude that, when LA allows teachers access to data, LA can be applied in classroom practice in a variety of ways. The design of LA can have an effect the extent of usage, teaching style, and student learning behaviour. From the referenced research in this study, it appears that LA usage often has a positive impact on student learning and performance. Implementation of LA by itself does not necessarily lead to enhanced learning or teaching; the learning context also seems to play a big part in the impact of LA. To be helpful for students at all levels, teachers should support student usage of LA. Therefore, implementation should be accompanied by teacher training, so teachers do not have to use tools they have not been fully introduced to.

Consequently, we argue that LA implementation needs to be combined with a pedagogically matched teaching or learning model. When teaching or instruction is designed to "go along with" LA, we see a promising opportunity. We also argue that LA should take the content of different subjects into consideration. Here, we see great potential for guiding analytics as a way to support both teaching and learning, since such analytics can provide a conceptual map for teaching and promote SRL whether individually, for the entire class, or in student collaboration.

We do not claim to present a complete picture of the research in the field of LA. However, our results are consistent with, and further develop, results from other reviews, suggesting that our conclusions can be generalized to some extent to areas beyond K–12 mathematics education. For LA in general, we encourage the analysis of context as a way to bridge LA and the practices in which they are being used. In this review, we have been careful to bring forth both teaching and learning, trying to give them equal space. This is one reason we chose to discuss many of our findings using Wise et al.'s (2014) concepts of analytics for learners. For future researchers, two important questions are these: *How can studies be designed to incorporate students as active participants?* and *How can results from LA with educational potential be validated through empirical results from actual teaching situations*?

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Appendix A: Full Electronic Search Strategy with Search Terms (in one database)

Search terms in search strategy *are the following*: Search #16

Results: 398
Data base: Web of Science
Language: English, Swedish and Norwegian
From: 2000–2020[1] (updated / second search the 7th March 2023)
----

1 ts=(teacher* or instructor* or tutor* or educator*) (290,787)
2 ts=(student* or pupil* or learner* or “school child*”) (756,091)
3 ts=(“primary school” or “primary education” or “junior school*” or “junior education” or “elementary school*” or “elementary education” or “grade* school*” or “grade education” or “middle school” or “junior high” or “intermediate school” or grammar school” or “folk school” OR “preparatory school”) (46,509)
4 ts=(“secondary education” or “secondary school*” or “high school*” OR “prep school” OR ”sixth form”) (99,583)
5 ts=(k12 or k-12 or k9 or k-9) (17,882)
6 ts=(“learning analy*” OR “education* data*” OR “big data” OR “machine learning” OR “artificial intelligence” OR AI OR “Education* analy*” OR “data mining” OR “learner modelling” OR “prediction of performance” OR “behavio*r modelling” OR “learning pattern*” OR “learning sequence*” OR “learning behavio*r*” OR “learning strategy*” or “student* data” or “class* data”) (340,549)
7 ts=(learning or “learning outcome” or “learning result*” or achieve* or perform* or exam* or grade*) (12,412,667)
8 ts=(“trajector*” or “learning progression” or “learning path*” or “learning curve” or develop*) (7,349,194)
9 ts=(teaching) (326,898)
10 ts=(“learning activit*” or monitor*) (1,252,255)
11 ts=(“mathematics education” or math* or numerac* or algebra* or “number skills” or arithmetic* or “problem solving” or reasoning or statistic* or “mathematical thinking” or geometr*) (3,532,242)
12 1 or 2 (873,743)
13 3 or 4 or 5 (158,197)
14 7 or 8 or 9 or 10 (17,392,016)
15 12 or 13 or 6 or 14 or 11 (19,183,874)
16 12 and 13 and 6 and 14 and 11 (398)
17 12 or 6 or 14 or 11 (19,164,409)
18 12 and 6 and 14 and 11 (3,781)
19 18 not ts=(medicine or biology) (3,671)
20 16 not ts=(medicine or biology) (386)
21 18 not ts=(STEM or STEAM) (3,630)
22 16 not ts=(STEM or STEAM) (366)
23 ts=(school* or education* or grade or k12 or k-12 or k9 or k-9) (1,689,136)
24 18 and 23 (2,214)
----

ts = abstract, title, keyword, keyword plus

[1] When developing the electronic search to work with the interphase of our selected databases we limited the search to papers published between 2000–2020. The final version the electronic search presented in Appendix A was finalized on the 20th of January 2021. The final version was consequently used for our electronic searches up until the last search on the 7th of March 2023, to identify records from 2000 up to this date.

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Appendix B: Exclusion analysis

Analysis of search results, for example for the updated search between 2000–2023 the excluded articles could be categorised according to some common features/reasons for exclusion. There were 735 records identified from searching the chosen databases. 18 records were identified as duplicates. Besides those there were three major categories/ reasons for exclusion, summarised as *Wrong age, Wrong field, Wrong subject.*

Wrong age contained 23 records, where records often contained words as “higher education”, “university”, “undergraduate” or “preschool” etc. in the title.

Wrong field contained 118 records randomly looking at some titles we find research on: gender differences; tuberculosis; physical health in school; parenting style; training for college teachers; externalising behaviour; and much more. Analysing a part of those articles (n=47) which could be identified in the database Web of Science, visualisation of the research areas can be seen in Figure 1. Displaying that even the search results we consider to be out of our field still falls within relevant topics.

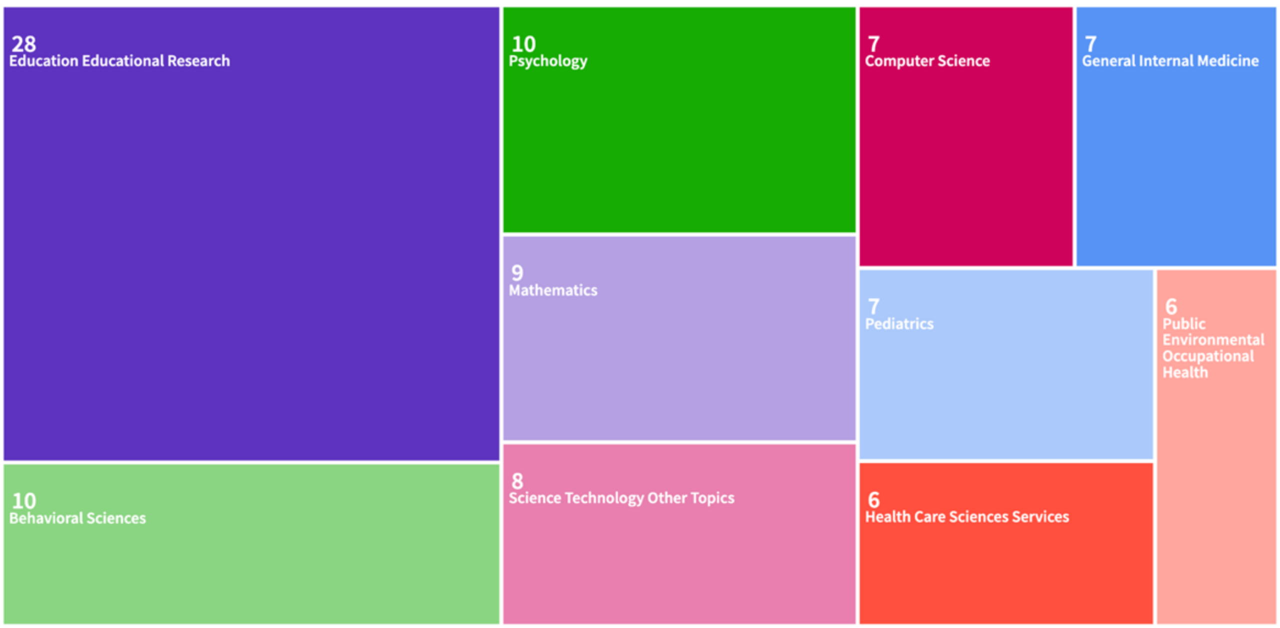

Figure B1. Research areas

Wrong subject contained 38 records studies which focused on specifics subjects but not mathematics, many in language, but also in for example biology, chemistry. Some articles could be excluded because of more than one reason but were only sorted in one of the rejection reasons.

Appendix C: Relevance Coding

All articles should meet the following criteria:

- published from 2000 to March 2023
- written in English, Swedish or Norwegian
- regarding pupils between 6 – 19 years old

Table C1. Template A

Title	Criteria 1: Publications address the use of DLMs in mathematics education	Criteria 2: Publications address the use of the analysis of digital data in mathematics education	Criteria 3: Publications address the use or analysis of digital data in relation to teaching and learning	Type of record	Quantitative and/or qualitative data	Comments

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Appendix D: Relevance Coding

Table D1. Template B

Title	C1 – Math the use of DLMs in mathematics education	C2 – LA the use of the analysis of digital data in mathematics education	C3a – Use the use of digital data	C3b – Analysis the analysis of digital data	C4 – learning In relation to learning (might include what was studied and how)	C5 – teaching In relation to teaching (might include what was studied and how)	Initial (Both) assessment – with reason	Final/joint assessment – with reason

Appendix E: Inter-Rater Reliability

Table E1. Inter-Rater Reliability Result and Score

Batch	Match[a]	No match[b]	Non-eligible[c]	Calculation
A N=1	4	1		
B N=2	4	1		
	4	1		
C N=2	4		1	
	2		3	
D N=2	5	0		
	5	0		
E N=1	5	0		
F N=2	4	1		
	---	---		
All	37	4	4	37/45=0,822

[a] *Match: content off cells were a match.*

[b] *No match: content off cells were not a match.*

[c] *Non-eligible: content off cells was insufficient or internally conflicting so comparison could not be performed.*

Appendix F: Full Data Extraction

Table F1. Data Extraction

Author	Year	Title	Location	Digital technology used	Method	Content[a]	Setting[b]
Campos et al.	2021	Making Sense of Sensemaking: Understanding How K–12 Teachers and Coaches React to Visual Analytics	USA	*Edsight*: a sensemaking tool for teachers and coaches which provides a suite of visual analytics tools, delivers classroom reports and allows for multiple queries, comparisons, and note taking.	The study reports on interviews and think-aloud sessions with middle-school mathematics teachers (n = 9) and instructional coaches (n = 9) from four districts. Responses to data were identified within three dimensions: *emotional, analytical,* and *intentional*.	M	P & S, Blended learning
Chen & Chen	2009	Mobile formative assessment tool based on data mining techniques for supporting web-based learning.	Taiwan	Personalised e-learning system (PELS) which includes adaptive learning capability and learning assessment features for individual learners.	The analysis of portfolio from 583 third-grade students were used to create learning rules. Then 69 students between 9 – 11 years old took a two-week online mathematics courseware to test the system empirically in the mathematics area of Fractions, with pre- and post-tests. A questionnaire was also distributed to students to assess PELS.	R	P, Blended learning, digital textbook
Confrey et al.	2019	A Validation Argument From Soup to Nuts: Assessing Progress on Learning Trajectories for Middle-School Mathematics	USA	Math-Mapper 6–8 (MM6–8): an adaptive learning system that covers the curricula for grades 6–8. The system includes diagnostic assessment and provides reports to students and teachers to help teachers interpret data to target instruction.	The performance data of 470 sixth-graders was analysed and presented in heatmaps; video recordings of teachers' interpretation of the heatmaps and discussion of the heatmaps with their classes were collected.	R	P, Blended learning, digital textbook
Faber et al.	2017	The effect of a digital formative assessment	Nether-lands	*Snappet:* The tool provides student feedback, adaptive assignments, feedback to	This study used a randomized experimental design with 1808 students in grade three across 79	M	P, Blended learning,

Author	Year	Title	Location	Digital technology used	Method	Content[a]	Setting[b]
		tool on math & motivation		teachers, teaching options and progress monitoring.	primary schools. Experimental schools (n = 40, 822 students) used a digital formative assessment tool for 5 months whereas control schools (n = 39, 986 students) used their regular teaching methods and materials. Standardized achievement pre-post-test data, student motivation survey data, classroom observation data measuring teacher usage items, and student log files were collected and processed in a multilevel analysis.		digital textbook
Hawn	2019a	Study 1: Exploring Teachers' Online Usage of Student Testing Data	USA	"Benchmark Data": a data and assessment platform for managing several types of student test data especially for testing and monitoring.	The platform was used at one school with around 500 students from grade 6–12 to explore patterns of student data usage in relation to content area and level, and to analyse teachers' online activity and use of student data.	Primary: M, Secondary: A, G & T	P & S, Pen & Paper
Hawn	2019b	Study 2: Connecting Teacher Roles and Data Use Attitudes to Online Behaviours	USA	"Benchmark Data" (same as above)	User and survey data from 35 (middle / high school) teachers was analysed to describe the variation in teachers' online data use and attitudes. Study 2 builds on Study 1, expanding the method to explore DBDM in schools.	Primary: M, Secondary: A, G & T	P & S, Pen & Paper
Kalloo & Mohan	2011a	An Investigation Into Mobile Learning for High School Mathematics	Caribbean	*MobileMath*: a game-based learning system which offer the learner personal activity recommendations and send alerts with learning suggestions. Teacher can communicate and follow student progress via the application.	Evaluation study with a pre-, post-test, and questionnaire consisting of students between 12–18 years old. Group 1 (n=19) used MobileMath on their own for 3 weeks, while Group 2 (n=20) used MobileMath with teacher support (via the application and in person).	A	S, Blended learning
Kalloo & Mohan	2011b	Correlation between student performance and use of an mLearning application for high school mathematics	Caribbean	*MobileMath*: a game-based learning system which offer the learner personal activity recommendations and send alerts with learning suggestions. Teacher can communicate and follow student progress via the application.	An evaluation study in which one teacher taught 6th-grade students (ages 11–12) who were learning algebra for the first time. The experimental group (n=18) used MobileMath, while the control group (n=54) did not. After 3 weeks both group took a post-test and the experimental group also answered a questionnaire.	A	S, Blended learning
Lin & Yang	2021	Multiple scaffolds used to support self-regulated learning in elementary mathematics classrooms	Taiwan	*Adaptive Instruction and Learning* (AI&L): a digital learning platform covering mathematics intended to support Self-Regulated Learning (SRL) with tools for students to self-monitor and for teachers to understand students' learning progress. The platform includes: a learning map which can offer visualised individual learning paths; teaching media with possibility for students to do diagnostic tests, take notes, ask teachers question, and receive teacher feedback. Teachers can view student activity.	Three schools participated with one (5th grade) class from each, totally 85 students. A quasi-experimental research method with pre- and post-tests was used. Two different versions of the experimental teaching model were used, and results compared with the control group who had traditional teaching.	A	P, Blended learning, digital textbook
Molenaar et al.	2020	Personalized Visualisations to Promote Young Learners' SRL	Nether-lands	Adaptive learning technology (ALT) which runs on tablet computers offering adaptive exercises, instant feedback, and personalised visualisations (PV) featuring an overview, goal setting and learning path with recommendations for the student. The ALT also offers teacher dashboard.	A quasi-experimental design with pre-, post- and transfer tests was used, involving 92 5th-grade students from five classes from four schools. In the experimental groups the teachers assisted students' use of the ALT with PV during 4 consecutive lessons. The control group used the ALT without the PV.	Ar	P, Blended learning, digital textbook

Author	Year	Title	Location	Digital technology used	Method	Content[a]	Setting[b]
Molenaar & Knoop-van Campen	2019	How Teachers Make Dashboard Information Actionable	Nether-lands	*Snappet*: an adaptive educational technology software which runs on tablet computers for primary school featuring adaptive exercises and dashboards.	38 teachers in eight elementary schools were observed during mathematics lessons with a focus on pedagogical actions in terms of feedback following dashboard consultation. After the observations, teachers discussed the dashboard consultation in stimulated recall interviews.	M	P, Blended learning, digital textbook
Moltudal et al.	2022	Adaptive Learning Technology in Primary Education: Implications for Professional Teacher Knowledge and Classroom Management	Norway	*Multi Smart Øving* (MSØ): an adaptive learning system software with instant feedback for basic mathematic learning, in line with Norwegian curriculum. MSØ also includes a teacher dashboard and a function for teachers to provide feedback.	This study used design-based research which combined fieldwork, classroom observation and interviews with 3 teachers teaching in grades 5–7 (ages 10–12) at one case school. During a four-week intervention, students used MSØ for a minimum of 15 min per day and 60 min per week as homework, and teachers were also free to implement MSØ in their practices.	R	P, Blended learning, home-work
Qushem et al.	2022	Learning Management System Analytics on Arithmetic Fluency Performance: A Skill Development Case in K6 Education	United Arabs Emirates	*ViLLE*: a tutoring system integrated with learning analytics and game-based learning offering adaptive exercises, instant feedback, automated assessment, learning paths and communication channels. It also offers teacher dashboard and possibilities to create learning paths and content in the system.	A single-group quasi-experiment design with pre- and post-tests was used, involving 720 4–6th-grade students. ViLLE was used for homework and during at least one lesson per week for 9 months.	Ar	P, Blended learning, digital textbook
Rodríguez-Martínez et al.	2023	Building personalised homework from a LA based formative assessment: Effect on fifth-grade students' understanding of fractions	Spain	*ResponseCard RF LCD clicker, Turning Point* (ARS-based technology): student errors detected and categorised according to a taxonomy of eight different types; personalised homework exercise generated based on LA of the student's errors.	A quasi-experimental design with pre- and post-tests was used on the topic of fractions involving 127 5th-grade students from five classes in two schools. In the control groups, the homework consisted of generic activities for all the participants, while students in the experimental group were given a personalised set of activities.	R	P, Blended learning, home-work
Schwarz et al.	2018	Orchestrating the emergence of conceptual learning: a case study in a geometry class	Israel	System for Advancing Group Learning in Educational Technologies (SAGLET) and Virtual Mathematics team (VMT) rooms: SAGLET used data-mining techniques to evaluate the interaction logs of student groups to send alerts to the teacher when there were *idleness, off-topic talk, technical problems, explanation or challenge, confusion, correct solutions and incorrect solutions* during the lessons.	The study involved observations on one teacher and 19 students from fifth and sixth grade during a six-week-long teaching unit. Analyses focused on the teacher's use of the VMT room to check on the work of the students and the kind of intervention she deployed.	G	P, Digital
Stecker & Foegen	2022	Developing an online system to support algebra progress monitoring: Teacher use and feedback	USA	*Algebra Instruction and Assessment: Meeting Standards* (*AAIMS*): an online PD (professional development) system to make algebra progress monitoring accessible and efficient.	29 teachers received training over 10-weeks and used the system in their practice. Researchers examined the extent to which the online system worked as intended and whether it led to improved teacher knowledge and skills. Efficiency of the system and teacher satisfaction with instructional modules were examined through teacher self-report information and rating scales.	A	S, Pen & Paper
Wang et al.	2022	Development and Application of an Intelligent Assessment System for Mathematics Learning	China	"The Intelligent Batch Assessment of Mathematics Learning Quality for Primary and Secondary School Students—Learning Strategies"	The intervention provided instruction and intervention for 3 individual students for 3 months to test the efficacy of the intelligent assessment system	M	S, Blended learning

Author	Year	Title	Location	Digital technology used	Method	Content[a]	Setting[b]
		Strategy among High School Students—Take Jianzha County as an Example		– can identify learning needs in different dimensions of mathematics learning, allowing teachers to intervene based on the improvement plan automatically generated by the system.	alongside guidance from the teachers to help students to improve their strategies. In-depth interviews were conducted before and after the intervention and the effect of the improvement plans was assessed in both quantitative and qualitative terms.		
Yang & Chen	2023	What increases learning retention: employing the prediction-observation-explanation learning strategy in digital game-based learning	Taiwan	A game-based learning system that integrated a *Prediction-Observation-Explanation* (POE) learning strategy, which provided learners with appropriate guidance and feedback during the learning process to improve retention. The game automatically records the learning behaviour exhibited by students to facilitate lag sequence analysis.	52 fifth graders participated in a quasi-experiment with pre- and post-test. One class (N = 26 students) learned with the POE-integrated digital game-based instruction; the other class (N = 26 students) learned with a conventional digital game-based instruction. The only difference between the two groups was in the learning task guidance part of the game.	R	P, Blended learning, digital textbook
Yang & Lu	2021	Towards the successful game-based learning: Detection and feedback to misconceptions is the key	Taiwan	A game that diagnoses the learner's possible misconceptions through two-tier testing and provides appropriate feedback. Lag sequence analysis is used to analyse the behavioural patterns of students during gameplay to understand the influence of different types of feedback content and reading time on learning effectiveness.	An experimental design with pre- and post-test involving 53 fifth graders in elementary school, 27 of whom were in the experimental group and 26 in the control group. The participants all received the same computer skill training courses, and all were instructed by the same teacher.	Ar	P, Blended learning, digital textbook

[a] *Mathematics in general (M), Ratio (R), Algebra (A), Arithmetic (Ar) Geometry (G), Trigonometry (T)*

[b] *Primary school (P), Secondary school (S)*