Received: 6 December 2021 | Revised: 17 April 2023 | Accepted: 21 May 2023

DOI: 10.1111/jcal.12842

ORIGINAL ARTICLE

Journal of Computer Assisted Learning WILEY

Measuring self-regulated learning in a junior high school mathematics classroom: Combining aptitude and event measures in digital learning materials

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Abstract

Background: Measurement of students' self-regulation skills is an active topic in education research, as effective assessment helps devising support interventions to foster academic achievement. Measures based on event tracing usually require large amounts of data (e.g., MOOCs and large courses), while aptitude measures are often qualitative and need careful interpretation. Precise and interpretable evaluation of self-regulation skills in a normal K-12 classroom thus poses a challenge.

Objectives: The present study proposes and explores a learning analytics method of combining aptitude and event measures to evaluate student's self-regulation skills.

Methods: An explorative learning analytics study was conducted in a junior high school mathematics class ($N = 20$ students), using a three-lesson intervention with digital learning materials. Students first assessed their self-regulation skills with a self-report questionnaire, after which trace logs and observations of student behaviour were collected. Learning sessions were extracted from trace logs, clustered, and linked to learning strategies. Students were clustered by the self-report results and learning behaviour profiles. Session clusters, student behaviour clusters and assignment grades were also tested for association.

Results and Conclusions: The detected session and student behaviour types were linked to learning tactics and strategies found in prior studies. Additionally, association was found between self-reported self-regulation skills and the student behaviour obtained from trace logs.

Implications: The results demonstrate the feasibility of concurrently using aptitude and event measures on a classroom scale, providing teachers with a tool to evaluate and support self-regulated learning. Combined with further measures like predictive learning analytics, teachers can obtain an early and highly interpretable picture of at-risk students in their classes.

The article is based on a Master's thesis of the first author available from http://urn.fi/URN:NBN:fi:jyu-202106304100.

KEYWORDS
aptitude measures, event measures, junior high school, learning analytics, mathematics, self-regulated learning

1 | INTRODUCTION

Self-regulation of learning, a student's ability to plan out learning, adaptively adjusts learning behaviour with learning strategies, and maintaining focus and motivation to achieve academic goals is a well-known and widely researched area (Schunk & Greene, 2017). With its positive effect on students' academic achievement, self-efficacy and prospects (Broadbent & Poon, 2015; Dent & Koenka, 2016; Dignath & Büttner, 2008), self-regulated learning is of interest to teachers and researchers. Understanding and supporting self-regulated learning has become more relevant than ever with the current shift towards digital learning environments, online learning and, generally, a more student-centric learning culture (Boelens et al., 2017; Rajaram, 2021; Rasheed et al., 2020). One approach to supporting self-regulated learning has been teaching better self-regulation practices via practical interventions (Panadero et al., 2016). However, applying any kind of intervention to affect a student's self-regulation skills without first assessing the student's current level of self-regulation might not yield any useful changes to the student's learning behaviour. Moreover, the lack of timely assessment of self-regulated learning might cause teachers to omit students who could benefit from supporting self-regulation skills.

Self-regulated learning is usually assessed via students' aptitude or student behaviour patterns (Zimmerman, 2008). Aptitude measures, like self-report tools and questionnaires, are easy to use and have been commonly applied in classrooms and large courses (Wang & Sperling, 2020). However, self-reports have been often critiqued for inaccuracy and susceptibility to subjectivity (Roth et al., 2016). In contrast, behaviour-based measures collect student interactions from the learning environment, reducing this inaccuracy and subjectivity. While these measures, like trace logs, are considered precise, it is difficult to interpret the self-regulatory processes from them (Jovanović et al., 2017). Additionally, the use of trace logs for analysing self-regulated learning has been generally employed with large sample sizes: trace logs are often used in MOOCs (Wong et al., 2019), and most prior studies analyse trace log data from multiple sessions and large courses (e.g. Gašević et al., 2017; Jovanović et al., 2017; Matcha, Gašević, et al., 2020).

Because of the differences between aptitude and event measures, using both measures concurrently presents a way to obtain a holistic understanding of students' self-regulation skills. In a primary education context, however, scale is a challenge for reliable measuring: classrooms often have only dozens of students and learning topics change often. Nevertheless, the use of learning analytics for analysing student behaviour via both questionnaire and novel data sources has become more common in studies related to high schools (de Sousa et al., 2021). The present study explored the use of multiple self-regulated learning measures in digital learning materials on the scale of a single classroom with learning analytics. The purpose of the study was two-fold: to see what student behaviour profiles can be detected on a classroom scale and to study whether using aptitude and event measures concurrently in a classroom yields any useful association. The main research questions read as follows:

RQ1. What profiles of learning behaviour can emerge from event measures?

RQ2. How are students' self-reported self-regulation skills associated with the learning behaviour profiles?

2 | BACKGROUND AND THEORETICAL FRAMEWORK

2.1 | Self-regulated learning

Self-regulated learning is a cyclical, proactive, feedback-driven, strategic, social and context-bound process (Ben-Eliyahu & Bernacki, 2015; Zimmerman, 1990, 2005, 2008). Students who self-regulate their learning set goals, plan out their learning, use various learning strategies and adjust their learning processes based on feedback and changing learning conditions. Self-regulation plays a significant role in academic performance (e.g. Ergen & Kanadlı, 2017; Kitsantas & Zimmerman, 2008; Rao et al., 2000; van Harsel et al., 2021; Zimmerman, 1990) and self-regulated learning skills have been linked to metacognition, motivation, self-efficacy, self-esteem and emotion regulation (Sitzmann & Ely, 2011). Understanding and supporting self-regulated learning provides a practical means of equipping students with meta-skills that can help them with task-specific challenges such as skill-level assessment (e.g. Dunlosky & Rawson, 2012), and with adapting to larger learning environment changes, for example, when transferring from one educational institution to another (e.g. Hämäläinen & Isomöttönen, 2019).

In its most basic form, the self-regulated learning process is multi-phased and generally consists of repetitive and recursive preparation and planning, learning and plan enacting and self-reflection actions (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2005). During learning, a student may regulate several factors, such as cognition, motivation behaviour and context (Pintrich, 2000). Self-regulation may occur not just on the individual student level, but it may also be observable in groups (Hadwin et al., 2017). While there exist several other theoretical models on how self-regulation occurs and what can be self-regulated, all of them are based on students' use of learning strategies to adjust their learning behaviour (Panadero, 2017; Puustinen & Pulkkinen, 2001).

2.2 | Learning strategies and learning tactics in self-regulated learning

Self-regulated learning strategies can be described as planned actions to acquire information and skills relevant to the task at hand. The strategic approach to learning is one of the principles of self-regulated learning: in their original taxonomy, Zimmerman and Martinez-Pons (1986) described 14 general self-regulated learning strategy categories extracted from interviews with students. Such learning strategy categories were, for instance, rehearsing, seeking assistance and reviewing materials. The original presented strategy categories are still relevant and are used to guide design of e-learning environments and to categorise self-regulated learning research (Garcia et al., 2018). However, this general description of learning strategies is broad, which makes it difficult to study them in practice. For example, if a student is observed to complete some tasks and then read the textbook, it may be indicative of self-evaluation (checking that an answer is correct according to the learning resources), information seeking (consulting with the textbook while completing a task) or a lack of any self-regulation strategy at all.

A more fine-grained description of self-regulated learning strategies is provided by Winne (2001) and elaborated on by Winne and Marzouk (2019). In it, learning strategies are sequences of one or many *learning tactics*. Learning tactics, in turn, are sequences of atomic actions a student employs to process some task-related data and produce a result (Malmberg et al., 2010; Winne & Marzouk, 2019). A student decides on using specific learning tactics based on set goals and current conditions such as available time, results from previous tactics and prior knowledge of subject matter (Winne & Hadwin, 1998). Thus, learning strategies are not simple chains of actions, but rather they describe the student's process of choosing actions based on current conditions. In practice, learning strategies and learning tactics can be studied, for example, by graphically representing students' possible sequences of actions (Winne & Marzouk, 2019). Learning tactics can also be taught, which is a basis for various self-regulated learning interventions.

The learning strategies and tactics employed by students are influenced by the learning context and available resources. For instance, Matcha, Uzir, et al. (2020) investigated the learning behaviour of students in three STEM courses, identifying several commonly employed learning tactics such as use of text, video, lectures and completing either specific (e.g., only simple, or difficult) or different exercises. Furthermore, an analysis of self-regulated learning behaviour of first year programming course by Jovanović et al. (2017) examined self-regulated learning behaviour in a first year programming course, categorising students' learning strategies by the level of learning activity; high activity students consistently outperformed their peers who were more selective in their use of learning materials. Additionally, researchers have identified trial-and-error and time-management tactics as essential factors in the learning process of STEM courses (e.g. Uzir et al., 2020). Thus, while Zimmerman and Martinez-Pons (1986) offer general categories for the learning strategies students may adopt, measurements situated within authentic learning contexts enable a more comprehensive understanding and support of learning behaviour.

2.3 | Measuring self-regulated learning, tactics and strategies

Winne and Perry (2000) proposed two ways to conceptualise and measure self-regulated learning: as *aptitude* and as *events*. Both measure types yield a distinct perspective on self-regulated learning (Araka et al., 2020). Because of this, aptitude and event measures were used together in the study.

Aptitude measures describe self-regulated learning through the attributes and common behaviours of a student (Zimmerman, 2008). Commonly used aptitude measures are questionnaires, such as the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al., 1991). Researchers also make their own modifications to existing questionnaires or devise new ones for particular research topics (e.g. Jansen et al., 2017; Kramarski & Gutman, 2006). Questionnaires can be used to evaluate self-regulation skills of a cohort (e.g. Cicchinelli et al., 2018), but they can also be used with cluster analysis to detect more fine-grained self-regulation profiles in a group for further study (e.g. Beheshitha et al., 2015; Pardo et al., 2017). In addition to questionnaires, many self-report tools, such as learning diaries, observations and interviews, are used as aptitude measures (Winne & Perry, 2000; Zimmerman, 2008). While aptitude measures are simple to administer in any context (Roth et al., 2016), their use is criticised by some researchers regarding accuracy, increased cognitive load imposed on participants and difficulty of comparing results between studies (Jovanović et al., 2017; Panadero et al., 2017; Saint et al., 2020).

Event measures, in turn, analyse self-regulated learning via student behaviour. Although qualitative tools, such as think-aloud protocols and observations, exist, learning analytics tools are more commonly employed for event measures (Viberg et al., 2020; Zimmerman, 2008). These research studies primarily employ trace logs to capture student behaviour. For instance, Jovanović et al. (2017) used sequence and cluster analysis on trace logs to group students based on study patterns to identify applied sequence and cluster analysis to trace logs, grouping first-year engineering students based on study patterns in a flipped classroom to identify and compare various learning strategies. Building upon this, Matcha, Gašević, et al. (2020) combined process mining with sequence analysis to detect self-regulated learning tactics and strategies, comparing their effects on academic performance. Similarly, Fan et al. (2021) applied cluster analysis and process mining to trace logs and course performance data within a MOOC context. They employed epistemic network analysis to identify the relationships between commonly used learning tactics and learning outcomes. Although the specific learning patterns discovered in these studies varied depending on the learning context, all generally classified learning strategies into those aimed at either surface learning or deep learning applied cluster analysis and process mining to trace logs and course performance data within a MOOC context. They employed epistemic network analysis to identify the relationships between commonly used learning tactics and learning outcomes. Although the specific learning patterns discovered in these studies varied depending on the learning context, all generally classified learning strategies into those aimed at either surface learning or deep learning (see Biggs, 1987). Overall, the primary goal of behaviour measures is to analyse patterns and connect them to learning tactics and strategies, providing insights into students' self-regulated learning processes.

While both types of measures are employed, their concurrent use has been relatively less frequent (Araka et al., 2020). For instance, in the realm of mathematics, self-reports combined with academic achievement measures tend to be the most prevalent (Wang & Sperling, 2020). To enhance interpretability, event measures may be integrated with aptitude measures (e.g. Endedijk et al., 2016; Salehian Kia et al., 2021; Zhou, 2013); nevertheless, other noteworthy examples exist. Beheshitha et al. (2015) employed a questionnaire to gather information on learning approaches from 22 students, subsequently clustering them based on self-report measure scores. They then utilised process mining to analyse strategies employed by each cluster. Conversely, Gašević et al., 2017 applied sequence and cluster analysis to discover learning strategies adopted by 290 engineering students during a course. They compared differences between the clusters using a self-reported Study Process Questionnaire, ultimately connecting self-reported deep and surface learning approaches to observed learning behaviours. In a more recent study, Jansen et al. (2022) employed a Self-regulated Online Learning Questionnaire in conjunction with cluster analysis within a MOOC, uncovering self-regulated learning profiles adopted throughout the course. They then applied process mining to each profile, revealing behaviour patterns consistent within the profile, akin to Beheshitha et al. (2015). Consequently, creative combination of both measures mitigates the primary drawbacks of employing them independently: the reliability of aptitude measures and interpretability of event measures.

2.4 | Research aims

Effective self-regulation skills are essential for academic success. Fostering and evaluating these skills in early education can prove to be more beneficial and straightforward than in later stages of education, where students are already expected to possess such skills (Dignath & Büttner, 2008). Event measures serve to collect valuable data on student behaviour, which can then be associated with learning tactics and strategies. In contrast, aptitude measures offer a comprehensive, self-reported perspective on an individual's self-regulation abilities. Research that integrates both measures tends to yield more in-depth insights into students' self-regulated learning experiences. Consequently, drawing upon the relevant literature, our study endeavoured to investigate the potential of combining multiple self-regulated learning measures in early education (see end of Section 1, RQ1 and RQ2).

3 | MATERIALS AND METHODS

The overall study design, data collection procedures and analysis tools are depicted in Figure 1. This study integrated aptitude and event measures into digital learning materials that were then tested with a junior high school mathematics class. The study followed a general research question-oriented explorative approach used in similar studies (e.g. Ameloot et al., 2021; Pijeira-Díaz et al., 2018; Yu et al., 2018).

3.1 | Study context

An eighth grade Finnish junior high school class ($N = 20$ students) from the teacher training school of the University of Jyväskylä was selected for the study. The school was chosen because each student possessed a personal tablet that they could use for studying that allowed for easier use of the developed materials. The students' dispositions to learning mathematics and their levels of general achievement were discussed with the class's teacher before study. The class was chosen because it contained mostly similarly achieving students, but it also had some high achievers and a few students who required the presence of a special education teacher.

During the study, students learned about three topics: the definition of 'percentage', converting fractions to percentages and computing the percentage of an amount. The topics were studied over three 75-minute sessions in the spring of 2021. The topics were chosen from the class's curriculum after discussion with the class's teacher to ensure the collected data came from authentic lessons. The researcher developed the materials[1] used for the study in cooperation with the class's teacher. The materials included multiple learning resources, such as theory texts, videos, worked examples and exercises on two difficulty levels. All exercises included automatic answer checking and automatic feedback, and some more challenging tasks had automatic hints. Additionally, students were required to solve graded tasks before the next lesson. The learning materials were hosted on the Open edX (https://open.edx.org) virtual learning environment on the servers provided by the University of Jyväskylä. In Open edX, each lesson was grouped into its own topic, and each learning resource was put into a separate subsection (Figure 2).

Before the study sessions, students were informed of the research and the study session structure. They were also instructed on how to use Open edX and the available learning resources. Finally, the class was asked to answer a questionnaire in which they self-evaluated their self-regulated learning skills.

The main study sessions were cyclical and structured around self-paced use of the learning materials on Open edX. At the start of the session, students first reviewed the personal feedback their received from the prior session with the ability to ask for clarifications from the class teacher. Then, the class were briefly introduced to the day's topic and were given the learning goals (Figure 1). After the lesson briefing, students were given time for self-paced learning the learning

[1] https://github.com/dezhidki/math-percent-edx-fi.

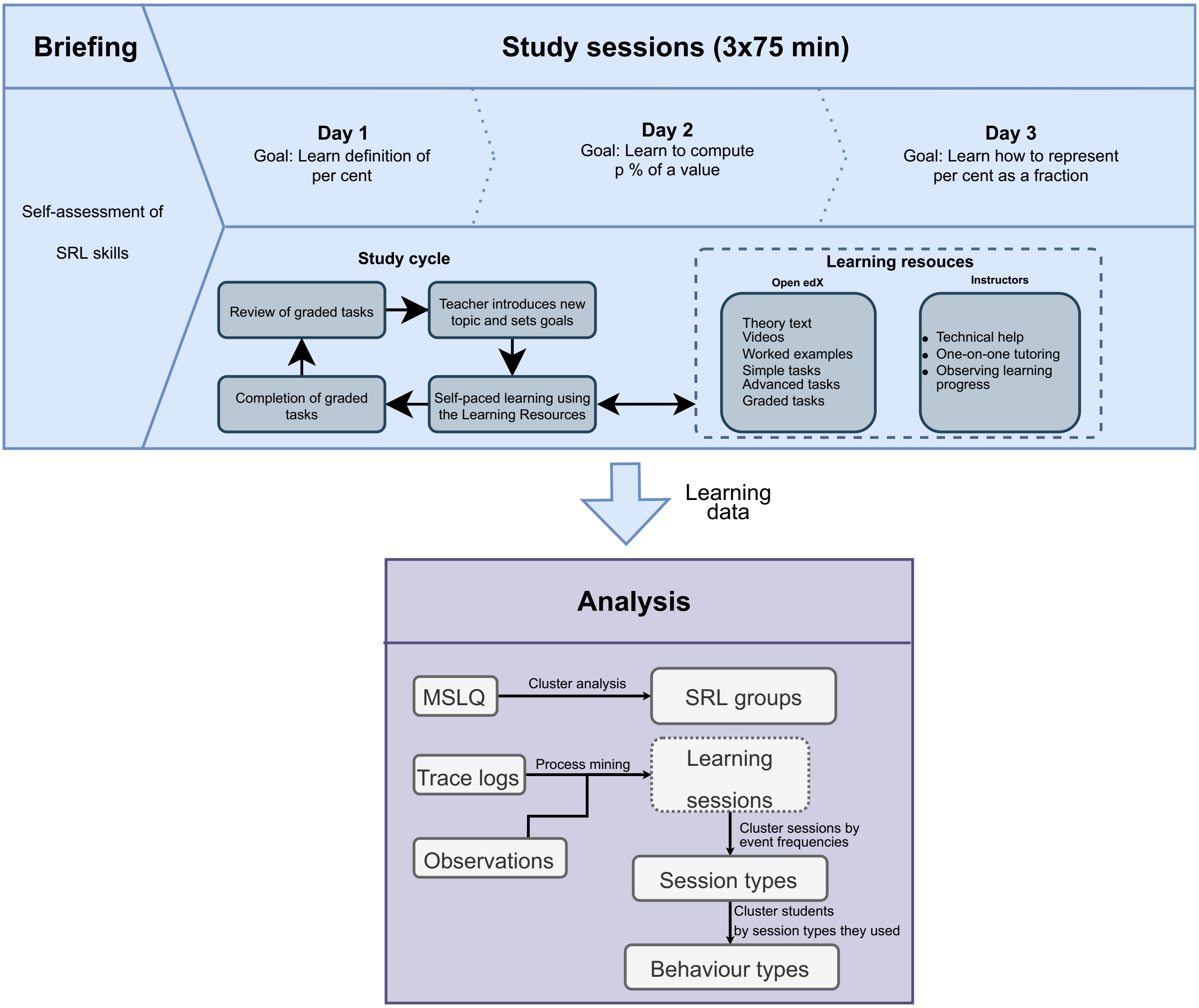

FIGURE 1 Study session design, data collection and analysis procedures of the present study. Learning data (Motivated Strategies for Learning Questionnaire survey answers, learning trace logs and observations) were obtained from a pre-study briefing and three 75 minute study sessions. Study sessions were structured around a self-paced study cycle in which students freely used the available learning resources.

resources available in the virtual learning environment. Students were given the freedom to work independently and select what learning resources they wanted to use. At the end of each session, students completed a set of graded tasks aimed at evaluating their progress. Students were allowed to complete the graded tasks in-class or take them as homework for the next study session.

During the sessions, students were also encouraged to seek help when needed. Both the class's teacher and special education teacher participated in the study as instructors. The instructors primarily provided practical technical support with the virtual learning environment, one-off help with specific tasks and one-on-one tutoring for students. At the same time, the instructors actively observed students' progress and learning behaviour. The researcher participated as a co-instructor during the lessons as technical help and as an 'outside observer'. Co-instruction was chosen to aid students faster and because it allowed the researcher to gain first-hand observations while interacting with the students.

At the end of the study, students were asked to provide brief anonymous feedback on the topic and the system used. The final questionnaire involved students in the research process and supplemented the observations made during class.

3.2 | Data collection

In total, indicators of self-regulated learning were collected in three ways to answer the research questions: student perceptions were collected via a self-report questionnaire, student behaviour was studied with trace logs and observations supplemented the two main measures. Each of the chosen data sources was motivated by different

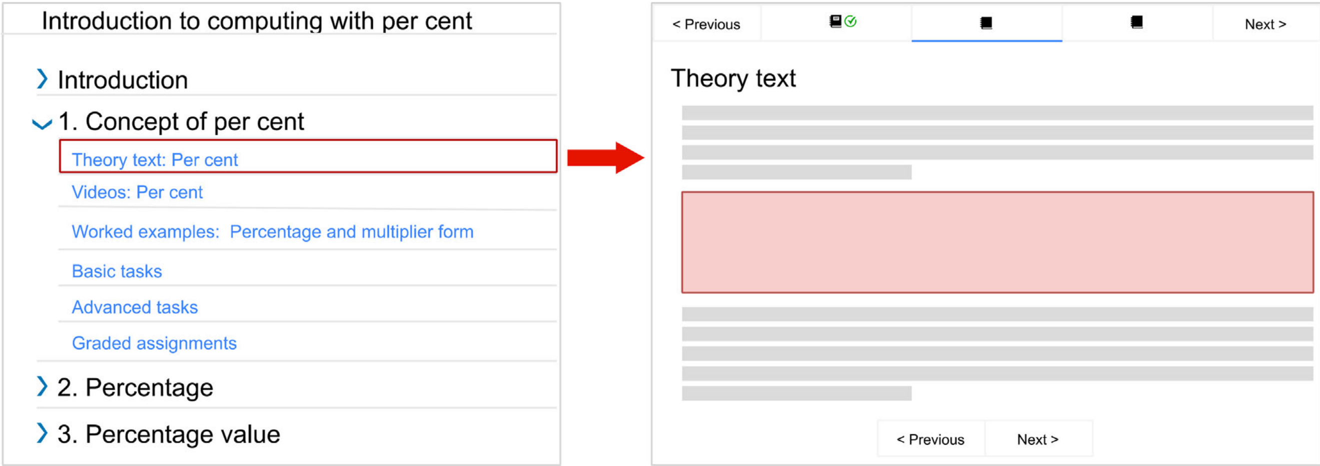

FIGURE 2 The layout of the digital learning materials used in the study. Each learning resource was separated into a section for every lesson (dashboard on the left). When a student clicked on the learning resource, resource contents opened (on the right). Students could freely move between learning resources and subsections using either the dashboard or 'Next' and 'Previous' buttons.

models of self-regulated learning (Järvelä & Hadwin, 2013; Pintrich, 2000; Winne & Hadwin, 1998). The data collection methods used are outlined in more detail next.

For self-evaluation, students answered the MSLQ before the three-lesson intervention. MSLQ is a Likert scale (value range 1–7) questionnaire comprised of 81 questions to measure 15 scales related to motivation and the use of learning strategies (Pintrich, 2004). In this study, a modified 50-item MSLQ provided by Kontturi (2016) was used because it was already translated into Finnish and had been successfully employed with primary school pupils. The modified questionnaire lacked scales related to motivation regulation and, instead, only included nine scales. The scales used were grouped according to Duncan and McKeachie (2005) into *cognitive strategies* (rehearsal, elaboration, organisation, critical thinking), *metacognitive strategies* (metacognitive self-regulation) and *resource management strategies* (time and study environment management, effort regulation, peer learning, help seeking). We used MSLQ as an aptitude measure to compare to a relevant event measure in order to address RQ2.

The primary data source of the study was the trace logs of students interacting with the virtual learning environment and digital learning materials. For this, logs were obtained directly from Open edX. Open edX saves all interaction events as textual data that contains relevant information about the event, such as event type, timestamp, student identifier and additional event metadata. Because the goal was set to detect general student behaviour profiles, all events related to student navigation or interaction with the material were preserved. Overall, 14 different event types were extracted based on five interaction types supported by the developed materials (see Table 1). Trace logs were collected as an event measure to analyse student behaviour patterns (RQ1) and compare them to MSLQ results (RQ2).

Finally, to supplement the quantitative data, students were observed by the researcher during lessons. Observations were primarily made to detect and describe possible group work and help-seeking interactions that can occur as part of the self-regulated learning process (Järvelä & Hadwin, 2013). In the study sessions, the researcher

TABLE 1 Different types of captured interactions and their respective event codes in the trace log.

Interaction type	Event codes
Student uses written materials	theory_test, worked_example
Student interacts with learning videos	video_play, video_pause, video_seek, video_stop
Student completes exercises	task_basic_correct, task_basic_incorrect, task_advanced_correct, task_advanced_incorrect, task_hint, see_answer
Student turns in a graded assignment	assignment
Student seeks help from teacher	help_seeking

observed how many students worked in groups and what kinds of group work were prevalent. Notable events related to group work or other forms of collaboration were written down. The time, place, people involved and a brief description of the event were recorded for each observation. Further, a short non-structured interview was given to the class teacher and special education teacher after each lesson to add to and elaborate on observations collected by the researcher. With this, observations served as a means to complement and compare results of aforementioned self-regulated learning measures (RQ2).

3.3 | Data analysis

In this study, 'learning analytics' was used for data collection and explorative analysis. In learning analytics, highly varied multimodal learner data is collected and combined from multiple data sources into useful visualisations to optimise learning (Reyes, 2015; Siemens, 2013). Compared to classical educational statistics, learning analytics are more explorative in nature and make use of various data mining techniques such as network and process analysis, prediction models, clustering and relationship mining (Avella et al., 2016; Hoppe, 2017; Saarela, 2017, p. 27). Learning analytics methods are applicable to a large variety of data and sample sizes, from analysing large national tests with thousands of participants to analysing student profiles (e.g. in classrooms) with only a few dozen students (Saarela & Kärkkäinen, 2017). As such, this study employed learning analytics and data mining techniques extensively. Owing to time and resource limitations at the time of the study, data analysis was implemented outside the Open edX system instead of integrating visualisations into the digital learning materials. Data analysis was completed using Pandas (Reback et al., 2021), PM4Py (Berti et al., 2019) and scikit-learn (Pedregosa et al., 2011).

To supplement explorative analysis, descriptive statistics and common statistical tests were used to aid in interpreting explored data. Because of the classroom scale, the number of observations was significantly lower than the number of variables and the use of statistical tests for normally distributed data may not be reliable (Wu & Leung, 2017). As such, the analysis was done using robust methods that are more stable for data with large deviations from normal distribution while still providing reasonable precision (Huber & Ronchetti, 2009).

3.3.1 | Student perceptions via MSLQ

The student self-reports collected via MSLQ can be analysed in numerous ways, from descriptive statistics to visualisations (Duncan & McKeachie, 2005). Here, cluster analysis was chosen to detect general profiles of how the students evaluated their self-regulatory skills in mathematics. First, the MSLQ scales for each student were computed using the MSLQ items, after which basic descriptive statistics, such as the spatial median (Vardi & Zhang, 2001), were computed. Then, the students were clustered by their MSQL scale scores using agglomerative hierarchical clustering (Aggarwal & Reddy, 2014, p. 103). Necessary clustering parameters, such as cluster count and linkage type, were verified via cluster validation with Silhouette Coefficient and by inspecting the resulting dendrogram. Student clusters were interpreted by inspecting each cluster's MSLQ scale score distributions and by comparing each cluster's MSLQ score's scale medians to that of other students. Because cluster sizes were expected to be small and the MSLQ scores between clusters heteroscedastic, the permuted Brunner-Munzel test (Neubert & Brunner, 2007) was used to test for the stochastic equality ($H_0: P = P(X < Y) + \frac{1}{2}P(X = Y) = 0.5$) of MSQL scale scores between the students in a cluster and the rest of students. As the permuted Brunner-Munzel test is an exact test, only the p value is reported. Effect size $\hat{p}$ estimating P is also reported, which is be used to estimate the distribution direction as follows: $P(X < Y) < P(X > Y)$ when $P < 0.5$ and $P(X < Y) > P(X > Y)$ when $P > 0.5$ (Wilcox, 2012, p. 192).

3.3.2 | Student behaviour via trace logs

In this study, the trace logs analysis method was derived from previous related works. Notably, this study uses a combined approach proposed by Jovanović et al. (2017) and Matcha, Uzir, et al. (2020), who analysed learning strategies by discovering and clustering students by the learning tactics they used. Per their approach, in this study, event logs captured event occurrences, and the goal was to attempt to detect session types from event patterns to gain insight into the learning tactics used. This method can also be employed to detect general student behaviour patterns, such as time management skills (Uzir et al., 2020). In this study, the analysis of trace logs involved two steps: detecting session types from events and grouping students into behaviour groups based on what session types they used. Once events had been collected from trace logs, we applied sequence analysis of learning sessions. A learning session is a sequence of consecutive event occurrences that happen within 40 min of each other. Every event occurrence represents a student-material interaction which is coded by an event type using codes described in Table 1. The 40-minute cut-off was chosen because it was half of the class's duration; this accounted for students taking at least one break. Next, learning sessions with just one event and sessions longer than the 95th percentile of all captured sessions were discarded, as suggested by Jovanović et al. (2017). Once the learning sessions were formed, they were converted into first-order Markov models in which each transition from one event to another was associated with a transition frequency. The first-order Markov models were then vectorised so that each vector element represented the transition frequency between two possible event types. These vector representations were clustered using Expectation Maximisation, as it does not require defining a separate similarity metric between these vectors' representations of learning sessions. The resulting clusters represent specific *session types* that describe student-material interaction patterns. We then referred to related work and the theoretical framework to infer learning tactics students used.

The discovered session types were then used to build each student's learning profile and group each one into student behaviour groups. For this, the process presented by Matcha, Uzir, et al. (2020) was followed by forming a frequency table of students' learning sessions by each session type. Each row was, thus, of the form $(\mathrm{taN}_1, \mathrm{taN}_2, \ldots, \mathrm{taN}_K, \Sigma\mathrm{taN})$, where $ta\mathrm{N}_i$ represented the number of learning sessions of a student that belonged to a specific session type and ΣtaN was the total number of learning sessions of a student. These profile vectors were clustered using agglomerative hierarchical clustering and validated, as was done with the MSLQ scales. As a result, the final clusters contained students grouped by session types and their frequency; these represented *student behaviour types*. The behaviour types were then interpreted using prior research and the used theoretical framework to infer learning strategies students used.

3.3.3 | Student observations and assignments

During the analysis, class observations were paired with quantitative data to describe detected clusters and explain certain behaviours. Observations of help-seeking were included in the trace logs as separate events. Additionally, observations regarding group work were interpreted using the socially regulated learning model by Hadwin et al. (2017). Finally, student behaviour and performance were compared by cross-tabulating discovered session types, student behaviour types and students' grades on graded assignments. Student and teacher feedback obtained via the final questionnaire was also considered based on the collected observations.

4 | RESULTS

4.1 | Students' self-report profiles

All participating students answered the MSLQ before the first lesson. The boxplot of the computed MSLQ scores of all the students, along with the spatial median as the centre line, are presented in Figure 3. The boxplot revealed usr2 and usr12 as outliers in the way they self-evaluated their self-regulation skills. In general, most students in the studied class reported relying on peer learning and help-seeking for learning mathematics. The Cronbach alphas of the MSLQ scales varied between 0.50 and 0.90 for all scales but Peer learning ($\alpha = 0.43$). Compared to the reference values reported by Pintrich et al. (1991) ($\alpha \in [0.52, 0.80]$), the scores computed in this study had good internal consistency.

The initial hierarchical clustering of students by MSLQ scores was achieved using average linkage based on comparing the Silhouette coefficient scores and visually inspecting the dendrogram. The initial dendrogram (Figure 4) showed that three students (usr2, usr12 and usr19) were the furthest from the neighbouring clusters. A secondary cluster validation with the three students excluded improved the Silhouette Coefficient (Figure 5). To improve the quality of clustering, students usr2, usr12 and usr19 were analysed separately from the clusters. Based on the visual analysis of the MSLQ scale distributions (Figure 6) for each cluster and comparison of students between clusters using the Brunner-Menzel test for stochastic equality (Table 2), the resulting MSLQ clusters were obtained:

- *Low use of cognitive and metacognitive strategies* ($N = 4$): Students' self-reported scores for most cognitive and metacognitive strategy scales are below 3. Compared to other clusters, students rated their metacognitive and some cognitive strategy use lower.
- *High use of cognitive and metacognitive strategies* ($N = 4$): Students self-reported high use of various cognitive and metacognitive strategies to achieve academic goals. Specifically, elaboration, critical thinking and metacognitive skill scores significantly differed from other clusters.

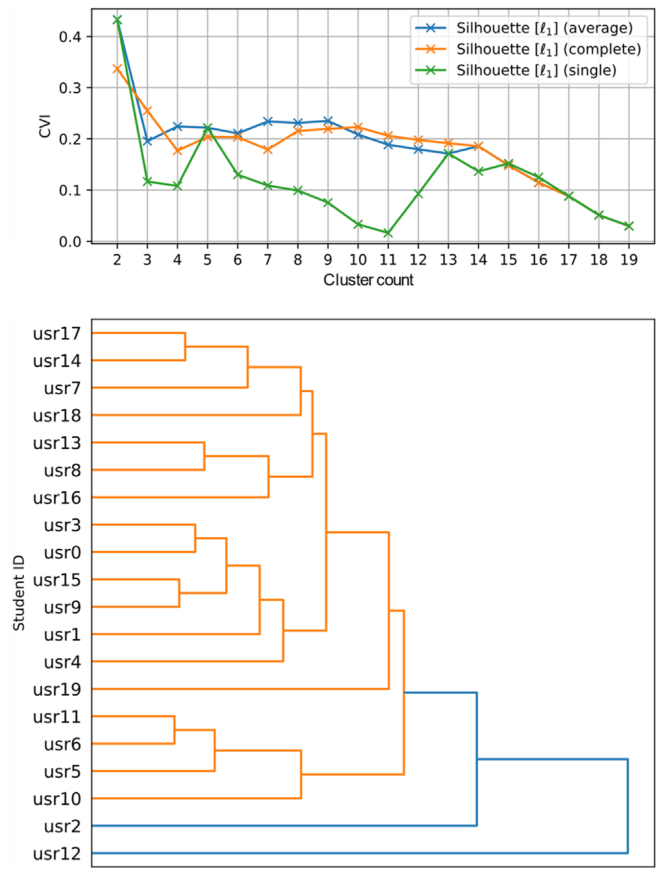

FIGURE 4 Top: plot of the Silhouette Coefficients for different linkage types when clustering all students ($N = 20$) by Motivated Strategies for Learning Questionnaire scores. Bottom: the resulting dendrogram of student clustering by MSLQ scores.

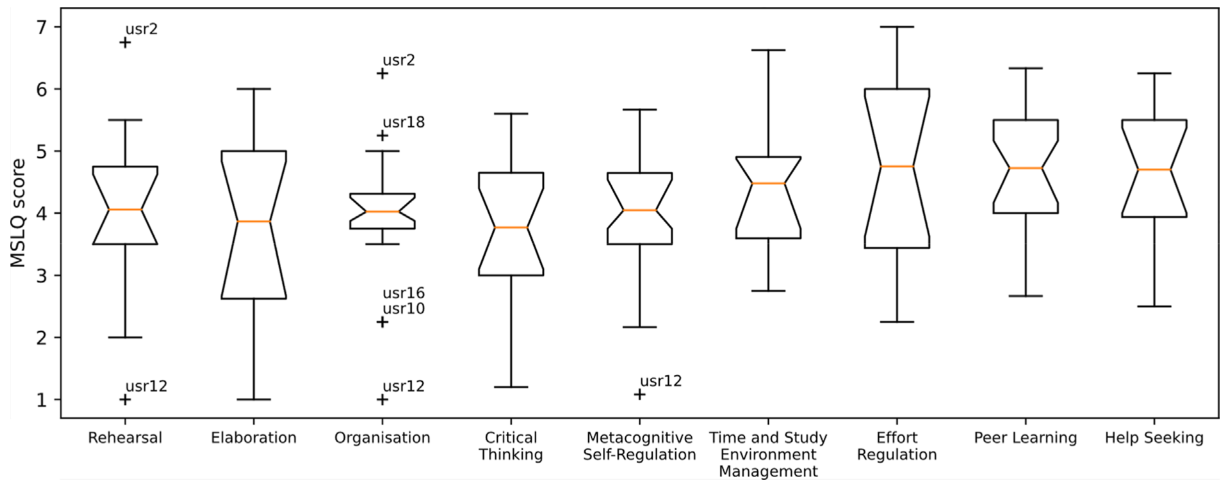

FIGURE 3 Boxplot of computed Motivated Strategies for Learning Questionnaire (MSLQ) scales for students. The centre line is the spatial median that approximates the average of the MSLQ scales.

- *Balanced self-regulation strategies* ($N = 6$): Self-reports contain no emphasis on a specific strategy when learning mathematics. In comparison with other clusters, these students rated their use of help-seeking lower.

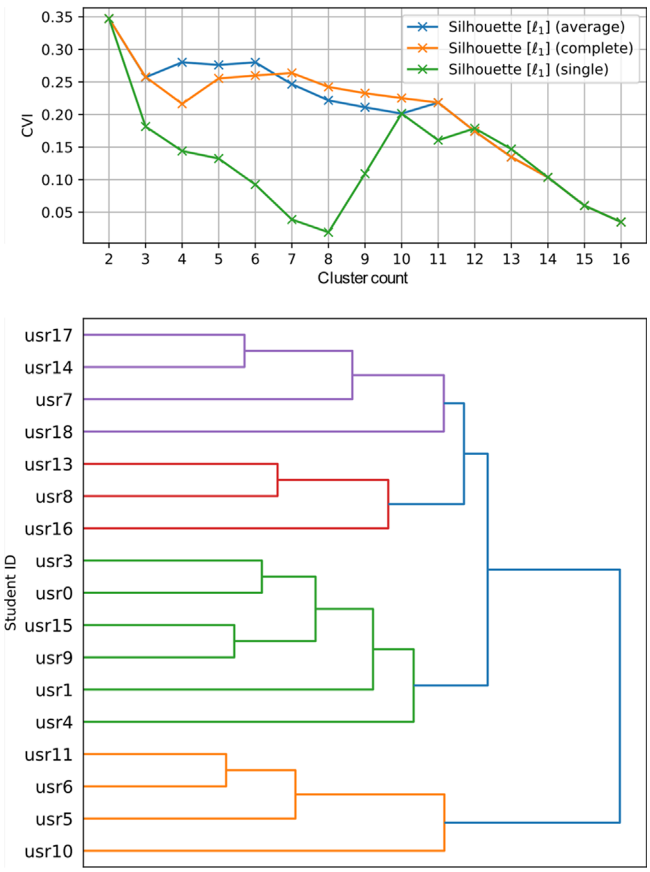

FIGURE 5 Top: plot of the Silhouette Coefficients for different linkage types when clustering students with usr2, usr12 and usr19 excluded ($N = 17$) by Motivated Strategies for Learning Questionnaire (MSLQ) scores. Bottom: the resulting dendrogram of student clustering by MSLQ scores.

- *High use of resource management strategies* ($N = 3$): Students' highest self-reported MSLQ scale scores were for time management strategies. Such students also preferred social strategies like peer learning and help-seeking over cognitive strategies. However, no statistically significant difference is detected for any MSLQ scale when comparing this cluster's students to others.
- Student usr2 assessed high use of all learning strategies, low use of social strategies.
- Student usr12 assessed low use of all self-regulation skills, normal use of social strategies.
- Finally, student usr19 assessed normal skills, emphasis on effort regulation and peer learning.

In summary, the studied students rated their peer learning and help-seeking skills highly, but their self-reported use of other strategies varied. Most students identified their self-regulation strategy usage as balanced, while only three emphasised resource management strategies over cognitive ones.

4.2 | Behaviour patterns and students' behaviour profiles

In total, 68 valid learning sessions (session length 1–52 events) from the three-day intervention were included in the cluster analysis. Using Silhouette Coefficient and the Baysian Information Criterion, cluster validation suggested five to nine session type clusters. Five clusters were chosen for the final cluster count to keep the clusters larger and easier to interpret. The resulting session clusters were interpreted by first plotting the event distributions for each session in every cluster (Figure 7). In addition, Heuristic Nets (Weijters et al., 2006) were constructed for each session cluster and to the event distribution (e.g. Figure 8). For each Heuristic Net, the dependency threshold was chosen so that no independent event loops were included, thus keeping each net simple. Following the conceptualisation and analysis procedure of learning tactics (see Materials and methods Background and theoretical framework section), the

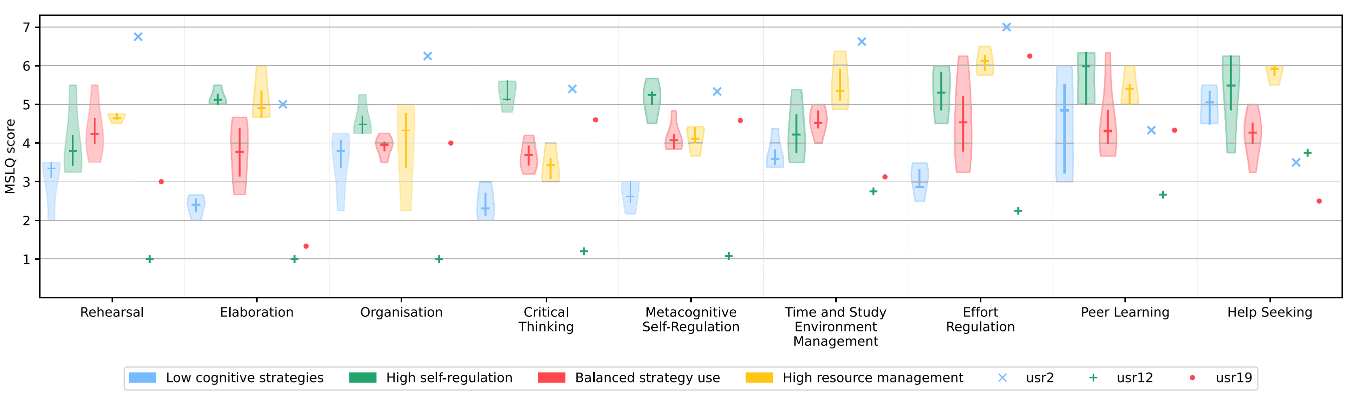

FIGURE 6 Violin plot of the Motivated Strategies for Learning Questionnaire (MSLQ) scores for the found MSLQ profile groups and three outlier students. The centre horizontal line of each violin plot represents the spatial median of the students in the same cluster.

TABLE 2 Statistically significant ($p < 0.05$) effect sizes $\hat{p}$ of Brunner-Munzel test between students in an Motivated Strategies for Learning Questionnaire (MSLQ) cluster and students in all other MSLQ clusters.

	R	E	O	CT	MSRL	TEM	ER	PL	HS
Low cognitive	–	0.01	–	0.09	0.00	0.10	0.03	–	–
High cognitive	–	0.92	–	1.00	0.98	–	–	–	0.68
Balanced	–	–	–	–	–	–	–	–	0.14
High resource	–	–	–	–	–	–	–	–	–

Note: Statistically insignificant effect sizes were left out. For scales with $\hat{p} < 0.5$, the scale's scores in the cluster are more likely to be lower compared to those in other clusters and vice versa.
Abbreviations: CT, critical thinking; E, elaboration; ER, effort regulation; HS, help seeking; MSRL, metacognitive self-regulation; O, organisation; PL, peer learning; R, rehearsal; TSEM, time and study environment management.

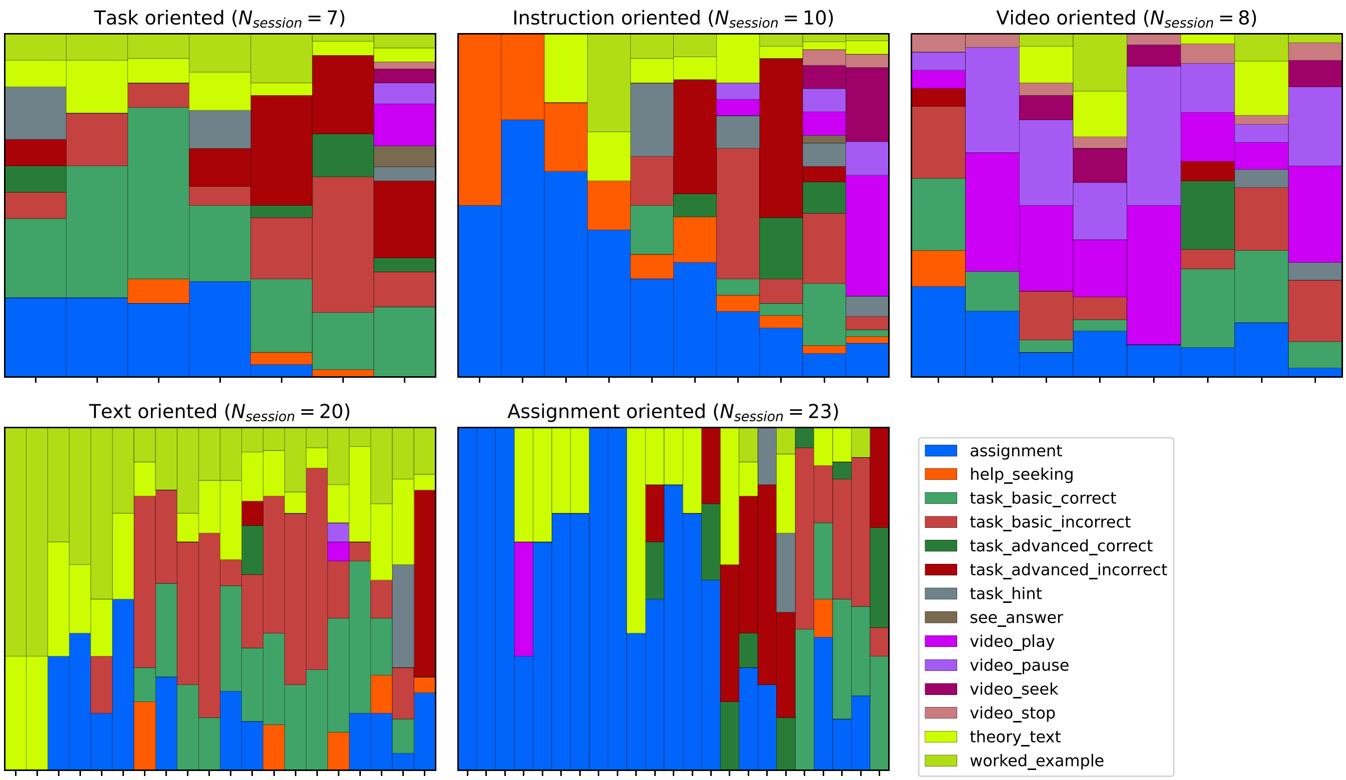

FIGURE 7 Event distributions of learning sessions (cf. Figure 5) for learning session clusters. Each bar represents a distribution of events in a learning session.

detected session clusters were labelled as the following session types:

- *Task oriented* ($N = 7$): Sessions where learning was carried out primarily by completing ungraded tasks either before or after completing the graded assignments.
- *Instruction oriented* ($N = 10$): Sessions where help-seeking or general teacher instruction was actively used between other actions. Help was used primarily to solve graded assignments.
- *Video oriented* ($N = 8$): Sessions where video materials were used as the primary resource alongside completing ungraded tasks.
- *Text oriented* ($N = 20$): Sessions where text materials such as theory, worked examples and ungraded tasks were used as the primary learning resource.
- *Assignment oriented* ($N = 23$): Sessions where completion of the graded assignment was prioritised before interacting with the other learning resources. Students used the available learning resources to complete the graded assignment as fast as possible in these sessions.

Cluster analysis and cluster validation of students using the student behaviour profiles generated from the session type frequencies revealed three clusters. Each cluster contained students' behaviour profiles that described what session types a student used during the lessons. Because learning sessions are time-bound, each behaviour cluster can be depicted as a frequency of different session types for each student and the frequency of session types during and outside of class (c.f. Jovanović et al., 2017). Using the number of session types grouped by students (Figure 9) and by the lesson in which they were captured (Figure 10), students' behaviour profiles were labelled as the following behaviour types using the presented conceptualisation of learning strategies (see Materials and methods Background and theoretical framework section):

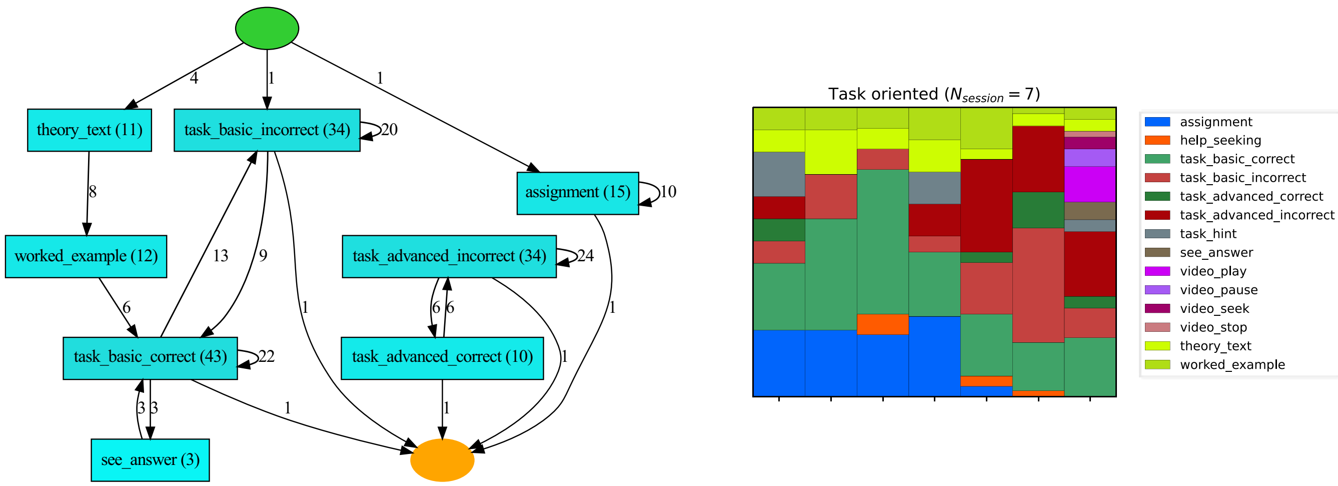

FIGURE 8 Left: task-oriented session type represented as a Heuristic Net. Right: event distribution of each session in task-oriented session type represented as stacked bars, in which each learning session is depicted as a vertical bar divided into coloured areas. Area sizes correlate to the frequency of the events in a session.

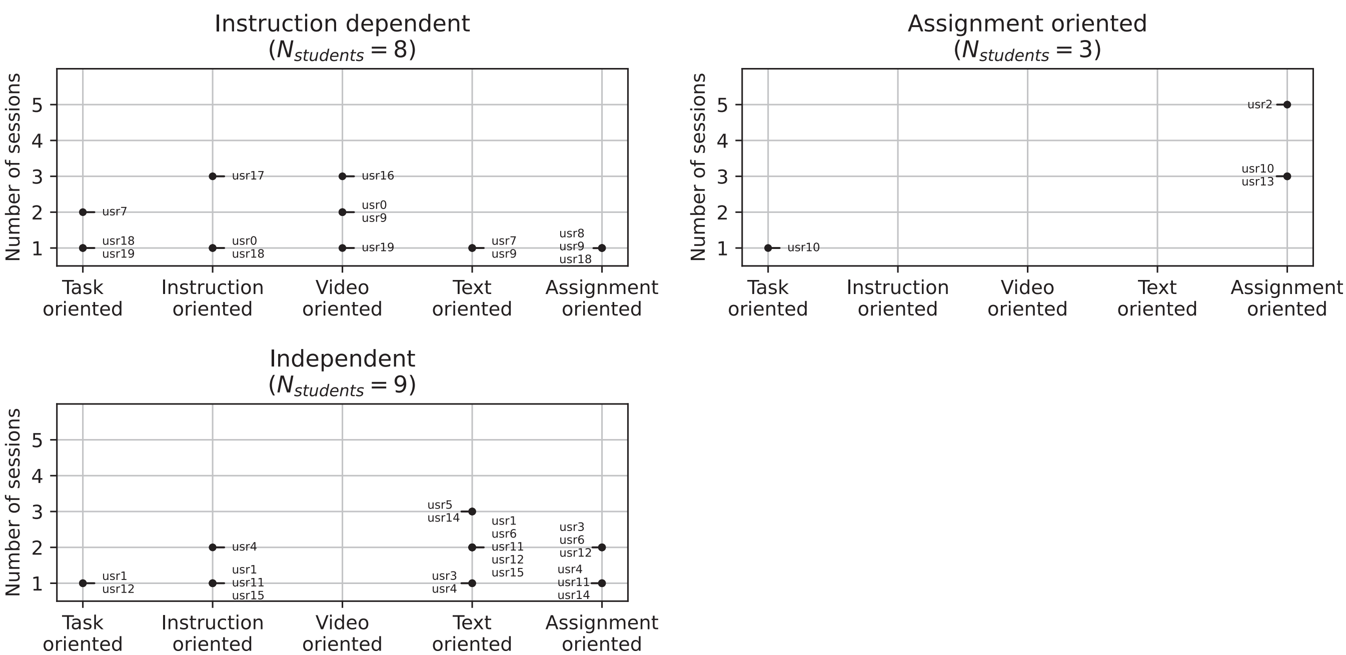

FIGURE 9 Scatter plot of captured sessions of every student grouped by session type for each student behaviour cluster.

- *Instruction dependent* (N = 8): Students in this cluster used video and instruction-oriented session types the most. Student sought help or got direct instructions on how to use the learning resources. These students also primarily learned in class with few learning sessions captured outside class. In total, 22 sessions with 528 events were completed by the students in the cluster, making the students in this cluster the most active compared to other clusters.
- *Assignment oriented* (N = 3): Students' sessions were almost solely assignment-oriented. Students used available learning resources minimally and primarily focused on completing each lesson's assignment. Moreover, most sessions work was captured outside the classroom. With 12 captured learning sessions and 162 events in total, the three students were moderately active with the learning materials.
- *Independent* (N = 9): Students' captured sessions were primarily text and assignment oriented. Interactive session types, such as video and instruction-oriented sessions, were captured for a few students. The primary learning sources were text materials and tasks. The students also actively engaged with the learning materials outside of class. However, the students in this cluster had noticeably short sessions, with 34 captured sessions and 387 events.

4.3 | Performance, behaviour and self-report associations and student observations

During the intervention, students were given 11 graded assignments to complete. The assignments were graded on a scale of 0–100 as requested by the class teacher. Because the scale is large compared to the number of students, students were divided into three grade groups based on grading criteria: low (mean grade in the range 0–60), middle (mean grade in the range 60–80) and high (mean grade in the range 80–100). Students were then grouped by graded assignment performance and observed learning session types and behaviour types, and the groups were cross tabulated. Student performance and observed clusters were tested for association using Fisher's exact test, as there were not enough students to fulfil the requirements of the χ^2-test. Based on Fisher's exact test, no significant association was observed between the grade groups and MSLQ profiles ($p = 0.388$) nor between the grade groups and the detected students' behaviour types ($p = 0.091$).

To test for association between the self-reported MSLQ profile clusters and the observed sessions, the sessions of all students in the MSLQ profile clusters ($N = 56$) were grouped and cross tabulated (Table 3, Table 4). For example, nine learning sessions related to instruction-dependent student behaviour were observed for students who self-reported the high use of cognitive learning strategies. With this approach, there were enough sessions in each group for the χ^2-test for association. From the test, statistically significant association was observed between the session types and the MSLQ profile clusters ($\chi^2(12) = 24.74$, $p < 0.05$); however, the Bonferroni-corrected post-hoc test using Fisher's exact test for odds ratio did not yield any statistically significant pairwise association. Moreover, the association between the student behaviour types and the MSLQ profile clusters is significant ($\chi^2(6) = 29.16$, $p < 0.001$). Post hoc tests using Fisher's exact test with the Bonferroni correction revealed some pairwise association: students with low self-reported cognitive strategy use level displayed less instruction-dependent behaviour than those with high self-reported cognitive strategy ($p < 0.05$, $OR = 0$, CI $[0, 0.61]$) and balanced self-regulation ($p < 0.05, OR = 0$, CI $[0, 0.82]$) levels. On the other hand, students with low self-reported cognitive strategy use had more independent student behaviour than self-reported balanced ($p < 0.05, OR = 0$, CI $[0, 0.55]$) and high resource management strategy use ($p < 0.05$, $OR = 0$, CI $[0, 0.49]$). Finally, students in the balanced self-report group displayed more independent behaviour than those who self-reported high resource management strategy use ($p < 0.05$, $OR = 0$, CI $[0, 0.60]$).

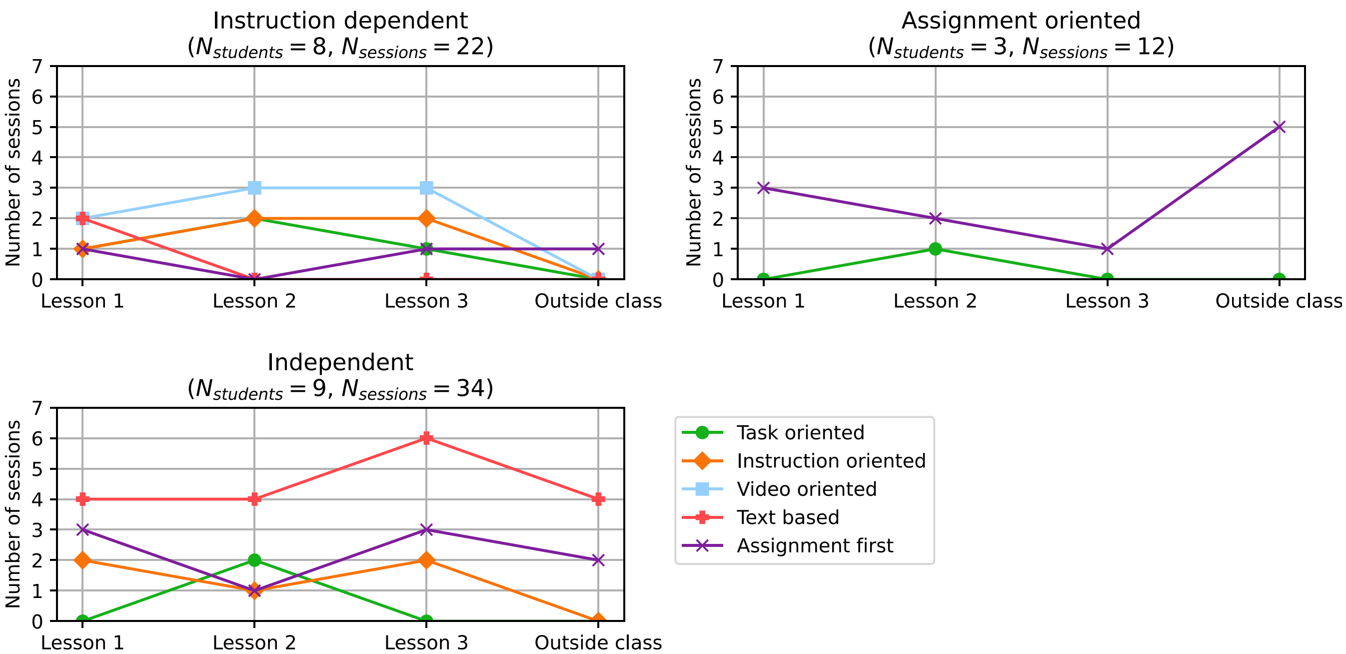

FIGURE 10 Clustered behaviour types depicted by the frequency of captured session types per lesson.

TABLE 3 Cross table of learning sessions ($N = 56$) grouped by clustered student behaviour types and Motivated Strategies for Learning Questionnaire (MSLQ) profile clusters.

	Low cognitive	High cognitive	Balanced	High resource management
Instruction dependent	0	9	7	4
Assignment oriented	4	0	0	3
Independent	11	4	14	0

TABLE 4 Cross table of learning sessions ($N = 56$) grouped by clustered session types and Motivated Strategies for Learning Questionnaire profile clusters.

	Low cognitive	High cognitive	Balanced	High resource management
Task oriented	1	3	1	0
Instruction oriented	1	4	5	0
Video oriented	0	0	4	3
Text oriented	7	4	7	0
Assignment oriented	6	2	4	4

Overall, the association between the MSLQ profiles and session and student behaviour types was observed. However, no significant association was found between student grades and the observed behaviour types. Some additional observation can be drawn from the studied group: for example, many of the students in the group were clustered into the independent behaviour group, regardless of the MSLQ profile they were grouped into (Table 3). Moreover, the students who were in the 'balanced' MSLQ profile used all session types (Table 4).

During all three lessons, the studied students actively interacted with the present instructors. This behaviour was relatively common for the studied class, as noted by the special education teacher who was present during the lessons. In general, there were two kinds of interactions observed: student-initiated, where a student asked directly for help to complete a task or a graded assignment and instructor-initiated, where the instructor checked on the student and instructed on how to proceed. While all students used the former interaction type, the latter was applied only to specific students when the teacher noted that the student was not using the materials. When questioned about this, the teacher noted that those were generally the same students who tended to slack off in class. Meanwhile, some students required instruction on selecting and pacing the learning resources. Both the class teacher and the special education teacher noted that the students generally appeared motivated and sought help themselves when they needed it.

When it came to using the learning resources and completing the learning goals, the students used different approaches. While some students usually read the theory first, some jumped over it entirely and went for the tasks. When the researcher evaluated the graded assignments after each lesson, it was noted that half the students regarded graded assignments as homework: they tended to do part of the graded assignments during class and the rest at home before the next lesson. When the researcher mentioned the observation to the students after the first lesson, a few students also expressed that they wanted to do assignments at home, but could not because they forgot the link to the virtual learning environment. Both the class teacher and the special education teacher commented that the assignment completion rate was slightly lower than that of regular homework, with a few students not turning in some assignments at all.

During the lessons, various kinds of collaboration were observed. The students were not restricted to working alone, which led to the spontaneous creation of temporary dyads and triads in the class. The duration of each collaboration effort ranged from between a few minutes to the entire duration of the lesson. The observed collaboration type varied from student to student. Notably, peer instruction, straightforward 'sharing the answers' work and co-learning were observed.

At the end of the last lesson, students were asked to give anonymous feedback on the materials and the teaching approach used in the lessons. Most students regarded both materials and a more self-regulated learning approach highly:

> I think this [study experiment] worked quite well, the materials were fine, learning was nice, and I am not sure what I would change.

> It was quite nice. The materials sometimes were bugging out a little. More free lessons were very nice. […]

Some enjoyed the given freedom but were less fond of the materials:

> The materials were boring and quite useless, [but] more freedom in lessons was fun. […]

One student would have preferred using a desktop to interact with the materials:

> The material didn't work out, and I didn't like this teaching method. I'd prefer to do the task on a PC in the future. Other than that, the lessons were interesting and nice.

Despite the students' different approaches to using the provided learning resources, the anonymous feedback was overwhelmingly positive. Out of 19 anonymous answers, 13 were positive, four were neutral and only two were negative. In the end, while the students had different opinions on the materials, they all appreciated the freedom to choose and complete tasks at their own pace.

5 | DISCUSSION

The present learning analytics study investigated the combined use of aptitude- and event-based self-regulation measures in a junior high school mathematics classroom. Our aim was to obtain a comprehensive view of self-regulation behaviour in a single classroom by combining these two types of measures. To achieve this, we set two main goals. Firstly, we aimed to map learning behaviour patterns and establish links between these patterns and higher-level learning tactics and learning strategies (RQ1). Secondly, we aimed to evaluate the relationship between the aptitude measures used, namely MSLQ and sequence analysis of trace logs (RQ2).

5.1 | Learning behaviour patterns when learning mathematics

With respect to RQ1, the sequence analysis of trace logs identified five session types characterising student usage of available learning resources and three behaviour patterns reflecting the level of active engagement with these resources. The session types captured were *assignment-oriented* (emphasising graded assignments), *text-oriented* (focusing on text-based materials such as theory and worked examples), *instruction-oriented* (relying on instructors), *video-oriented* (prioritising video materials), and *task-oriented* (learning through tasks). As for learning behaviour, during the three-session study, students were classified as *instruction-dependent* (frequently using instructors and videos), *independent* (actively varying text reading, completing assignments and tasks both in and outside class), or *assignment-oriented* (concentrating primarily on graded assignments). Overall, students utilised all available learning resources, including theory, worked examples, videos, tasks, and instructors.

The session types discovered generally align with learning tactics reported in previous research and appear relevant to the context under study. For instance, Jovanović et al. (2017) and Matcha, Gašević, et al. (2020) identified two comparable reading and video-centric learning tactics. In the Finnish mathematics context, these sessions are logical given the typical learning structure: students initially acquire theory, subsequently apply it to tasks, and ultimately are assessed via assignments (Hemmi & Ryve, 2014). Furthermore, the learning sessions closely correspond with Zimmerman and Martinez-Pons (1986)'s taxonomy of self-regulated learning: assignment-oriented, task-oriented, and video-oriented sessions mirror the 'rehearsing and memorising' strategies; text-oriented sessions resemble 'information-seeking' strategies; and instruction-oriented sessions relate to the 'seeking social assistance' strategy. Nonetheless, a direct comparison is infeasible as our detected session types are more refined and thus encompass multiple self-regulation strategies within the taxonomy. Consequently, the identified session types can be regarded as manifestations of higher-level learning tactics. Although these session types may prove challenging to associate with conceptual frameworks, their relevance to the learning context is readily discernible.

The three learning behaviour patterns depict the extent to which students actively varied their use of learning resources. None of these patterns correspond directly to Zimmerman and Martinez-Pons (1986)'s taxonomy, as their model comprises more atomic learning strategies. Instead, Winne and Hadwin (1998)'s conceptualisation better describes the patterns, as they delineate learning strategies based on how a student regulates the use of learning resources and specific processes. For example, Matcha, Uzir, et al. (2020) and Uzir et al. (2020) reported a similar differentiation between active, deep learning and low-variation, surface learning behaviour patterns in STEM courses. However, general learning strategies cannot be directly deduced from behaviour patterns, since trace logs fail to capture the cognitive processes underlying the observed behaviour (e.g. Jovanović et al., 2017). Nevertheless, the observed patterns offer valuable insights into student engagement with learning resources and mathematics, facilitating the identification of potentially struggling students who may not be employing effective learning behaviours.

5.2 | Association between aptitude and event measures

In addressing RQ2, our study identified self-regulated learning through three distinct aspects: students' evaluation of their skills (MSLQ), utilisation of learning resources (trace logs), and supporting observations. Our findings indicate a correlation between student profiles obtained via self-report and student behaviour profiles gathered through sequence analysis. For instance, the class under investigation generally reported high usage of help-seeking and peer learning strategies (Figure 3), which correlated with observed help-seeking behaviour. Similarly, students who self-reported extensive use of self-regulation skills were also found to actively vary their session types (Table 3, Table 4). Although not all self-reported profiles demonstrated significant statistical associations with student behaviour types, the MSLQ served to enhance the interpretability of observed student behaviour within the classroom. Consequently, self-reports may offer a valuable framework for interpreting trace logs.

Nonetheless, it is important to acknowledge that our study's employed measures do not entirely capture the self-regulation skills of students or their impact on performance. For example, we found a weak association between mathematical achievement and student behaviour, contradicting the results of similar studies (e.g. Duffy & Azevedo, 2015; Rosário et al., 2013). This discrepancy could be attributed to both the small sample size and the limited number of graded tasks, which hindered comprehensive evaluation of the learned content. Moreover, our observations unveiled complexities in student behaviour that eluded both the MSLQ and sequence analysis. While help-seeking was assessed through these methods, closer examination of observations revealed diverse group self-regulation behaviour (Hadwin et al., 2017): some students shared results or instructed their peers, whereas two students engaged in collaborative learning and mutually regulated one another's learning. Despite these limitations, using both measures in classrooms can offer practical benefits, yielding rapid and interpretable results. To enhance accuracy, practical implementations of self-regulated learning analytics could incorporate periodic collection of self-reports in the form of microanalytics (e.g. Salehian Kia et al., 2021).

5.3 | Practical considerations

This study serves as a case study, exploring the application of various learning analytics techniques on a small cohort to obtain a behaviour-based perspective of self-regulation skills. The primary focus lies on the analytics, as well as future work and practical implications. Firstly, our chosen analytics methods, namely cluster analysis of self-reports and sequence analysis of trace logs, were effortlessly integrated into existing tools for authoring digital learning materials, yielding interpretable results. Consequently, further incorporation of these learning analytics into digital learning materials is recommended. Secondly, practical implementation could be enhanced by integrating self-regulated learning interventions informed by the reports generated by the current study's analytics. Lastly, the practical learning analytics tools employed in classrooms ought to incorporate aptitude measures alongside event measures more actively, thereby improving accuracy and providing teachers with prompt information about students' self-regulation skills.

Nonetheless, the study's design imposes certain limitations on its practical application. Notably, the results presented herein warrant cautious interpretation when discussing general student behaviour in a mathematics classroom, as the small number of students limits broader generalisations. Moreover, while trace logs offer evidence of student behaviour, they fail to capture the internal self-regulatory processes driving such actions. A more accurate interpretation of student behaviour as learning strategies necessitates a stronger connection between students' cognitive processes (e.g. motivation, metacognition) and observed behaviour (Winne & Marzouk, 2019). Finally, the presence of the researcher in class as an instructor leaves the potential for selection bias when considering observations. Thus, the collected observation results are of interest when discussing limitations of measures used in this study, but they do not yield enough reliable information about self-regulated learning itself.

In summary, the present study exemplifies the use of learning analytics to identify and report students' self-regulation behaviour on a small scale. Our findings are generally comparable to similar studies conducted on larger cohorts (e.g. Fan et al., 2021; Jansen et al., 2022; Matcha, Gašević, et al., 2020), reinforcing the validity of our observations. Although the analysis approach does not yield general behaviour patterns in mathematics, it allows the quick acquisition of an overview of class behaviour patterns, which can prove valuable for teachers when determining suitable supportive interventions. For example, our analysis revealed a small number of students who self-reported good self-regulation skills yet did not vary their behaviour effectively. While simple, the information given by student behaviour and self-report profiles serve as an initial prompt for the teacher to further observe and support the struggling students. Furthermore, the high interpretability of the results suggests that the analysis procedure could be employed as a method for interpreting other analytics. Predictive learning analytics, for example, strive to identify at-risk students within a classroom but do not typically yield easily explainable models (Sghir et al., 2022). Thus, combining information about self-regulation tactics and strategies employed by students with predictive learning analytics can provide a robust foundation for implementing meaningful interventions to enhance learning and support struggling students.

6 | CONCLUSIONS

In this study, we investigated self-regulated learning in a Finnish junior high school mathematics class by providing students with various digital learning resources and allowing them to use the resources freely. Aptitude and event measures were used concurrently: student self-reports were collected with MSLQ and behaviour with trace logs. Data from event and aptitude measures were combined, analysed and visualised using learning analytics.

During the study, students used the learning resources in five ways: concentrating only on tasks, seeking teacher help, watching videos, using text materials or concentrating primarily on graded assignments. Three student behaviour profiles were captured. Most students studied independently using multiple learning resources. Some students relied primarily on instruction-oriented tactics such as help-seeking and video watching. A few students practised a highly selective strategy in which they structured learning resource usage around solely turning in the graded assignments.

This study suggests that including both event and aptitude measures in the learning process can provide teachers with valuable information about students' perceptions and actions. Importantly, the information gained from using aptitude and event measures complements each other: student self-evaluation can, for example, explain why specific learning resources were used. In turn, information about student behaviour can inform teachers about what self-regulated learning interventions to use. Designing learning materials and learning sessions, in general, should, thus, include tools to measure how students use the available learning resources. In a sense, learning materials for students can become a tool for teachers to not only assess their students but also evaluate class practices.

This was an initial pilot study with limited time and learning resources. While the created visualisations proved helpful in interpreting learning tactics and strategies, they were not directly displayed to the students and teachers. As such, future work is planned to integrate self-regulated learning measures and interventions tighter into digital learning materials. For example, Jääskelä et al. (2020) and Saarela et al. (2021) provide methods and examples for informing teachers and students about student agency using different visualisations of collected and analysed questionnaire data. Student agency involves various resources, such as student motivation, competence beliefs and self-efficacy (Jääskelä et al., 2017), which are also present in self-regulated learning and, as such, may be measured similarly. Consolidating and visualising measures benefits not only students, but also teachers, as they are able to better reflect on their actions and the learning environment (Heilala et al., 2022). Further, the work can be expanded by considering specific learning resources more closely. For example, help-seeking is a complex tactic that depends on peers, instructors and materials (Doebling & Kazerouni, 2021). Similarly, integrating the measurement of time management strategies could be used to further provide helpful information to teachers (Uzir et al., 2020).

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/jcal.12842.

DATA AVAILABILITY STATEMENT

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

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REFERENCES

Aggarwal, C. C., & Reddy, C. K. (2014). *Data clustering: Algorithms and applications* (1st ed.) (pp. 1–21). CRC Press LLC. https://doi.org/10.1201/9781315373515

Ameloot, E., Rotsaert, T., & Schellens, T. (2021). The supporting role of learning analytics for a blended learning environment: Exploring students' perceptions and the impact on relatedness. *Journal of Computer Assisted Learning*, *38*, 90–102. https://doi.org/10.1111/JCAL.12593

Araka, E., Maina, E., Gitonga, R., & Oboko, R. (2020). Research trends in measurement and intervention tools for self-regulated learning for e-learning environments—Systematic review (2008–2018). *Research and Practice in Technology Enhanced Learning*, *15*(1), 1–23. https://doi.org/10.1186/s41039-020-00129-5

Avella, J. T., Kebritchi, M., Nunn, S. G., & Kanai, T. (2016). Learning analytics methods, benefits, and challenges in higher education: A systematic literature review. *Online Learning*, *20*(2), 13–29. https://doi.org/10.24059/olj.v20i2.790

Beheshitha, S. S., Gašević, D., & Hatala, M. (2015). A process mining approach to linking the study of aptitude and event facets of self-regulated learning. In *265–269*. Association for Computing Machinery. https://doi.org/10.1145/2723576.2723628

Ben-Eliyahu, A., & Bernacki, M. L. (2015). Addressing complexities in self-regulated learning: A focus on contextual factors, contingencies, and dynamic relations. *Metacognition and Learning*, *10*(1), 1–13. https://doi.org/10.1007/s11409-015-9134-6

Berti, A., van Zelst, S. J., & van der Aalst, W. M. P. (2019). Process mining for python (PM4py): Bridging the gap between process- and data science. *CEUR Workshop Proceedings*, *2374*, 13–16.

Biggs, J. B. (1987). Student approaches to learning and studying. In *Research monograph*. Australian Council for Educational Research.

Boelens, R., de Wever, B., & Voet, M. (2017). Four key challenges to the design of blended learning: A systematic literature review. *Educational Research Review*, *22*, 1–18. https://doi.org/10.1016/J.EDUREV.2017.06.001

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, *27*, 1–13. https://doi.org/10.1016/J.IHEDUC.2015.04.007

Cicchinelli, A., Veas, E., Pardo, A., Pammer-Schindler, V., Fessl, A., Barreiros, C., & Lindstädt, S. (2018). *Finding traces of self-regulated learning in activity streams* (pp. 191–200). Association for Computing Machinery. https://doi.org/10.1145/3170358.3170381

de Sousa, E. B. G., Alexandre, B., Ferreira Mello, R., Pontual Falcão, T., Vesin, B., & Gašević, D. (2021). Applications of learning analytics in high schools: A systematic literature review. *Frontiers in Artificial Intelligence*, *4*, 132. https://doi.org/10.3389/frai.2021.737891

Dent, A. L., & Koenka, A. C. (2016). The relation between self-regulated learning and academic achievement across childhood and adolescence: A meta-analysis. *Educational Psychology Review*, *28*(3), 425–474. https://doi.org/10.1007/s10648-015-9320-8

Dignath, C., & Büttner, G. (2008). Components of fostering self-regulated learning among students. A meta-analysis on intervention studies at primary and secondary school level. *Metacognition and Learning*, *3*(3), 231–264. https://doi.org/10.1007/s11409-008-9029-x

Doebling, A., & Kazerouni, A. M. (2021). Patterns of academic help-seeking in undergraduate computing students. In *21st Koli calling international conference on computing education research*. Association for Computing Machinery. https://doi.org/10.1145/3488042.3488052

Duffy, M. C., & Azevedo, R. (2015). Motivation matters: Interactions between achievement goals and agent scaffolding for self-regulated learning within an intelligent tutoring system. *Computers in Human Behavior*, *52*, 338–348. https://doi.org/10.1016/j.chb.2015.05.041

Duncan, T. G., & McKeachie, W. J. (2005). The making of the motivated strategies for learning questionnaire. *Educational Psychologist*, *40*(2), 117–128. https://doi.org/10.1207/s15326985ep4002_6

Dunlosky, J., & Rawson, K. A. (2012). Overconfidence produces underachievement: Inaccurate self evaluations undermine students' learning and retention. *Learning and Instruction*, *22*(4), 271–280. https://doi.org/10.1016/J.LEARNINSTRUC.2011.08.003

Endedijk, M. D., Brekelmans, M., Sleegers, P., & Vermunt, J. D. (2016). Measuring students' self-regulated learning in professional education: Bridging the gap between event and aptitude measurements. *Quality and Quantity*, *50*(5), 2141–2164. https://doi.org/10.1007/s11135-015-0255-4

Ergen, B., & Kanadlı, S. (2017). The effect of self-regulated learning strategies on academic achievement: A meta-analysis study. *Eurasian Journal of Educational Research*, *17*(69), 55–74.

Fan, Y., Matcha, W., Uzir, N. A., Wang, Q., & Gašević, D. (2021). Learning analytics to reveal links between learning design and self-regulated learning. *International Journal of Artificial Intelligence in Education*, *31*(4), 980–1021. https://doi.org/10.1007/s40593-021-00249-z

Garcia, R., Falkner, K., & Vivian, R. (2018). Systematic literature review: Self-regulated learning strategies using e-learning tools for computer science. *Computers in Education*, *123*, 150–163. https://doi.org/10.1016/j.compedu.2018.05.006

Gašević, D., Jovanović, J., Pardo, A., & Dawson, S. (2017). Detecting learning strategies with analytics: Links with self-reported measures and academic performance. *Journal of Learning Analytics*, *4*(2), 113–128. https://doi.org/10.18608/jla.2017.42.10

Hadwin, A. F., Järvelä, S., & Miller, M. (2017). Self-regulation, co-regulation, and shared regulation in collaborative learning environments. In D. H. Schunk & J. A. Greene (Eds.), *Handbook of self-regulation of learning and performance* (2nd ed., pp. 83–106). Routledge. https://doi.org/10.4324/9781315697048

Hämäläinen, V., & Isomöttönen, V. (2019). What did CS students recognize as study difficulties? In *Frontiers in Education Conference (FIE)* (pp. 1–9). IEEE. https://doi.org/10.1109/FIE43999.2019.9028714

Heilala, V., Jääskelä, P., Saarela, M., Kuula, A., Eskola, A., & Kärkkäinen, T. (2022). "Sitting at the stern and holding the rudder": Teachers' reflections on action in higher education based on student agency analytics. In L. Chechurin (Ed.), *Digital teaching and learning in higher education* (pp. 71–91). Palgrave Macmillan.

Hemmi, K., & Ryve, A. (2014). Effective mathematics teaching in Finnish and Swedish teacher education discourses. *Journal of Mathematics Teacher Education*, *18*(6), 501–521. https://doi.org/10.1007/s10857-014-9293-4

Hoppe, U. (2017). Computational methods for the analysis of learning and knowledge building communities. In C. Lang, G. Siemens, A. F. Wise, &

D. Gaševic (Eds.), *The handbook of learning analytics* (1st ed., pp. 23–33). Society for Learning Analytics Research (SoLAR). https://doi.org/10.18608/hla17.002

Huber, P. J., & Ronchetti, E. M. (2009). *Robust statistics* (2nd ed.). John Wiley & Sons, Inc. https://doi.org/10.1002/9780470434697

Jääskelä, P., Heilala, V., Kärkkäinen, T., & Häkkinen, P. (2020). Student agency analytics: Learning analytics as a tool for analysing student agency in higher education. *Behaviour & Information Technology*, *1–19*, 790–808. https://doi.org/10.1080/0144929X.2020.1725130

Jääskelä, P., Poikkeus, A. M., Vasalampi, K., Valleala, U. M., & Rasku-Puttonen, H. (2017). Assessing agency of university students: Validation of the AUS scale. *Studies in Higher Education*, *42*(11), 2061–2079. https://doi.org/10.1080/03075079.2015.1130693

Jansen, R. S., van Leeuwen, A., Janssen, J., & Kester, L. (2022). Exploring the link between self-regulated learning and learner behaviour in a massive open online course. *Journal of Computer Assisted Learning*, *38*(4), 993–1004. https://doi.org/10.1111/jcal.12675

Jansen, R. S., van Leeuwen, A., Janssen, J., Kester, L., & Kalz, M. (2017). Validation of the self-regulated online learning questionnaire. *Journal of Computing in Higher Education*, *29*(1), 6–27. https://doi.org/10.1007/s12528-016-9125-x

Järvelä, S., & Hadwin, A. F. (2013). New frontiers: Regulating learning in CSCL. *Educational Psychologist*, *48*(1), 25–39. https://doi.org/10.1080/00461520.2012.748006

Jovanović, J., Gašević, D., Dawson, S., Pardo, A., & Mirriahi, N. (2017). Learning analytics to unveil learning strategies in a flipped classroom. *Internet and Higher Education*, *33*, 74–85. https://doi.org/10.1016/j.iheduc.2017.02.001

Kitsantas, A., & Zimmerman, B. J. (2008). College students' homework and academic achievement: The mediating role of self-regulatory beliefs. *Metacognition and Learning 2008 4:2*, *4*(2), 97–110. https://doi.org/10.1007/S11409-008-9028-Y

Kontturi, H. (2016). *The occurrence and promotion of self-regulated learning in a primary school learning context*. University of Oulu. http://urn.fi/urn:isbn:9789526210940

Kramarski, B., & Gutman, M. (2006). How can self-regulated learning be supported in mathematical E-learning environments? *Journal of Computer Assisted Learning*, *22*(1), 24–33. https://doi.org/10.1111/J.1365-2729.2006.00157.X

Malmberg, J., Järvenoja, H., & Järvelä, S. (2010). Tracing elementary school students' study tactic use in gStudy by examining a strategic and self-regulated learning. *Computers in Human Behavior*, *26*(5), 1034–1042. https://doi.org/10.1016/j.chb.2010.03.004

Matcha, W., Gašević, D., Ahmad Uzir, N., Jovanović, J., Pardo, A., Lim, L., Maldonado-Mahauad, J., Gentili, S., Pérez-Sanagustín, M., & Tsai, Y.-S. (2020). Analytics of learning strategies: Role of course design and delivery modality. *Journal of Learning Analytics*, *7*(2), 45–71. https://doi.org/10.18608/jla.2020.72.3

Matcha, W., Uzir, N. A., Gasevic, D., & Pardo, A. (2020). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies*, *13*(2), 226–245. https://doi.org/10.1109/TLT.2019.2916802

Neubert, K., & Brunner, E. (2007). A studentized permutation test for the non-parametric Behrens–fisher problem. *Computational Statistics & Data Analysis*, *51*(10), 5192–5204. https://doi.org/10.1016/J.CSDA.2006.05.024

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, *8*(APR), 1–28. https://doi.org/10.3389/fpsyg.2017.00422

Panadero, E., Jonsson, A., & Botella, J. (2017). Effects of self-assessment on self-regulated learning and self-efficacy: Four meta-analyses. *Educational Research Review*, *22*, 74–98. https://doi.org/10.1016/j.edurev.2017.08.004

Panadero, E., Klug, J., & Järvelä, S. (2016). Third wave of measurement in the self-regulated learning field: When measurement and intervention come hand in hand. *Scandinavian Journal of Educational Research*, *60*(6), 723–735. https://doi.org/10.1080/00313831.2015.1066436

Pardo, A., Han, F., & Ellis, R. A. (2017). Combining university student self-regulated learning indicators and engagement with online learning events to predict academic performance. *IEEE Transactions on Learning Technologies*, *10*(1), 82–92. https://doi.org/10.1109/TLT.2016.2639508

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., & Duchesnay, É. (2011). Scikit-learn: Machine learning in python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Pijeira-Díaz, H. J., Drachsler, H., Kirschner, P. A., & Järvelä, S. (2018). Profiling sympathetic arousal in a physics course: How active are students? *Journal of Computer Assisted Learning*, *34*(4), 397–408. https://doi.org/10.1111/jcal.12271

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451–502). Elsevier. https://doi.org/10.1016/b978-012109890-2/50043-3

Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review*, *16*(4), 385–407. https://doi.org/10.1007/s10648-004-0006-x

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). A manual for the use of the motivated strategies for learning questionnaire (MSLQ). https://eric.ed.gov/?id=ED338122

Puustinen, M., & Pulkkinen, L. (2001). Models of self-regulated learning: A review. *Scandinavian Journal of Educational Research*, *45*(3), 269–286. https://doi.org/10.1080/00313830120074206

Rajaram, K. (2021). Student-centric learning: A transformation in the learning culture. In *Evidence-based teaching for the 21st century classroom and beyond* (pp. 175–198). Springer. https://doi.org/10.1007/978-981-33-6804-0_5

Rao, N., Moely, B. E., & Sachs, J. (2000). Motivational beliefs, study strategies, and mathematics attainment in high- and low-achieving chinese secondary school students. *Contemporary Educational Psychology*, *25*(3), 287–316. https://doi.org/10.1006/ceps.1999.1003

Rasheed, R. A., Kamsin, A., & Abdullah, N. A. (2020). Challenges in the online component of blended learning: A systematic review. *Computers & Education*, *144*, 103701. https://doi.org/10.1016/J.COMPEDU.2019.103701

Reback, J., McKinney, W., jbrockmendel, Bossche, J. V. den, Augspurger, T., Cloud, P., gfyoung, Hawkins, S., Sinhrks, Roeschke, M., Klein, A., Petersen, T., Tratner, J., She, C., Ayd, W., Naveh, S., Garcia, M., patrick, Schendel, J., … h-vetinari. (2021). *pandas-dev/pandas: Pandas 1.2.3*. Zenodo. https://doi.org/10.5281/ZENODO.4572994

Reyes, J. A. (2015). The skinny on big data in education: Learning analytics simplified. *TechTrends*, *59*(2), 75–80. https://doi.org/10.1007/s11528-015-0842-1

Rosário, P., Núñez, J. C., Valle, A., González-Pienda, J., & Lourenço, A. (2013). Grade level, study time, and grade retention and their effects on motivation, self-regulated learning strategies, and mathematics achievement: A structural equation model. *European Journal of Psychology of Education*, *28*(4), 1311–1331. https://doi.org/10.1007/S10212-012-0167-9/TABLES/3

Roth, A., Ogrin, S., & Schmitz, B. (2016). Assessing self-regulated learning in higher education: A systematic literature review of self-report instruments. *Educational Assessment, Evaluation and Accountability*, *28*(3), 225–250. https://doi.org/10.1007/s11092-015-9229-2

Saarela, M. (2017). *Automatic knowledge discovery from sparse and large-scale educational data: Case Finland*. University of Jyväskylä.

Saarela, M., Heilala, V., Jääskela, P., Rantakaulio, A., & Kärkkäinen, T. (2021). Explainable student agency analytics. *IEEE Access*, *9*, 137444–137459. https://doi.org/10.1109/ACCESS.2021.3116664

Saarela, M., & Kärkkäinen, T. (2017). Knowledge discovery from the programme for international student assessment. *Studies in Systems, Decision and Control*, *94*, 229–267. https://doi.org/10.1007/978-3-319-52977-6_8

Saint, J., Whitelock-Wainwright, A., Gašević, D., & Pardo, A. (2020). Trace-SRL: A framework for analysis of micro-level processes of self-regulated learning from trace data. *IEEE Transactions on Learning Technologies*, *13*(4), 861–877. https://doi.org/10.1109/TLT.2020.3027496

Salehian Kia, F., Hatala, M., Baker, R. S., & Teasley, S. D. (2021). Measuring students' self-regulatory phases in LMS with behavior and real-time self report. In *ACM International Conference Proceeding Series* (pp. 259–268). Association for Computing Machinery. https://doi.org/10.1145/3448139.3448164

Schunk, D. H., & Greene, J. A. (2017). Historical, contemporary, and future perspectives on self-regulated learning and performance. In D. H. Schunk & J. A. Greene (Eds.), *Handbook of self-regulation of learning and performance* ((2nd ed.) ed., pp. 1–15). Routledge. https://doi.org/10.4324/9781315697048

Sghir, N., Adadi, A., & Lahmer, M. (2022). Recent advances in predictive learning analytics: A decade systematic review (2012–2022). *Education and Information Technologies*, *2022*, 1–35. https://doi.org/10.1007/S10639-022-11536-0

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist*, *57*(10), 1380–1400. https://doi.org/10.1177/0002764213498851

Sitzmann, T., & Ely, K. (2011). A meta-analysis of self-regulated learning in work-related training and educational attainment: What we know and where we need to go. *Psychological Bulletin*, *137*(3), 421–442. https://doi.org/10.1037/A0022777

Uzir, N. A., Gašević, D., Matcha, W., Jovanović, J., & Pardo, A. (2020). Analytics of time management strategies in a flipped classroom. *Journal of Computer Assisted Learning*, *36*(1), 70–88. https://doi.org/10.1111/JCAL.12392

van Harsel, M., Hoogerheide, V., Verkoeijen, P., & van Gog, T. (2021). Instructing students on effective sequences of examples and problems: Does self-regulated learning improve from knowing what works and why? *Journal of Computer Assisted Learning*, *38*, 19–39. https://doi.org/10.1111/JCAL.12589

Vardi, Y., & Zhang, C. H. (2001). A modified Weiszfeld algorithm for the Fermat-weber location problem. *Mathematical Programming, Series B*, *90*(3), 559–566. https://doi.org/10.1007/PL00011435

Viberg, O., Khalil, M., & Baars, M. (2020). Self-regulated learning and learning analytics in online learning environments: A review of empirical research. In *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 524–533). Association for Computing Machinery. https://doi.org/10.1145/3375462.3375483

Wang, Y., & Sperling, R. A. (2020). Characteristics of effective self-regulated learning interventions in mathematics classrooms: A systematic review. *Frontiers in Education*, *5*, 5. https://doi.org/10.3389/FEDUC.2020.00058

Weijters, A. J. M. M., van der Aalst, W. M. P., & de Medeiros, A. K. A. (2006). *Process mining with the heuristics miner-algorithm* (Vol. 166, pp. 1–34). Technische Universiteit Eindhoven.

Wilcox, R. (2012). Introduction to robust estimation and hypothesis testing. In *Introduction to robust estimation and hypothesis testing* (4th ed.). Elsevier. https://doi.org/10.1016/C2010-0-67044-1

Winne, P. H. (2001). Self-regulated learning viewed from models of information processing. In B. J. Zimmerman & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: Theoretical perspectives* (pp. 153–189). Routledge.

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Erlbaum.

Winne, P. H., & Marzouk, Z. (2019). Learning strategies and self-regulated learning. In *The Cambridge handbook of cognition and education* (pp. 696–715). Cambridge University Press. https://doi.org/10.1017/9781108235631.028

Winne, P. H., & Perry, N. E. (2000). Measuring self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 531–566). Academic Press.

Wong, J., Baars, M., Davis, D., van der Zee, T., Houben, G. J., & Paas, F. (2019). Supporting self-regulated learning in online learning environments and MOOCs: A systematic review. *International Journal of Human Computer Interaction*, *35*(4–5), 356–373. https://doi.org/10.1080/10447318.2018.1543084

Wu, H., & Leung, S.-O. (2017). Can Likert scales be treated as interval scales?—A simulation study. *Journal of Social Service Research*, *43*(4), 527–532. https://doi.org/10.1080/01488376.2017.1329775

Yu, L. C., Lee, C. W., Pan, H. I., Chou, C. Y., Chao, P. Y., Chen, Z. H., … Lai, K. R. (2018). Improving early prediction of academic failure using sentiment analysis on self-evaluated comments. *Journal of Computer Assisted Learning*, *34*(4), 358–365. https://doi.org/10.1111/jcal.12247

Zhou, M. (2013). Using traces to investigate self-regulatory activities: A study of self-regulation and achievement goal profiles in the context of web search for academic tasks. *Journal of Cognitive Education and Psychology*, *12*(3), 287–305. https://doi.org/10.1891/1945-8959.12.3.287

Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist*, *25*(1), 3–17. https://doi.org/10.1207/s15326985ep2501_2

Zimmerman, B. J. (2005). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press.

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal*, *45*(1), 166–183. https://doi.org/10.3102/0002831207312909

Zimmerman, B. J., & Martinez-Pons, M. (1986). Development of a structured interview for assessing student use of self-regulated learning strategies. *American Educational Research Journal*, *23*(4), 614–628. https://doi.org/10.3102/00028312023004614

How to cite this article: Zhidkikh, D., Saarela, M., & Kärkkäinen, T. (2023). Measuring self-regulated learning in a junior high school mathematics classroom: Combining aptitude and event measures in digital learning materials. *Journal of Computer Assisted Learning*, 1–18. https://doi.org/10.1111/jcal.12842