A Systematic Review on Student Engagement in Undergraduate Mathematics Conceptualization, Measurement, and Learning Outcomes

Papageorgiou, E.; Wong, Jacqueline; Liu, Qinyi ; Khalil, Mohammad; Cabo, A.J.

DOI
10.1007/s10648-025-10046-y

Publication date
2025

Document Version
Final published version

Published in
Educational Psychology Review

Citation (APA)
Papageorgiou, E., Wong, J., Liu, Q., Khalil, M., & Cabo, A. J. (2025). A Systematic Review on Student Engagement in Undergraduate Mathematics: Conceptualization, Measurement, and Learning Outcomes. *Educational Psychology Review*, *37*(3), Article 66. https://doi.org/10.1007/s10648-025-10046-y

Educational Psychology Review (2025) 37:66
https://doi.org/10.1007/s10648-025-10046-y

REVIEW ARTICLE

A Systematic Review on Student Engagement in Undergraduate Mathematics: Conceptualization, Measurement, and Learning Outcomes

Elissavet Papageorgiou[1] · Jacqueline Wong[2] · Qinyi Liu[3] · Mohammad Khalil[3] · Annoesjka J. Cabo[1]

Received: 10 January 2025 / Accepted: 19 June 2025

Abstract

Undergraduate mathematics education is essential for building a foundation for success in various scientific disciplines. Curriculum reforms in mathematics education have emphasized the need for cultivating learning skills that depend on effective student engagement (SE). Consequently, there has been growing research on the mechanisms that facilitate SE and promote its development. To gain insights into the state of SE research in undergraduate mathematics, the current systematic review addresses the varied research by examining four key aspects: a) theoretical grounding and research aims, b) definitions, c) measurement, and d) learning outcomes. Following the PRISMA guidelines, a literature search identified 1,584 records, with 48 papers meeting the inclusion criteria. The findings reveal three primary research aims and three approaches to grounding SE research, with most studies using an instruction-focused framework to evaluate instructional methods. Nearly half of the papers provided a definition of SE, with analysis showing varied uses of elements like psychological investment and multidimensionality. Studies that used multiple elements offered more concise definitions. Measurement of SE predominantly focused on online learning through log files or course participation via self-reports, with behavioral engagement being the most commonly examined dimension. Less than half of the studies explored the relationship between SE and learning outcomes, using both variable-oriented and person-oriented approaches to examine this connection. Based on the current findings, the review offers recommendations for aligning conceptualizations, definitions, measurement, and context in future research to foster a shared understanding and guide interventions.

Keywords Student engagement · Undergraduate mathematics · Conceptualization · Measurement · Learning outcomes

Extended author information available on the last page of the article

Published online: 03 July 2025

Introduction

Student engagement (SE) is viewed as a multifaceted fundamental educational construct comprising affective, behavioral, and cognitive components (Fredricks et al., 2016a). Studies provide unequivocal support for the positive association between SE and learning outcomes, such as grades and performance, course completion, and persistence in one's studies (Fredricks et al., 2016a; Tinto, 2022). Consequently, SE has been extensively researched in education to understand how and why instruction can be effective (Lowe & Hakim, 2020). While there is a general agreement among researchers about SE's multidimensionality, prior systematic reviews have shown that the construct's conceptualizations and measurement methods are vastly diverse (e.g., Bond et al., 2020; Martin, 2023). At the same time, the theoretical grounding and definitions are often unclear (Bond et al., 2023; Henrie et al., 2015). This heterogeneity and lack of transparency hinder a greater understanding among researchers of what is meant by the term "engagement" in a certain research context and how this engagement can be supported and in turn, support learning outcomes (Azevedo, 2015). Wong and Liem (2022) identified two main perspectives of SE: learning engagement entails students' active involvement in learning and school engagement encompasses interpersonal involvement in the school community. Given that the current review focuses on undergraduate mathematics, the perspective of SE as learning engagement is used in the paper. For the rest of the paper, the terms SE and learning engagement are used synonymously.

A crucial characteristic of SE is that it always involves an object, i.e., the learning activity in which SE occurs (Sinatra et al., 2015). Learning activities refer to "any tasks, actions, or experiences—in lectures, homework, self-readings, etc.—that lead to learning" (Wong & Liem, 2022, p. 121). The subject domain and the type of learning activities can significantly influence how students engage during learning (Bergdahl, 2022; Sinatra et al., 2015; Wang & Hofkens, 2020). For example, how SE is manifested in mathematics tasks, such as problem-solving, is expected to differ from SE in language learning tasks, such as vocabulary learning (Fredricks et al., 2016b).

However, few systematic reviews have investigated SE within specific subject domains. For example, Hiver et al. (2024) focused on SE conceptualization and measurement in language learning activities, highlighting the need for clear definitions and assessment methods, but did not examine links to learning outcomes. In medical education, Kassab et al. (2022) found that cognitive engagement predicted academic achievement, yet behavioral engagement was most studied. However, SE conceptualization and definition were not explicitly addressed. These examples point to the need for more holistic, domain-specific investigations of SE. In undergraduate mathematics courses, there is an emphasis on the development of mathematical competencies, such as reasoning, modelling, and use of tools, through cognitively challenging tasks (Niss & Højgaard, 2019). Even though supporting and scaffolding meaningful engagement in such tasks has been at the center of attention in mathematics education (Smith et al., 2021), there is still growing evidence of low achievement associated with poor engagement in mathematics contexts (Murphy & Ingram, 2023). In mathematics education, such reviews remain particularly scarce (e.g., Fredricks et al., 2016b). We identified four systematic reviews that focused on the impact of specific instructional methods, such as educational technology (Ali et al., 2023; Kuncoro et al., 2024; Ní Shé et al., 2023) and flipped classrooms (Lo & Hew, 2021). Moreover, while they identified various indicators of SE, they did not examine their conceptual basis or connections to academic achievement. The current review addresses these gaps by examining how SE has been conceptualized, defined, and measured in a broad context of undergraduate mathematics learning activities, and how it is linked to learning outcomes. Drawing on the notion of SE as activity-specific (Sinatra et al., 2015; Wong & Liem, 2022), we build on the contextualized approach of Hiver et al. (2024) by further exploring the connections between learning context, SE-related theoretical frameworks, data types, and learning outcomes. Specifically, we focus on: a) research aims and theoretical grounding, b) definitions, c) measurement approaches, and d) associations with learning outcomes. Our synthesis of the various research practices aims to offer actionable insights and practical guidance for both researchers and educators.

Conceptualizing and Defining Student Engagement

SE has three main conceptual elements. First, SE is *malleable* and therefore is responsive to variations in student and instructional factors (Reschly & Christenson, 2022). How these factors influence SE has been examined via various theoretical and conceptual frameworks (Wong & Liem, 2022). Frameworks drawing from motivational theories have emphasized the role of *student factors* in explaining SE development. For example, expectancy-value-cost theories (Gladstone et al., 2022) and the Self-System Model of Motivational Development (SSMMD) (Skinner et al., 2008) have attempted to answer the question of *what gets students moving toward what activities or tasks* (Martin, 2023). Similarly, frameworks drawing from metacognitive theories, such as self-regulated learning (SRL) models, have been used to answer the question of *how students get what they want* by focusing on the means by which students translate their needs, beliefs, and goals into action (Cleary & Zimmerman, 2012). Frameworks drawing from instructional theories (e.g., cognitive load theory) have focused on examining how *instructional factors* (e.g., scaffolding or feedback provision) can improve SE (e.g., Martin, 2023).

Second, SE is perceived as a *multidimensional* construct comprising various facets and components. Even though SE components have been examined by various frameworks, research has shown that the most common perspective among researchers is that SE comprises three main dimensions, i.e., affective (or emotional), behavioral, and cognitive, that correspond to the extent to which students are enthusiastic, productive, and focused in learning activities (Wong & Liem, 2022). However, there is significant heterogeneity in how researchers define SE and its components (Reschly & Christenson, 2022). Therefore, a clear and explicit *definition* of the term “engagement” is needed in each study to support conceptual coherence and cumulative understanding (Sinatra et al., 2015). In this review, affective engagement refers to positive (interest, alertness) or negative feelings of activation (tiredness, boredom), behavioral engagement refers to the effort students intentionally exert, and cognitive engagement refer to the degree to which students concentrate and think strategically about specific activities (Wong & Liem, 2022). Prior research found that the social component combined with the three main dimensions, i.e., social-affective (e.g., caring about others' ideas), social-behavioral (e.g., helping others), and social-cognitive (e.g., building on others' ideas) engagement, was important for learning mathematics (Fredricks et al., 2016b; Jansen et al., 2023). Researchers have also introduced agentic engagement, which refers to students' constructive and proactive contribution to shaping their learning conditions (Reeve, 2013), and productive disciplinary engagement, which refers to the extent to which students make intellectual progress in the context of specific disciplinary practices and norms (Engle & Conant, 2002). Third, SE is a *dynamic* construct characterized by changes over time (Symonds et al., 2024). Recent studies have adopted this perspective and have utilized the framework of complex dynamical systems to examine the longitudinal dynamics and evolution of SE (e.g., Järvinen et al., 2022; Saqr et al., 2023).

Measuring Student Engagement

The multiple facets of SE have resulted in a plethora of measurement methods and instruments (Betts, 2022). To ensure that the appropriate measurement approach will be selected, researchers should be guided by their SE conceptualization and research questions and accordingly specify the level of granularity, data types and methods (Sinatra et al., 2015). Selecting the appropriate level of granularity is crucial for understanding the role, triggers, emergence, and development of a particular engagement process during learning (Azevedo, 2015). Researchers need to decide the unit-of-analysis of a) time, which ranges from very fine-grained (e.g., seconds, minutes) to more coarse-grained forms (e.g., weeks), b) task, which ranges from a single task to multiple activities, and c) agent, which ranges from the level of the individual to the whole classroom (Symonds et al., 2024). Concerning the data types and methods, prior domain-general reviews show the variety of approaches that can be used to measure SE (e.g., Henrie et al., 2015; Wiedbusch et al., 2023). The most popular approaches include the use of a) process data, i.e., SE processes during learning, via log files, think-aloud protocols, physiological measures, and observations, b) product data, representing knowledge and mastery through test scores, task outcomes, and successful task completion and c) self-reports via surveys and interviews (Azevedo, 2015; Wiedbusch et al., 2023). Other measures include teacher ratings and administrative records (Mandernach, 2015). Provided that each channel captures only specific components of SE and that each method has strengths and weaknesses, current approaches to SE measurement propose the convergence of data channels and methods (Wiedbusch et al., 2023).

The Association Between Student Engagement and Learning Outcomes

SE is broadly considered one of the strongest predictors of positive learning outcomes, such as performance scores, skill development, retention, and transfer of knowledge (Reschly & Christenson, 2022). While an extensive amount of evidence suggests that SE positively predicts achievement (Fredricks et al., 2016a), some studies found weak or no correlation (e.g., Appleton et al., 2006; Saqr et al., 2023; Shernoff & Schmidt, 2008), indicating the need for further research on the relationship between the two constructs. Two recent meta-analyses in domain-general contexts (e.g., Lei et al., 2018; Wong et al., 2024) showed that overall SE and the three SE dimensions (i.e., affective, behavioral, cognitive) were positively correlated with academic achievement. When looking at each dimension separately, behavioral engagement showed the strongest association, followed by cognitive and affective engagement. However, when examining the relationship between SE and subjective well-being, affective engagement showed the strongest association followed by cognitive engagement, suggesting that the significance of each SE dimension in learning depends on the type of learning outcomes under investigation (Wong et al., 2024). Moreover, the meta-analyses revealed that the measurement of SE moderates the relationship between SE and achievement, highlighting the critical role of SE operationalization in linking SE to achievement within specific learning activities (Lei et al., 2018; Wong et al., 2024).

Student Engagement Investigation in Mathematics Contexts: Insights from Prior Reviews

Mathematics learning is an incremental process that requires students to integrate new with previous knowledge by working on tasks that involve intricate operations and abstract concepts (Wang et al., 2021). This process often entails increasing complexity, setbacks, and struggles, and for many students, it might lead to SE decline, failing grades, and even drop out (e.g., Bigotte de Almeida et al., 2021; Schoenfeld, 2022). Consequently, promoting SE with mathematics learning activities has gained increasing focus (Cevikbas & Kaiser, 2022).

Even though the role of SE in mathematics is vital, systematic reviews of SE in the mathematics domain are still scarce. We identified four reviews that examined the influence of educational technology and instructional approaches on SE (Ali et al., 2023; Kuncoro et al., 2024; Lo & Hew, 2021; Ní Shé et al., 2023). Ali et al. (2023) examined remote and online learning environments, analyzing 15 papers, and found that multimedia, e-books, tablets, mobile apps, video lectures, and augmented reality positively impacted SE and achievement. Kuncoro et al., (2024) examined the use of AR for promoting SE. Results from 18 papers showed that AR increased interaction with the learning content, and provided opportunities for collaboration and immersive learning. Ní Shé et al. (2023) explored SE with technology-enhanced resources in undergraduate mathematics education, finding that technology affordances, pedagogy, and student goals impacted SE. Since only 14 studies were identified in the domain of undergraduate mathematics, the scope was expanded to general higher education. Despite the insights, these three reviews did not address how SE aspects were conceptualized, operationalized, and measured.

Lo and Hew (2021) reviewed 33 papers to examine the effects of the flipped classroom approach on SE in mathematics compared to traditional lecturing across all educational levels. They found that the use of the flipped classroom approach could increase certain aspects of behavioral engagement (i.e., interaction and attention/participation), emotional engagement (i.e., satisfaction), and cognitive engagement (i.e., understanding of mathematics and preference for challenges). Moreover, self-reports were the most commonly used measurement method. The four reviews suggest an increased interest in using active learning practices to enhance SE in mathematics classrooms. However, the identified reviews employed a limited pool of papers (e.g., Ní Shé et al., 2023) or adopted the lens of a specific instructional approach, i.e., the flipped classroom (Lo & Hew, 2021), suggesting the need for a broader investigation of SE in mathematics contexts. Moreover, despite the extended evidence on the association between SE and learning outcomes, prior systematic reviews have rarely addressed this relationship, suggesting an important gap in the literature.

The Current Study

Mathematical skills taught in higher education are essential for societal progress, making mathematics courses vital across STEM and other fields (Hochmuth, 2020). Student learning experiences and performance in gateway mathematics courses have been considered important predictors of successful study paths (Cohen & Kelly, 2020). Despite its significance, undergraduate mathematics education has been facing challenges related to high dropout rates and failing grades (Geisler et al., 2023; Heusel et al., 2023). Mathematics education has tackled these challenges by adopting student-centered practices, encouraging students to develop their own strategies and build an understanding of mathematical concepts (Cabo & Klaassen, 2018; Capone, 2022; Slavich & Zimbardo, 2012).

Considering that SE in mathematics subjects declines over the years (e.g., Collie et al., 2019) and that instructional reforms in undergraduate mathematics courses require students' effective engagement with the learning materials (Cevikbas & Kaiser, 2022), a systematic review of SE research within the field is critical. Understanding how students engage effectively in various learning activities and how this engagement affects achievement is essential for designing and implementing efficient curricula and interventions (Kahu & Nelson, 2018). By adopting a contextualized (i.e., activity-specific) view (Wong & Liem, 2022) on SE, this systematic review aims to provide a comprehensive understanding of SE in undergraduate mathematics learning activities by addressing the following research questions (RQ):

RQ1: *What are the aims and the theoretical grounding for student engagement investigation?*
RQ2: *How is student engagement defined?*
RQ3: *How is student engagement measured across learning activities?*
RQ4: *How is student engagement related to learning outcomes?*

Method

The systematic literature review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009) and was conducted in three phases: a) search strategy and inclusion criteria development, b) identification and quality appraisal of relevant publications, and c) data analysis and synthesis. Figure 1 provides an overview of the paper selection process.

Phase One: Search Strategy and Criteria for Inclusion

Based on previous reviews on student engagement (Fredricks et al., 2004) and mathematics (Lo & Hew, 2021), we developed a search query comprising relevant terms and synonyms for the three main concepts of the study: a) student engagement, b) mathematics, and c) higher education (see Fig. 2). The search was performed in September 2024 using four high-coverage databases, three of which were selected for their multidisciplinary character (SCOPUS, Science Direct, and Web of Science) and one for its breadth in educational research (Education Resources Information Center – ERIC). No time limits were imposed in our search.

Paper management and screening were performed with the use of Rayyan software (Ouzzani et al., 2016). Four screening criteria were implemented on the search results: 1) the publication should be an empirical study, 2) written in the English language, 3) with full access available, and 4) references to student engagement and mathematics in an undergraduate context in the title or abstract. Searching in the three databases resulted in 1,579 papers. Five papers were also identified from additional sources.

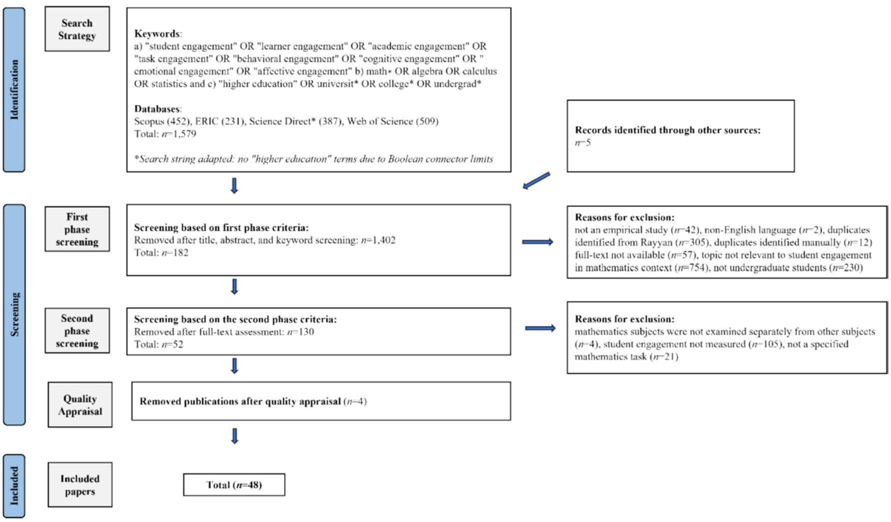

Fig. 1 PRISMA flowchart

Quality Criteria

1. The study clearly addresses the research problem by providing a reasonably thorough review of relevant literature.
2. There is a clear statement of the aims of the research, expressed through well-defined objectives or research questions.
3. There is an adequate description of the context in which the research was carried out, including relevant details such as the educational setting, participant characteristics, and instructional context.
4. The research design appropriately addresses the aims of the research by using a methodologically sound approach that aligns with the research questions and provides justification for the employed procedures.
5. The data analysis is sufficiently rigorous, with a clear description of the analysis linked to the research questions. For quantitative studies, this includes an explanation of statistical procedures; for qualitative studies, coding or thematic analysis is described with justification and transparency.
6. There is a clear statement of findings, which are explicitly connected to the research questions or aims and supported by appropriate evidence such as data excerpts, tables, or figures.
7. The study is of value for research or practice by offering implications or insights that are applicable to future research, policy, or educational practice.

Fig. 2 The 7-item quality appraisal checklist. Adapted from Liu and Khalil (2023)

Phase Two: Identification and Quality Appraisal of Relevant Publications

First, we conducted a screening of titles, abstracts, and keywords. After removing duplicate publications and papers that did not meet the first-phase screening criteria, we obtained 182 papers. Then, we carried out a full-text screening to assess the relevance of the 182 papers with regard to the PICo (Population, Interest, Context) elements of the research questions (Cumpston et al., 2021). In particular, the following inclusion criteria were applied:

1. Population: Undergraduate students or people who are involved in undergraduate teaching.
2. Interest: The study must explicitly investigate, measure, or track SE. To ensure conceptual clarity and consistency, inclusion was limited to papers that explicitly used the term "engagement" in their framework or analysis. Studies that referred only to related but distinct terms, such as *participation*, *involvement*, or *interest*, without referencing "engagement", were excluded. This decision reflects our aim to synthesize how engagement is specifically conceptualized, defined, and operationalized in undergraduate mathematics research.
3. Context: SE should be observed and measured in the context of a specific mathematics learning activity (e.g., class groupwork or self-study). The study should explicitly state the learning activity on which SE focuses (object of student engagement).

At this stage, 130 papers did not meet the criteria and therefore, were excluded. The remaining 52 papers were included for quality appraisal (see Fig. 1). The quality of the studies was appraised using a set of seven criteria based on Critical Appraisal Skills Checklist (Galdas et al., 2015) as adapted by Liu and Khalil (2023) (see Fig. 2). For each criterion, each study was scored using "yes", "no" or "unclear". When a study scored "no" or "unclear" in at least one of the criteria, it was excluded. Of the 52 papers, 48 met the quality criteria and therefore, were included in the analysis (see Supplementary Material).

Phase Three: Data Analysis and Synthesis

To analyze the included publications, we performed a content analysis (Hsieh & Shannon, 2005). In RQ1, RQ2, and RQ4, we aimed to examine researchers' interpretations of SE and therefore we applied an inductive analysis. For RQ1, we analyzed the research questions and objectives presented in the reviewed papers to identify the research aims of each study. We further analyzed the theoretical or conceptual frameworks used to conceptualize SE to understand how researchers approached and investigated their stated research aims. For RQ2, we explored whether researchers provided an SE definition. Definitions could be "explicit", including a clear statement about how SE is defined in a given study by the researchers, or "implicit", including more general descriptions and interpretations of the construct. We further coded the identified definitions to examine which definitional elements were used by the researchers. For RQ4, we explored whether the relationship between SE and learning outcomes was examined. Variables that denoted anticipated positive results of a learning activity were coded as learning outcomes. Moreover, we examined the types of analysis and the reported effect sizes.

In RQ3, we applied a combination of deductive with inductive analysis. In particular, we explored which SE dimensions were reported by the authors, in which learning context SE was observed and measured (i.e., the object of the investigated SE aspect), which grain size of measurement was applied, and what types and channels of engagement data were reported for SE measurement. To address the heterogeneity of SE operationalization and measurement methods, we used representative and generalized models that would provide sufficient insights for coding the majority of the studies (Azevedo, 2015; Fredricks et al., 2004; Wong & Liem, 2022). For example, to maintain the authors' perspectives on SE conceptualization and operationalization, we followed their provided categorization of the investigated SE indicator into a particular SE dimension (see Supplementary Material). When papers did not provide a clear alignment between the investigated SE indicator and an SE dimension, we used the reported operationalization to infer the appropriate dimension based on Wong and Liem's (2022) comprehensive definitions (see Section on Conceptualization and Measurement).

We assessed inter-coder reliability between two coders using Cohen's Kappa method (Cohen, 1960). To establish agreement and mutual understanding on the coding framework, a random sample of six papers (representing approximately 12.5% of the full dataset) was selected and independently coded by two coders. This proportion aligns with recommended practices (Campbell et al., 2013; O'Connor & Joffe, 2020) and prior related research (Banihashem et al., 2022; Jansen et al., 2019), suggesting that 10–25% of the data is typically sufficient to establish inter-coder reliability. The Kappa results indicated very good agreement ($\kappa = 0.89$, $p < 0.001$), demonstrating high reliability and consistency in the coding process (Gisev et al., 2013). Following this, the first author coded the remaining papers. Throughout this process, coding was continuously calibrated through discussion among the authors to resolve ambiguities, refine the application of the coding framework, and ensure consistent interpretation across all studies (O'Connor & Joffe, 2020; Banihashem et al., 2022). The results of the content analysis were further synthesized into larger groups so that each group contains papers that follow a similar approach in investigating SE.

Results

Overview of the Selected Papers

The year of publication of the 48 included papers ranged from 2009 to 2024, but the majority ($n=30$, 63%) of the papers were published after 2019. Regarding the document type, 85% of the papers are journal articles ($n=41$) and the rest are conference papers ($n=7$). These papers were set in 23 different counties. The majority of the papers ($n=37$) were located in 14 Western countries, especially the United States ($n=13$), followed by three each from Portugal, Germany, and The Netherlands. Papers from nine countries/regions in the global south such as Malaysia, Fiji, Uzbekistan, Oman, Taiwan, Kenya, Indonesia, and Hong Kong, represented 23% of the total sample. As for the type of study, the papers mainly used quantitative ($n=35$, 73%) and mixed methods ($n=10$, 21%), with qualitative papers representing only 6% ($n=3$).

Regarding student academic year, there's a notable absence of data in 23 instances, yet first-year students are well represented ($n=20$), with subsequent years, such as second-year ($n=8$), third-year ($n=5$), and fourth-year ($n=2$), progressively less so. Regarding the mathematics subject, the reviewed papers reported a total of 45 subject, with 16 emphasising statistics, 10 emphasizing algebra, and 10 emphasizing calculus. The remaining nine included various subject, such as developmental mathematics or complex analysis courses. Lastly, 37 papers reported the students' major subject, with five papers including student population coming from at least two major subjects. The students involved in these studies were mainly enrolled in programmes related to STEM disciplines ($n=23$), followed by social sciences and humanities ($n=10$), and business/finance disciplines ($n=6$), showcasing a diverse array of academic backgrounds. Two papers reported that students were non-mathematics majors, but did not specify the programme.

Research Aims and Theoretical Grounding for Student Engagement Investigation

Addressing the first research question, content analysis of the *research aims* described in the reviewed papers revealed three main categories: 1) evaluating instructional methods and tools ($n=33$), 2) understanding learning behavior ($n=10$), and 3) examining factors of academic success ($n=5$). Of the 48 papers, 35 explicitly referred to *theoretical and conceptual frameworks* to achieve the respective research aims. Table 1 shows the diverse set of theoretical and conceptual frameworks adopted for each research aim.

More than half of the included papers aimed to evaluate instructional methods and tools, with the majority following an *instruction-focused* approach ($n=15$) that emphasized the role of teaching practices and instructional design as facilitators of SE. *Instruction-focused* frameworks included active learning models, such as Mastery Learning (Paiva et al., 2017) and Triple E Framework (Wong et al., 2022a), which emphasize the development of structured learning activities that enhance autonomous learning, reflection, and progressive mastery. For instance, Paiva et al.

(2017) hypothesized that SE would be enhanced by the implementation of a mastery-based tutorial system that provided personalized feedback and enabled students to study in small modules, self-assess, and practice until achieving mastery. Other papers employed cognitive models, such as cognitive load theory and the ICAP model (Kang et al., 2017; Li et al., 2022), to examine the effects of learning materials that optimizing cognitive processing and promote understanding of mathematical concepts. For example, Kang et al. (2017) hypothesized that tablet-based tools, that allowed students to construct and manipulate visual representations, would promote constructive and interactive SE. Studies adopting this perspective conceptualized SE as the outcome of student-centred learning environments and optimized instruction.

Despite the aim of evaluating instructional design, three papers adopted a *student-focused* framework that emphasized the role of student factors in driving SE (Gomes et al., 2023; Lee et al., 2023; Sancho-Vinuesa et al., 2013). In this category, papers adopted the assumption that instructional strategies that cultivate motivation are key to fostering meaningful engagement. For example, Gomes et al. (2023) hypothesized that instructors' in-class behavior can enhance SE through practices that fulfil students' sense of autonomy, competence, and relatedness. Another small set of papers ($n=5$) adopted an *integrative* approach, i.e., a combination of instruction- and student-focused approaches. In these papers, motivation theories and SE frameworks were often combined with instructional models (e.g., Evans et al., 2022; Plak et al., 2023). In the integrative approach applied by Evans et al. (2022), the instructional principles of Puzzle-Based Learning were combined with the "SE framework on the educational interface". The study explored how non-routine problems could enhance SE. Drawing from Puzzle-Based Learning, these problems were intended to stimulate cognitive challenge and curiosity, while the SE framework accounted for SE activation through motivational mechanisms, such as self-efficacy and positive academic emotions. This integration allowed the authors to link specific instructional features with underlying psychological drivers of SE. Studies using the integrative approach reflected a growing recognition that engagement emerges from the interplay between instructional design and individual learner characteristics.

Papers aiming to understand how students learn adopted a *student-focused* framework ($n=9$), drawing mainly from models on motivation (expectancy-value-cost theory), SRL, affect (e.g., control-value theory), and growth-mindset. Papers in this category investigated the influence of affective, motivational, and metacognitive factors on SE, as well as the impact of SE on learning performance (e.g., González et al., 2016; Sutter et al., 2022). For example, González et al. (2016) examined whether motivation (i.e., intrinsic value and self-concept) and emotion (i.e., anxiety in statistics) would predict SE and final grade. Papers in this category often conceptualized SE not just as an outcome, but as a process that mediates the relationship between internal learner characteristics and academic success (e.g., Hong & Chien, 2023; Thorson et al., 2019), underscoring its dynamic role in learning.

Our analysis reveal that only five papers aimed to examine factors contributing to academic success and only two explicitly employed a theoretical framework for SE (Akimov et al., 2023; Wu, 2021). Both studies positioned SE as a potential predictor of achievement in mathematics courses. Akimov et al. (2023) adopted a *student-focused* perspective, drawing on Case's (2008) "Alternative Framework on Student

Table 1 Theoretical grounding of student engagement research across the three research aims ($N=48$). A detailed list of the papers categorized by theoretical approach and research aim is provided in the supplementary material

Research Aims	Frameworks			
	Student-focused	Instruction-focused	Integrative	Framework not identified
Evaluate instructional methods and tools ($n=33$)	$n=3$ Motivation (Self-determination) School Engagement Framework Classroom Engagement Framework	$n=15$ Cognitive Models: e.g., Cognitive Load Theory, Constructivist Theory, Theoretical Model Of Proof Comprehension Active Learning Models: e.g., ICAP model, Triple E Framework, Transactional Engagement, Game-based Learning Frameworks on Course Design: e.g., ACE (Activity, Classroom Discussion, Exercise), Didactical Tetrahedron, Course Transaction Space Model	$n=5$ Motivation (Expectancy-Value-Cost) and Course transaction space model Fogg Model Motivation and Engagement Wheel and Technological Pedagogical Content Knowledge and Instrumental Genesis SE in the Educational Interface and Puzzled-based Learning Cognitive load and Motivation (Expectancy-Value-Cost)	$n=10$
Understand student learning behavior ($n=10$)	$n=9$ Motivation (Expectancy-Value-Cost) SRL Control-Value Theory of Achievement Emotions Stress And Coping Framework Growth Mindset School Engagement Framework			$n=1$
Examine factors of academic success ($n=5$)	$n=1$ Framework on Alienation and Engagement		$n=1$ SRL and Personal Learning Environment (PLE)	$n=3$

Learning," which emphasizes the interplay between engagement and alienation as influenced by students' motivations, sense of belonging, and ability to meet course expectations. Wu (2021), in contrast, used an *integrative* approach, combining the Personal Learning Environment framework with self-regulated learning (SRL) theory to explore how both instructional and learner-centered elements support academic success.

Student Engagement Definitions

Of the 48 papers reviewed, 48% ($n=23$) provided an explicit definition of SE. A closer analysis of the provided definitions shows that 17 papers included a direct description (e.g., Capone & Lepore, 2022) and six gave indirect descriptions of the construct (e.g., Kang et al., 2017). Eight definitions included the subject domain (i.e., STEM, statistics) (e.g., Thorson et al., 2019; Tucker et al., 2023) or the context (i.e., LMS, digital textbooks, offline settings) in which SE was studied. Not surprisingly, this finding indicates a lack of explicit definition of SE, and even when defined, the elements included in the SE definitions varied among the researchers.

We conducted a content analysis on the 23 definitions to identify and organize keywords denoting an engagement-related aspect (Table 2). More than half of the papers ($n=13$) used the element of *multidimensionality* to define SE. These papers explicitly stated that SE is a construct that comprises various components (Carbonneau et al., 2020; González et al., 2016) and drew on Fredricks et al.'s (2004) framework, which includes affective/emotional, behavioral, cognitive, and social dimensions (e.g., Carbonneau et al., 2020; González et al., 2016). Despite agreement on the multidimensional structure of SE, these papers varied in terminology. Some used the broader term"student engagement"(e.g., Evans et al., 2022), while others referred to"academic engagement"to emphasize engagement with learning tasks and processes (e.g., Hong & Chien, 2023), or"classroom engagement"to highlight participation and interaction within the classroom setting (e.g., Gopal et al., 2019). Most papers defined each dimension independently, with limited discussion of their interrelationships. An exception is Dibbs (2019), who proposed that affective and cognitive engagement act as prerequisites for behavioral engagement. The remaining papers ($n=10$) either defined SE in general terms without reference to specific dimensions (e.g., Hart et al., 2017) or focused exclusively on a single dimension (e.g., Thorson et al., 2019).

In addition to multidimensionality, our analysis identified two recurring elements in SE definitions: *psychological investment*, emphasizing non-observable affective, conative, and cognitive aspects ($n=16$), and *observable behavior* ($n=20$). We examined how these elements were used to define various SE-related components. Several papers defined the term "student engagement" as general psychological investment in learning, drawing on earlier SE conceptualizations (e.g., Newmann, 1992; D'Mello et al., 2008). These papers described SE as effort directed toward understanding or mastering academic goals, and a willingness, need, or compulsion to participate (e.g., Gopal et al., 2019; Syarifuddin & Atweh, 2021). Others emphasized the interaction between students and the learning context. For instance,

Table 2 Analysis of student engagement definitions ($n = 23$) Based on the three elements. A detailed list of the papers categorized by definitional element is provided in the supplementary material

SE definition elements	Number of keywords	Example keywords	Example definitions	Example papers
Multidimensionality ($n = 13$)	14	i. combine, encompass ii. multidimensional, complex iii. aspects, dimensions, forms	i. Student engagement is one's psychosocial state that combines behavioral, emotional, and cognitive connection to learning ii. As a multi-faceted construct involving students' emotion, behavior, and cognition, engagement is usually manifested through three distinct yet connected dimensions viz. behavioral, emotional (affective), and cognitive engagement	Evans et al., (2022); Gopal et al., (2019); Gomes et al., (2023); Hart et al., (2017); Hong and Chien, (2023); Sutter et al., (2022)
Psychological investment ($n = 16$)	55	i. thinking, feeling, being interested ii. effort, persistence, willingness, energy, commitment, quality of mental resources	i. Affective engagement involves positive and negative reactions to content, classmates, and teachers ii. Behavioral engagement is one component of student engagement that examines the amount of effort and perseverance a student exerts in learning ii. Cognitive engagement is connected to the investment in learning, self-regulation, being strategic, desiring to go beyond the requirements, and valuing challenge	Carbonneau et al., (2020); Capone & Lepore, (2022); Evans et al., (2021); Evans et al., (2022); Gomes et al., (2023); Rach (2023)

Table 2 (continued)

SE definition elements	Number of keywords	Example keywords	Example definitions	Example papers
Observable behavior ($n=20$)	60	i. viewing, participating, questioning, communicating, attending ii. time, clicks, policies, conduct, interaction, involvement	i. In this study we define engagement with digital textbooks as encompassing two aspects, viewing of the digital textbooks (that can be done with automatic tracking) and self-reported use of that textbook at the times of viewing ii. Behavioral engagement is closely related to student participation in the classroom. Active participation in the classroom is demonstrated by compliance with classroom procedures, taking initiative in the group and classroom, becoming involved in classroom activities, asking questions, regularly attending class, and comprehensively completing assignments	Castro-Rodríguez et al., (2022); González (2016); Hart et al., (2017); Hong and Chien, (2023); Kang et al., (2017); Lavidas et al., (2020); Plak (2023); Rach (2023); Rienties et al., (2019); Syarifuddin and Atweh, (2021); Thorson et al., (2019)

Capone and Lepore (2022), drawing on Kuh (2003), defined SE as the time and effort devoted to educationally purposeful activities, while Evans et al. (2022), influenced by Kahu and Nelson (2018), framed SE as an active process within an "educational interface". Definitions based on observable behavior described SE as active involvement in learning, time investment, or learner-content interaction (e.g., Castro-Rodríguez et al., 2022; Hart et al., 2017). Some papers presented SE along a continuum—from disengagement (e.g., talking to a friend during a lecture about a topic non-related to the lecture) and passive engagement (e.g., listening to a lecture without taking notes), to active (e.g., listening to a lecture and taking notes) and interactive engagement (e.g., asking questions during the lecture) (Capone & Lepore, 2022; Kang et al., 2017). Notably, Gomes et al. (2023) were among the few to bridge psychological and behavioral perspectives, defining SE as encompassing both observable actions and subjective experiences.

Similarly, the reviewed papers defined behavioral engagement through varied conceptual lenses ($n = 13$). Definitions based on psychological investment described this dimension as mental effort, including perseverance, concentration, and attention (e.g., Carbonneau et al., 2020; Sancho-Vinuesa et al., 2013). In contrast, definitions emphasizing observable behavior conceptualized behavioral engagement as general participation and adherence to academic expectations, such as positive conduct and completion of school tasks (e.g., Hong & Chien, 2023; Lavidas et al., 2020). Some papers adopted a more contextualized approach, describing behavioral engagement as actions during learning—such as time on task, number of clicks, or asking questions (e.g., Sancho-Vinuesa et al., 2013; Sutter et al., 2022). González et al. (2016) argued that not all actions qualify as behavioral engagement; rather, only those that are active, goal-directed, flexible, constructive, and persistent. In addition, papers addressed social-behavioral engagement, defined as interactions that support collaborative learning, particularly in small groups or open idea exchanges (e.g., Gomes et al., 2023; Gopal et al., 2019; Thorson et al., 2019; Ting et al., 2020). Ting et al. (2020) introduced the term interactive engagement to capture the extent to which flipped classroom activities promote learner interaction and idea sharing.

Cognitive and affective engagement were less frequently defined in the corpus. Definitions of cognitive engagement ($n = 7$) were largely based on Fredricks et al. (2004) and emphasized psychological investment and effort beyond routine learning, aimed at mastering difficult skills (e.g., Dibbs, 2019; Gopal et al., 2019; Li et al., 2022). Some papers also highlighted the use of learning strategies and self-regulation (Gomes et al., 2023). Two studies described the dimension as a spectrum of strategies, from shallow (e.g., memorization, test-taking) to deep and self-regulatory (e.g., summarizing, connecting knowledge) (González et al., 2016; Syarifuddin & Atweh, 2021). Affective or emotional engagement was defined in six papers, most drawing on Fredricks et al. (2004) and academic emotion research. They described it as students' positive or negative reactions to content, peers, and teachers, influencing their willingness to participate in school activities (e.g., Dibbs, 2019; Gomes et al., 2023; Li et al., 2022). Only Syarifuddin and Atweh (2021) contextualized affective engagement within mathematics, focusing on interest, achievement orientation, anxiety, and frustration. Gopal et al. (2019) offered a broader classroom-based definition, combining emotional reactions with students' sense of belonging and perceived value, drawing from Finn's (1989) Identification Model. Two additional SE components were defined by Gomes et al. (2023): agentic engagement as constructive contributions to the flow of instruction, and volitional engagement as the enactment of intentions.

The findings indicate that incorporating psychological investment allowed researchers to link their SE definitions to theorized aspects of the construct. However, some definitions show overlap in how SE is conceptualized as a broad concept, and in how behavioral and cognitive engagement are defined, often all being described in terms of energy and effort. Providing clearer definitions to establish the conceptual boundaries between overall SE and its dimensions is needed to advance our understanding of SE in undergraduate mathematics. Moreover, the results reveal that observable behavior was defined in diverse ways, reflecting how SE manifests across specific learning contexts. Some papers addressed this diversity by highlighting in their definitions what aspects of SE are associated with anticipated learning outcomes. For example, authors defined SE as a continuum (Capone & Lepore, 2022; González et al., 2016; Kang et al., 2017), emphasizing that SE is not merely the presence of activity but a form of involvement characterized by qualities necessary for achieving desired outcomes.

Other papers combined multiple definitional elements to bridge the gap between theory and the learning context of the targeted SE aspect. For example, Carbonneau et al. (2020) used their definition to connect theorized aspects of behavioral engagement with the specific learning activity under investigation. They defined behavioral engagement as the effort and perseverance a student exerts in learning. Because the study focused on the use of manipulatives in problem-solving, the authors argued that perseverance—completing a task despite challenges—was the most appropriate indicator. In another example, Thorson et al. (2019) emphasized discipline-specific considerations in their definition of SE. They defined socio-behavioral engagement in STEM activities as students' attention to individuals who are useful sources of information and their interactions with others. In the study context, attention and interaction were further specified as listening carefully to a professor's lecture or asking STEM-related clarification questions. These examples illustrate how definitional elements can be used to connect theorized psychological aspects of SE with context-specific observable behaviors.

Student Engagement Measurement

As shown in Fig. 3, SE was measured using four main data channels—process data, self-reports, product data, and attendance records—to capture behavioral (including social-behavioral), cognitive, and affective dimensions of SE.

Process data captured engagement as it unfolded during learning, employing log files, classroom observations, knowledge construction traces, and physiological measures ($n = 26$). A strong pattern emerged around the use of log files ($n = 17$), primarily to assess behavioral engagement in online self-study or homework contexts (e.g., Azevedo et al., 2019). These data captured (a) frequency of student actions, such as problem attempts or discussion posts (Hart et al., 2017; O'Sullivan et al., 2021; Rienties et al., 2019), (b) duration of activity (Wong et al., 2022b), and (c) regularity of access patterns, such as consistency in engagement over time (Akimov et al., 2023). Cognitive engagement was far less frequently measured via process data and appeared in only two studies using textual analysis (Tucker et al., 2023; Wu, 2021). For instance, Wu (2021) applied supervised machine learning to Facebook interactions, classifying posts by relevance to statistics learning to infer cognitive involvement.

Classroom observations used momentary time sampling to monitor both behavioral (on-task behavior) and cognitive (strategy use) engagement in response to instructional practices (Evans et al., 2022; Gomes et al., 2023; Hora & Holden, 2013) ($n = 3$). These studies highlighted engagement as responsive to environmental cues—for example, Gomes et al. (2023) found that instructor behaviors (e.g., guiding, waiting) and student actions (e.g., group work) predicted higher collective behavioral engagement. Two papers focused on single in-class activities. Knowledge construction data, as used by Carbonneau et al. (2020), offered a more fine-grained look at behavioral engagement, defined as perseverance, during problem-solving. Engagement was inferred from students' willingness to revise and retry, such as drawing new representations after failed attempts. Finally, physiological data were used to assess cognitive engagement in proof comprehension activities (Hodds et al., 2014). Eye-tracking revealed depth of processing through fixation duration, with longer fixations suggesting more sustained attention.

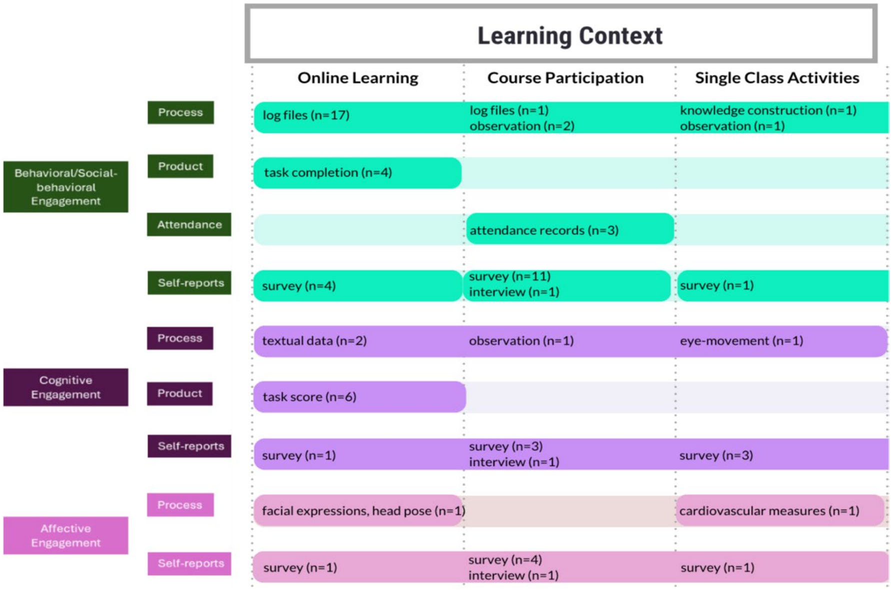

Fig. 3 Overview of the data channels and methods for measuring each SE dimension across the three learning contexts

Self-reports, primarily using questionnaires (e.g., Büchele et al., 2021; Hong & Chien, 2023; Lavidas et al., 2020; Sidekerskienė & Damaševičius, 2023) and, less frequently, semi-structured interviews (Dibbs, 2019), were also commonly employed ($n = 21$) to assess SE. These tools captured various dimensions, including (socio-) behavioral (e.g., participation, effort), cognitive (e.g., strategy use), and affective (e.g., enjoyment, interest) (see Table 3 for a detailed presentation of the items and scales reported). The majority of studies administered self-reports at a single time point, typically at the end of the course, to measure students' overall engagement levels. One study applied a pre–post design to examine changes in SE across the semester (Syarifuddin & Atweh, 2021). The authors found increases in most SE indicators, though no change was observed for attentiveness and achievement orientation, suggesting differentiated patterns of development across SE dimensions.

Self-reports were also used to examine SE in the context of single-classroom activities, particularly to evaluate the implementation of active learning interventions. These studies employed tailored measures reflecting the nature of the instructional tool. For example, SE with augmented reality was assessed via perceived behavioral activation and focus (Wong et al., 2022a); SE during tablet-based graphing tasks was measured through perceived cognitive load, mental effort, and usability (Kang et al., 2017); and SE with manipulatives and prompts was captured through perceived absorption and interest (Belenky & Nokes, 2009). These findings suggest that the operationalization of SE was closely aligned with the affordances of the instructional context.

Product data captured SE outcomes related to task completion and participation ($n = 9$). Product data focused on students' completion of online quizzes and formative assessments as indicators of behavioral engagement (e.g., Evans et al., 2021; Jack et al., 2024; Sancho-Vinuesa et al., 2013). Other papers assessed the average score on online quizzes, homework, and formative assessment (e.g., Gleason, 2012; Juma et al., 2022; Shaker et al., 2023), which can be perceived as an indicator of cognitive engagement (Azevedo, 2015). Notably, while most of the reported behavioral indicators were explicitly connected to the behavioral dimension of SE, this was rarely the case for the cognitive indicators (see Wu, 2021, for an example). This finding shows that when using process (e.g., time spent) and product (e.g., score) data, SE in online learning can take various forms (Hart et al., 2017). However, it is important that researchers establish a connection between these forms and existing SE frameworks. Administrative data, specifically attendance records for lectures, tutorials, and seminars, were used in a small number of studies ($n = 3$) to assess behavioral engagement in face-to-face contexts (Akimov et al., 2023; Arjomandi et al., 2023; Burke et al., 2013).

A few papers combined multiple data channels to enhance the understanding of student engagement. For instance, Rienties et al. (2019) combined behavioral engagement measures (e.g., number of attempts and solutions) with a mastery variable, offering insights into cognitive engagement. Similarly, Yu et al. (2021) combined log files with physiological measures, using facial expressions and head pose to assess cognitive and affective engagement during online problem-solving. Other studies integrated self-reports with log files and task scores to measure behavioral engagement (e.g., Castro-Rodríguez et al., 2022; Evans

Table 3 Survey items and scales used in the reviewed studies to measure student engagement. A detailed list of the papers using survey instruments is provided in the supplementary material

Dimension	Indicators	Method	Example papers
Affective	Interest, achievement, anxiety, frustration, enjoyment	**Scales:** Student Engagement in the Mathematics Classroom (SEMC), Math and Science Engagement Scale, Bergdahl et al.'s scale on SE with technology (2020) **Survey Items:** "I think the "Yummy Mathematics" class is fun."	(Gopal et al., 2019; Li et al., 2022; Syarifuddin & Atweh, 2021)
(Social-) Behavioral	Persistence, on-task and off-task behavior, note-taking, effort, use of material, time spent	**Scales:** Student Engagement subscale ($\alpha = 0.897$) from Mathematics Classroom Observation Protocol for Practices/MCOP2, Attitude toward Mathematics Survey ($\alpha = 0.85$), Math and Science Engagement Scale **Survey Items:** "To what extent were students engaged with the non-routine problems? Was there any evidence of engagement?","Did students' engagement change over time?","How often did you take selective notes from the lectures of the Statistics course?","How much time did you usually spend studying before taking a quiz?"	(Bowers et al., 2017; González, 2016; Gopal et al., 2019; Hong & Chien, 2023; Syarifuddin & Atweh, 2021; Ting et al., 2020)
	Participation, attentiveness, diligence	**Scales:** Learning Behavior Scale for Elementary School Students, Student Engagement in the Mathematics Classroom (SEMC) **Survey Items:** "How regularly did you attend the lectures of the Statistics course?","How often did you participate in the live-streaming lectures?',"Did you come to class prepared by having completed the assignments?"	
	Active Learning	**Scales**: Triple E Framework (Kolb, 2020)	
	Communication with other students, collaboration, ideas, and opinions expressions	**Scales**: Active Engagement Student Perception Survey (AESPS)	

Table 3 (continued)

Dimension	Indicators	Method	Example papers
Cognitive	Self-regulatory strategies, Surface strategy, deep strategy, reliance, task-related thoughts	**Scales**: Attitude toward Mathematics Survey ($\alpha = 0.85$), Student Engagement in the Mathematics Classroom (SEMC), Math and Science Engagement Scale	(Belenky & Nokes, 2009; González, 2016; Gopal et al., 2019; Kang et al., 2017; Li et al., 2022; Syarifuddin & Atweh, 2021; Wong et al., 2022a)
	Perceived learning, usability, cognitive load	**Scales**: USE Questionnaire (NASA-TLX, Task Load Index)	
	Focus, absorption	**Scales**: Triple E Framework, Bergdahl et al.'s scale on SE with technology (2020) **Survey Items**: "I was engrossed in the materials as I went through the packet"	

et al., 2021), while Thorson et al. (2019) combined cardiovascular data with observational data to explore socio-affective engagement. The combination of data types served two main purposes: 1) enhancing the understanding of online learning behaviors (Gleason, 2012; Yu et al., 2021) and 2) identifying individual differences among students (Juma et al., 2022; Rienties et al., 2019).

Finally, it was observed that the majority of studies on online learning employed aggregated measures of SE ($n = 17$), with only a few using temporal analyses to explore changes in SE over time ($n = 7$). These studies measured SE multiple times during the course, aligning data collection with assignment deadlines (Shaker et al., 2023; Sutter et al., 2022; Tucker et al., 2023) or key learning phases, such as before tutorials, quizzes, and exams (Rienties et al., 2019). This approach highlights the importance of learning design in understanding how SE evolves. In a different approach, Rach (2023) conducted repeated measures of self-reported effort within individual lectures, finding substantial variability in effort between students, despite minimal variation between lessons or time points. This suggests that experience-sampling self-reports could be valuable for capturing individual differences in engagement during learning.

In summary, the results illustrate how studies aligned their measurement practices with the specific characteristics of the learning contexts they examined. As shown in Fig. 3, each context—online learning, course participation, and single in-class activities—was associated with distinct patterns of data use. While some data types appeared across multiple contexts (e.g., surveys), the instructional setting clearly influenced how SE was operationalized. Notably, cognitive and affective dimensions were underrepresented in process data, temporal approaches were rare, and few studies combined multiple data sources. Moreover, while single in-class activities often employed tailored engagement measures, broader course-level studies tended to rely on generic, post-hoc tools, suggesting a need for more context-sensitive instruments across all settings.

Relationship between Student Engagement and Learning Outcomes

Less than half of the reviewed papers ($n = 21$) examined the relationship between SE and learning outcomes. Our analysis shows two approaches for examining the relationship between these two variables:1) a variable-oriented approach ($n = 14$), and 2) a person-oriented approach ($n = 7$).

Variable-oriented Approaches

Papers using a variable-oriented approach to examine the association between SE and learning outcomes applied various methodologies, such as regression analysis (e.g., Akimov et al., 2023; Wu, 2020), correlation analysis (e.g., Hong & Chien, 2023; Raza & Reddy, 2021), structural equation modelling (e.g., González et al., 2016; Lavidas et al., 2020), and analysis of variance (ANOVA) (e.g., Belenky & Nokes, 2009; Derr et al., 2018).

The majority of the papers ($n = 11$) focused on the impact of behavioral engagement on four types of outcomes, i.e., course performance, task performance, strategy use, and motivational beliefs. Indicators of course participation were found to be positively associated with course performance. For example, self-reported participation in various course activities, the number of lectures attended, materials downloaded, and assignments submitted showed a positive and statistically significant relationship with final grades (Akimov et al., 2023; Burke et al., 2013; Hong & Chien, 2023; Lavidas et al., 2020). Büchele et al. (2021) found that students who reported that they attended all lectures and solved all exercise sheets outperformed non-participating students, suggesting that supporting student levels of participation in course activities can enhance academic success.

Mixed results about the links between online learning indicators and course performance were found. The number of attempts and completion of formative assessment tests were significantly positively related to course grades in Derr et al. (2018) and Sancho-Vinuesa et al. (2013), but quiz attempts showed no significant relationship in Hart et al. (2017). Moreover, Hart et al. (2017) found significant results for forum posting, but not viewing, highlighting the value of active forum participation. However, forum posting did not yield significant results in Derr et al. (2018), suggesting that not all SE indicators are related to academic performance and that more research is needed to understand how SE in online materials enhances student success. Hart et al. (2017) also emphasized the high positive correlation identified between submitting the peer review grading assignment on time and course grades. The authors connected this finding to time-management skills and their importance for successful online learning. Two papers focused on the effects of SE regularity (Akimov et al., 2023; Sutter et al., 2022. Activity completion at the beginning and the middle of the course positively predicted final grades (Sutter et al., 2022), while in Akimov et al. (2023) regularity was positively but non-significantly related to final grades, indicating the need for more research to address the measurement of regularity in SE with the learning materials. Only Raza and Reddy (2021) examined the effects of behavioral engagement on both course and task performance. They found that interactions with online self-study activities (e.g., assignments, homework) significantly improved performance in the activity itself, overall formative assessment, and course grades. However, Spearman's correlation coefficient is between 0 and $+0.5$, suggesting that the identified relationships were weak. Nevertheless, the results highlight that SE in a learning activity can have both proximal and distal learning outcomes. Despite the mixed findings, the results highlight the importance of sustaining behavioral engagement with homework and self-study materials during the course period in academic achievement.

Two papers examined the effect of behavioral engagement on strategy use and motivational beliefs. Self-reported socio-behavioral engagement in interactive mathematics videos was found to have a significant positive effect on a deep approach to learning, consisting of intrinsic motivation to study and use of deep learning strategies (Ting et al., 2020). Sutter et al., (2022) found that mid-course activity completion positively predicted utility value beliefs about the course content. These findings illustrate that SE can be a predictor (i.e., antecedent) for learning outcomes other than grades and scores. Only three papers examined the effects of cognitive engagement on course/task performance. The number of statistics-related Facebook posts (Wu, 2021) and self-reported self-regulatory and deep processing strategies (González et al., 2016) positively predicted course grades. Belenky and Nokes (2009) found that the interaction between self-reported absorption and prompt type had an effect on problem-solving scores. In particular, for students who reported high levels of absorption, problem-focused prompts resulted in more correct answers. Conversely, for students who reported lower levels of absorption, metacognitive prompts resulted in better test results.

Given the substantial variation in undergraduate students' cognitive and motivational characteristics, it is crucial to consider such factors when examining the relationship between SE and academic achievement. This is particularly important in university mathematics contexts, where differences in factors, such as prior knowledge, may influence both engagement and learning outcomes. Notably, in the current review, we identified only a few studies ($n=6$) that controlled for confounding variables in the relationship between engagement and academic outcomes. Studies conducting regression analysis controlled for prior knowledge (e.g., entrance and diagnostic test scores, secondary school GPA), cognitive strategies (e.g., memorizing), as well as motivational factors (e.g., mathematics self-efficacy and interest) (Akimov et al., 2023; Büchele et al., 2021; Derr et al., 2018; Hart et al., 2017; Wu, 2021). Using structural equation modelling, Sutter et al., (2022) also accounted for prior GPA and demographic factors, showing that behavioral engagement remained a significant predictor of final grades even after these variables were controlled. These findings, while limited in number, suggest the unique contribution of SE to academic achievement.

Person-oriented Approaches

Studies in this category used a person-oriented approach based on the assumption that students who differed in their engagement levels in a certain activity would also differ in their learning outcomes and vice versa. Analyses under this approach included t-test (Al Shuaily et al., 2018), ANOVA (Evans et al., 2021; Rienties et al., 2019), clustering (Juma et al., 2022; Rienties et al., 2019; Shaker et al., 2023), and comparison of confidence intervals (Tucker et al., 2023). Some papers found that groups with higher SE would demonstrate higher learning outcomes (e.g., Al Shuaily et al., 2018; Rienties et al., 2019; Tucker et al., 2023). For example, Rienties et al. (2019) found four SE profiles that varied in the number of attempts, mastery, and time spent at problem-solving: Early Mastery, Strategic, Exam-driven, and Inactive learners. Early Mastery and Strategic profiles performed consistently higher than Exam-driven, and Inactive profiles. Tucker et al. (2023) found that students who improved their attitudes toward using R for learning statistics showed higher SE levels (e.g., more attempts, higher scores on R exercises, and longer chapter summaries) than those who did not.

Other findings indicate that SE and achievement were not always linearly associated (e.g., Evans et al., 2021; Juma et al., 2022; Shaker et al., 2023; Wong et al., 2022b). For example, Shaker et al. (2023) found that incentivizing weekly readings had an effect only for students with low initial cognitive engagement and assignment performance, but no effect was found for highly engaged students, suggesting that not all SE profiles benefit from the same interventions. Students who had low engagement and high performance before the intervention showed an increase only in their engagement, suggesting that higher engagement may not always be sufficient to result in higher performance. Evans et al. (2021) found that low-performers spent less time between attempts on pre-lecture quizzes compared to medium and high-performers, with significant differences in time spent before the second attempt between low- and high-performers and low- and medium-performers. It is possible that medium- and high-performers differ from the low-performers in how they used their time to process provided automated feedback before reattempting to solve the quiz, suggesting the importance of examining both the quantity and quality of SE to infer its relationship with learning outcomes. Nevertheless, examining SE profiles was found to be a useful approach for understanding why students perform differently.

Discussion

The acquisition of mathematical competencies and skills is a fundamental goal of many higher education study programs and requires effective SE with the learning materials (Hochmuth, 2020; Smith et al., 2021). Considering that SE is affected by the learning context (e.g., discipline, learning activity), the role of context has been increasingly included in SE research (e.g., Bergdahl, 2022; Fredricks et al., 2016b; Sinatra et al., 2015; Wang & Hofkens, 2020). However, the number of systematic reviews that have adopted a context-specific view is still limited (e.g., Hiver et al., 2024; Kassab et al., 2022). Previous reviews in the domain of mathematics have focused on the impact of a particular instructional tool or method on SE (e.g., Lo & Hew, 2021), and consequently, many aspects of SE research have been unexplored. Therefore, the current review fills the gap by adopting a context-specific perspective on SE investigation by focusing on studies conducted in undergraduate mathematics learning activities. In the review, 48 empirical studies conducted within undergraduate mathematics courses were examined to understand a) what the prevalent research approaches to SE are in the particular context and how they are anchored to existing conceptual SE frameworks, and b) how these approaches can enhance our understanding of promoting effective SE. Below, we discuss our main findings and propose several recommendations for future research.

Research Aims and Theoretical Grounding for Student Engagement Investigation

Our results show three main research aims and three approaches for grounding SE research. The majority of papers examined SE as an outcome using an *instruction-focused* framework when evaluating instructional methods and tools. This outcome is expected given the growing research focus on improving teaching and learning in undergraduate mathematics (Hochmuth, 2020). In line with prior reviews on SE in higher education (e.g., Bond et al., 2020), many papers in this category (29%) did not use an explicit framework, suggesting the need for more theoretically grounded research to understand how instruction improves SE.

Student- and instruction-focused frameworks were almost equally represented in the corpus, suggesting that, in undergraduate mathematics, SE is an important concept from both approaches. A pattern emerged: while instruction-focused frameworks showed a large diversity that reflects the variability of the instructional practices and tools examined, student-focused frameworks tend to converge to motivation theories, suggesting an interest in understanding motivational factors to explain SE in various settings. This finding is in line with prior research suggesting the crucial role of motivation in mathematics learning (Schukajlow et al., 2023). Our results also revealed an underrepresentation of frameworks on SE and metacognitive and affective factors in the corpus. Finally, only a few papers used an integration of the two approaches. For example, even though an activity is designed using instructional theories, such as cognitive load (e.g., Tucker et al., 2023), students might not engage if they are not motivated or skilled enough (Evans et al., 2021; Plak et al., 2023). These examples demonstrate the value of an integrative approach in understanding the connections between instructional and psychological theories.

Student Engagement Definitions

Aligned with prior reviews (e.g., Bond et al., 2020; Henrie et al., 2015; Hiver et al., 2024), we found a relatively large number of studies that did not (explicitly) define SE and that among the provided definitions an overlap emerged (particularly between behavioral and cognitive engagement) hindering our understanding of how each dimension was defined in the corpus. Even though the identified definitions were characterized by heterogeneity, our analysis showed that they contained at least one of the three following elements: observable behavior, psychological investment, and multidimensionality. The finding that most SE definitions included at least two elements indicates that the papers recognize SE as a multifaceted and multilevel construct.

The analysis of SE definitional elements identifies three main directions. First, a strong focus was found on observable behaviors, such as time, reactions, or asking questions (Capone & Lepore, 2022; González et al., 2016; Thorson et al., 2019). The specification of the observable behavior that is perceived as an indicator of SE in each context can be useful for the development of consistent operationalization and measurement (e.g., Carbonneau et al., 2020). Second, some definitions included aspects of SE quality and were based on the notion that not every SE indicator of SE is relevant for achieving the anticipated learning outcomes in a given context. However, only a few definitions used the element of quality (e.g., Capone & Lepore, 2022) or specified the domain or the activity of investigation (e.g., Thorson et al., 2019). As incorporating the context in which SE occurs in the definition can promote the conceptual clarity of the construct (Wong & Liem, 2022), future studies are encouraged to include this element in the definition of SE. Third, there seems to be a convergence among the papers to well-established SE frameworks, such as the three-dimensional framework (Fredricks et al., 2004) and learning constructs, such as effort, persistence, and attention (González et al., 2016; Rach, 2022; Thorson et al., 2019), suggesting that the use of such frameworks and constructs can enhance a shared understanding of SE between researchers. Consistent with prior reviews (e.g., Bond et al., 2020; Hiver et al., 2024), the findings indicated that behavioral engagement was most extensively defined, while other dimensions were described more broadly and with weaker connections to the specific learning context, highlighting a valuable direction for future research.

Student Engagement Measurement

The results suggest that SE measurement approaches differed across the settings, which highlights the critical role of the learning context in SE investigation (Wong & Liem, 2022). In the current corpus, SE was mainly investigated in three main learning settings: online learning, course participation, and in-class single activities. In online learning, SE was examined as study behavior and effective interaction with the online learning materials using mostly process (e.g., log files) and product data (e.g., activity scores). SE in course participation was examined as attendance, effort, on-task behavior, enjoyment, and use of learning strategies in the various course activities and was measured using mostly self-reports. SE in single in-class activities was examined as active learning via various methods, such as self-reports, physiological, and knowledge construction data. The majority of the reviewed papers focused on SE in online learning and course participation, suggesting that how students engage in both settings is important for succeeding in their mathematics courses. Only a few studies investigated SE in single activities in class. Such investigations can enhance our understanding of how the characteristics of a learning activity (e.g., design, content, difficulty) can influence SE and therefore, provide useful insight into developing effective learning materials. Consequently, more studies focusing on SE in single class activities are needed.

Aligned with previous findings (Bond et al., 2020; Henrie et al., 2015), most papers operationalized SE from a behavioral perspective, while cognitive and affective indicators were less studied. Moreover, log files were the most frequent measurement method. This contrasts with reviews in other fields, such as language learning and medical education (Hiver et al., 2024; Kassab et al., 2022), where self-reports were the most prevalent method. Log files can be a useful, unobtrusive method for capturing real-time learning behavior (Azevedo, 2015). However, a clear connection between the investigated log-type indicators and the existing SE models and dimensions is required to understand which types of engagement processes are investigated in each study (Wiedbusch et al., 2023). Furthermore, we found that only a few papers combined data types and channels to investigate SE. These studies focused mainly on online learning, whereas SE in course participation was examined using single methods. Multimodal data approaches were used to examine the interconnections between different engagement variables (e.g., Thorson et al., 2019) or gain a more holistic understanding of how students engage in a specific learning activity (e.g., Castro-Rodríguez et al., 2022; Derr et al., 2018). Provided that each approach has strengths and weaknesses, employing methods that converge different approaches is necessary to gain a deeper understanding of SE in a particular learning context (Wiedbusch et al., 2023).

Relationship between Student Engagement and Learning Outcomes

Consistent with previous reviews (Martins et al., 2022), the relationship between SE and learning outcomes was addressed only in half of the corpus. Studies found that behavioral engagement indicators related to course participation predicted course performance (e.g., Akimov et al., 2023; Hong & Chien, 2023). Yet, the low number of papers in this category suggests further investigation of the relationship between the two variables. Moreover, the effects of online indicators on performance were not clear in this review. It was found that regular practice and self-testing can possibly enhance course performance. However, not all online metrics yielded the same result. Given that several SE indicators with the course materials can be identified, it is important to determine which ones are associated with important learning outcomes and develop targeted instructional support or interventions (e.g., Derr et al., 2018).

While variable-oriented approach studies found a positive relationship between SE and achievement, person-oriented analyses revealed more complex patterns. For example, some student groups showed high performance despite scoring low on the investigated SE indicators (e.g., Shaker et al., 2023). This discrepancy may stem from the chosen indicators, as students might have engaged with the material in unexamined ways. Consequently, measures that capture as many relevant SE aspects as possible are important for understanding how SE relates to learning outcomes (Rienties et al., 2019). Nevertheless, person-oriented analyses offer valuable insights into how different profiles respond to instructional interventions, aiding the development of systems for personalized learning support (Shaker et al., 2023).

Given that few studies focused on cognitive engagement and no study examined affective engagement, future studies should explore how these SE dimensions are related to achievement. Furthermore, more research is required to investigate how SE interaction with different learning materials influences student performance during learning activities. In this review, only Belenky and Nokes (2009) investigated this interaction and showed that varying levels of cognitive engagement require different types of prompts for succeeding in problem-solving. Future studies in undergraduate mathematics could enhance support tailored to students' momentary engagement during activities. Finally, only a subset of studies in this review accounted for potential confounding variables such as prior knowledge and motivation. This is particularly relevant in undergraduate mathematics contexts, where students often differ widely in their prior knowledge, making it difficult to determine whether engagement leads to improved academic performance or vice versa. Longitudinal designs can help clarify the direction of this relationship. For example, Sutter et al., (2022) used latent change models to examine how prior GPA was related to changes in behavioral engagement over time, which in turn were associated with final grades. Further research using longitudinal approaches, with repeated measurements of both engagement and academic performance, could help clarify how these variables influence each other over time.

Theoretical and Practical Implications

This review identifies several key areas for improvement in how SE is studied within undergraduate mathematics learning contexts. To support future theoretical development and empirical research, we propose three main recommendations aimed at refining the definition, conceptualization, and measurement of SE. The first recommendation concerns working towards SE definitional clarity. Our results show that only a few definitions included the context of SE investigation (e.g., Thorson et al., 2019; Ting et al., 2020). Moreover, not all papers provided a clear description of the learning activities in which SE was investigated. For example, it is not sufficient to state that SE was studied in statistics tasks since different activity types (e.g., homework, in-task problem solving) or formats (e.g., collaborative, individual) might be associated with different SE aspects. SE can occur in any learning activity (Boekaerts, 2016). Future studies can enhance definitional clarity by explicitly describing the contextual characteristics in which SE is examined, such as the academic discipline, activity type, and activity format. Including these details can help delineate the specific SE processes under investigation and distinguish them from other related SE constructs.

In addition, the current review reveals that SE was often a) undefined or insufficiently conceptualized, or b) defined using general terms like active involvement or positive conduct, with unclear links to the investigated indicators. We propose two approaches to enhance SE definitional clarity. First, researchers can use models on SE that are specific to learning activities, such as the flow theory (Csikszentmihalyi, 1990), the schoolwork engagement model (Salmela-Aro & Upadaya, 2012), or the three-dimensional framework on SE in learning activities (Ben-Eliyahu et al., 2018). Such models can guide researchers in selecting definitions that are more aligned with the specific notion of "learning engagement". Second, researchers using general models, such as the school engagement framework (Fredricks et al., 2004), should clarify how the broad components of engagement (e.g., affective, behavioral, and cognitive) relate to the specific characteristics of the learning context under investigation. For example, if SE in collaborative problem-solving is defined as active involvement, strategic thinking, or positive and negative reactions, researchers should explain how these aspects manifest within the context of that specific activity (e.g., Carbonneau et al., 2020).

Finally, our results are aligned with prior evidence (Wong & Liem, 2022) that the distinction between behavioral and cognitive engagement should be better clarified in applied research. Some definitions showed an overlap between the two components (e.g., both are defined as effort). Moreover, other definitions described behavioral engagement as purely observable (e.g., conduct, participation) and cognitive engagement as purely mental (e.g., energy). It should be further investigated whether behavioral engagement is the enactment of cognitive engagement as suggested by some models (e.g., Wiedbusch et al., 2023) or if behavioral engagement is a different construct connected to volitional and conative processes (Wong & Liem, 2022). Therefore, to work towards SE definitional clarity, future studies can explicitly describe the context of investigation, adopt models tailored to specific learning activities, and distinguish between different dimensions of engagement, such as behavioral and cognitive processes.

The second recommendation concerns the enhancement of SE research theoretical groundings. Despite the broad agreement between the reviewed papers about the importance of motivational, metacognitive, and affective factors on the development of SE, only a few studies examined the relationship between these factors and SE. These studies provided evidence of bidirectional relationships between SE and motivational constructs, such as expectancy and value beliefs (Sutter et al., 2022). However, the relationship between SE and SRL was not clearly established in the corpus. While some papers suggested that SRL-related skills (e.g., cognitive processing) were antecedents of SE (Rienties et al., 2019; Wu, 2021), other papers examined SRL as part of SE (e.g., González et al., 2016; Kang et al., 2017). Previous research (Boekaerts, 2016; Wiedbusch et al., 2023) has emphasized the need to clarify the relationship between the two constructs to better understand the mechanisms for enhancing and sustaining SE over time. The use of integrated models of SE and SRL that describe how the various SE aspects are situated within the SRL processes could be beneficial (Cleary & Zimmerman, 2012). For example, in studying SE during self-study activities, SRL processes like reviewing answers might constitute SE, while processes like planning the activities could serve as facilitators. Relatedly, recent work by Tempelaar et al., (2024) suggests that integrating dispositional learning analytics with behavioral data from formative assessments may offer new opportunities to better understand how learner characteristics interact with self-regulatory processes to influence engagement.

We found that several papers examined the influence of instruction on SE without using a theoretical framework or by using broad theories and models (e.g., constructivism) (e.g., Azevedo et al., 2019; Jin, 2023). With the growing emphasis on enhancing SE, interventions should be based on specific theoretical frameworks that allow researchers to quantify the mechanisms driving the instructional effects on SE. Additionally, the examination of the effects of SE on learning outcomes will advance our understanding of the role of SE in learning mathematics, as well as other disciplines, and in turn, will improve the development of instructional interventions. This review showed that these effects were studied only in a few papers, while findings from these papers suggested that not all the investigated SE variables were found to predict achievement. Consequently, we suggest that future research on instructional interventions should include the examination of the SE effects on various learning outcomes (e.g., performance, motivational beliefs, skills). For long-term interventions, researchers should examine both proximal (e.g., activity performance) and distal (e.g., course grades) outcomes (e.g., Raza & Reddy, 2021).

The third recommendation concerns the alignment between definition and measurement of SE. An extensive use of online measures was identified in the corpus. In some cases, we found a misalignment or an unclear connection between the provided SE definitions and the corresponding indicator. For example, some studies defined SE as a multidimensional or psychological construct but used a single indicator without explaining the rationale behind this decision. However, such practice raises the question of how indicators such as on-task behavior, the completion of voluntary activities, or the number of assessment tests relate to psychological investment, effort, and energy. When employing log files, the use of multiple relevant indicators instead of a single one could result in a more meaningful representation of complex SE aspects (Bond et al., 2023). However, we propose that the alignment between such data and theorized aspects of SE should be drawn with caution and should be guided by the employed SE framework (Level 1).

While the view of SE as a dynamic process is gaining traction, our review found limited studies examining SE's dynamic development (e.g., Rienties et al., 2019). These studies revealed that both the frequency and timing of student engagement impact learning. Future research could consider employing longitudinal methodologies to better capture the dynamic changes in SE. Approaches, such as growth curve modeling, hidden Markov models, and dynamic structural equation modelling, offer robust frameworks for analyzing temporal patterns, state transitions, and underlying mechanisms driving SE development over time (e.g., Saqr et al., 2023).

Limitations

There are several limitations in our review. First, the review was based on only 48 papers. Despite performing our systematic search in various databases without posing any time restrictions to retrieve as many papers as possible, we could have missed relevant literature that was not published yet (e.g., grey literature). We also excluded non-English papers. Therefore, our conclusions may be limited to the published literature in English and not fully representative of all studies conducted within the domain. Additionally, by focusing exclusively on papers that explicitly used and defined the term *engagement* in the context of a learning activity, it is possible that some relevant studies, where engagement was examined under related constructs or broader learning processes, may not have been included in our review. Given that one of the main goals of this review was to examine how engagement itself has been conceptualized and measured in the field, our search string intentionally included various versions of the term'engagement'(e.g., student engagement, task engagement, academic engagement), but did not include broader or potentially overlapping synonyms such as'participation 'or'involvement'. This targeted approach was necessary to maintain conceptual clarity in addressing our research questions. Nevertheless, the number of included papers in this review is comparable to previous reviews on student engagement and therefore, can offer valuable insight into SE within the mathematics domain (e.g., Kassab et al., 2022; Lo & Hew, 2021; Martins et al., 2022).

Another limitation concerns the heterogeneity of the papers reviewed, limiting the conclusion that could possibly be drawn from a more rigorous quantitative method (e.g., meta-analysis). To gain insights into the field's current state, we deliberately did not restrict the research designs of the studies, resulting in a diverse set of papers. This approach resulted in a heterogeneous pool of papers. To synthesize the findings, we employed a narrative approach where we used a combination of deductive and inductive approaches to categorize the papers. While existing SE frameworks informed the deductive component, certain categorizations, particularly in cases where SE dimensions were not explicitly defined by the authors, required interpretive judgment. Although these coding decisions were made collaboratively and guided by established definitions (e.g., Wong & Liem, 2022), we acknowledge the potential for subjectivity. To enhance transparency, we documented our coding rationale in detail and provided supporting textual evidence in the supplementary materials. Nonetheless, since this systematic review aims to provide a comprehensive overview of SE research practices, this approach remains valuable.

Conclusion

Despite these limitations, this systematic review reveals key aspects of SE research in undergraduate mathematics. It identifies and organizes research approaches for conceptualizing, defining, measuring SE, and examining its learning outcomes. The literature highlights SE as both an instructional outcome and a mediator between student factors (e.g., motivational beliefs) and academic performance, underscoring SE's crucial role in undergraduate mathematics learning. Our findings stress the importance of aligning theory and context in SE conceptualization, definition, and measurement. Additionally, the review highlights the value of incorporating anticipated learning outcomes into SE studies to guide instructional interventions. To support these efforts, this review offers key directions for SE scholars and practitioners examining SE in specific domains. In conclusion, despite the challenges of SE research, investigators can contribute meaningfully to the field by addressing foundational elements such as clear conceptualizations, consistent definitions, and alignment between theoretical frameworks and measurement (Sinatra et al., 2015).

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10648-025-10046-y.

Author contribution E.P., J.W., and A.J.C. substantially contributed to the conception and the design of the work. E.P. drafted the manuscript and the remaining authors critically reviewed the work. E.P. was responsible for literature search and data extraction. E.P. and Q.L. were responsible for the literature selection and data analysis. J.W. and A.J.C. provided guidance in data interpretation. M.K. made important contributions during the research design and manuscript revision. All authors agreed on all aspects of the work and approved the version to be published.

Funding No funding was received for conducting this study.

Data Availability All data generated or analyzed during this study are available in the supplementary material accompanying this article.

Declarations

Ethics Approval and Consent to Participate/Consent for Publication Not applicable.

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

References

Akimov, A., Malin, M., Sargsyan, Y., Suyunov, G., & Turdaliev, S. (2023). Student success in a university first-year statistics course: Do students' characteristics affect their academic performance? *Journal of Statistics and Data Science Education, 32*(1), 24–35. https://doi.org/10.1080/26939169.2023.2184435

Al Shuaily, H., Lacap, E. M., Ramos, J. F., & Dela Cruz, G. A. (2018). Towards facilitating student's learning and engagement in an online pedagogy: A search for a personalized online learning framework for a technology-enhanced learning. *Majan International Conference (MIC), 2018*, 1–5. https://doi.org/10.1109/MINTC.2018.8363151

Ali, M., Yasmeen, R., & Munawar, Z. (2023). The Impact of Technology Integration on Student Engagement and Achievement in Mathematics Education: A systematic review. *International Journal of Computer Integrated Manufacturing, 6*, 222–232. https://doi.org/10.17605/ijie.v6i3.4182

Appleton, J. J., Christenson, S. L., Kim, D., & Reschly, A. L. (2006). Measuring cognitive and psychological engagement: Validation of the student engagement instrument. *Journal of School Psychology, 44*(5), 427–445. https://doi.org/10.1016/j.jsp.2006.04.002

Arjomandi, A., Paloyo, A., & Suardi, S. (2023). Active learning and academic performance: The case of real-time interactive student polling. *Statistics Education Research Journal, 22*(1), 3. https://doi.org/10.52041/serj.v22i1.122

Azevedo, R. (2015). Defining and measuring engagement and learning in science: Conceptual, theoretical, methodological, and analytical issues. *Educational Psychologist, 50*(1), 84–94. https://doi.org/10.1080/00461520.2015.1004069

Azevedo, A., Oliveira, M., Barreiras, A., Azevedo, J., Marcos, G., & Ferreira, H. (2019). Collecting and analysing learners data in a massive open online course for mathematics. *Proceedings of the 11th International Conference on Computer Supported Education*, 681–688. https://doi.org/10.5220/0007905306810688

Banihashem, S. K., Noroozi, O., van Ginkel, S., Macfadyen, L. P., & Biemans, H. J. A. (2022). A systematic review of the role of learning analytics in enhancing feedback practices in higher education. *Educational Research Review, 37*, 100489. https://doi.org/10.1016/j.edurev.2022.100489

Belenky, D. M., & Nokes, T. J. (2009). Examining the role of manipulatives and metacognition on engagement, learning, and transfer. *The Journal of Problem Solving, 2*(2), 6. https://doi.org/10.7771/1932-6246.1061

Ben-Eliyahu, A., Moore, D., Dorph, R., & Schunn, C. D. (2018). Investigating the multidimensionality of engagement: Affective, behavioral, and cognitive engagement across science activities and contexts. *Contemporary Educational Psychology, 53*, 87–105. https://doi.org/10.1016/j.cedpsych.2018.01.002

Bergdahl, N. (2022). Engagement and disengagement in online learning. *Computers & Education, 188*, 104561. https://doi.org/10.1016/j.compedu.2022.104561

Betts, J. (2022). Measuring student engagement: New approaches and issues. In A. L. Reschly spsampsps S. L. Christenson (Eds.), *Handbook of Research on Student Engagement* (pp. 647–658). Springer International Publishing. https://doi.org/10.1007/978-3-031-07853-8_32

Bigotte de Almeida, M. E., Queiruga-Dios, A., & Cáceres, M. J. (2021). Differential and integral calculus in first-year engineering students: A diagnosis to understand the failure. *Mathematics, 9*(1), 1. https://doi.org/10.3390/math9010061

Boekaerts, M. (2016). Engagement as an inherent aspect of the learning process. *Learning and Instruction, 43*, 76–83. https://doi.org/10.1016/j.learninstruc.2016.02.001

Bond, M., Buntins, K., Bedenlier, S., Zawacki-Richter, O., & Kerres, M. (2020). Mapping research in student engagement and educational technology in higher education: A systematic evidence map. *International Journal of Educational Technology in Higher Education, 17*(1), 2. https://doi.org/10.1186/s41239-019-0176-8

Bond, M., Viberg, O., & Bergdahl, N. (2023). The current state of using learning analytics to measure and support K-12 student engagement: A scoping review. *LAK23: 13th International Learning Analytics and Knowledge Conference*, 240–249. https://doi.org/10.1145/3576050.3576085

Bowers, J., Smith, W., Ren, L., & Hanna, R. (2017). Integrating active learning labs in precalculus: Measuring the value added. *Investigations in Mathematics Learning, 11*(1), 1–15. https://doi.org/10.1080/19477503.2017.1375355

Büchele, S., Liebendörfer, M., & Lankeit, E. (2021). Increasing the effect of a remedial mathematics course by switching to an online format during the COVID-19 crisis: Evidence from a German university. *Teaching Mathematics and Its Applications: An International Journal of the IMA, 40*(4), 478–496. https://doi.org/10.1093/teamat/hrab013

Burke, G., Mac anBhaird, C., & O'Shea, A. (2013). The effect of a monitoring scheme on tutorial attendance and assignment submission. *International Journal of Mathematical Education in Science and Technology*, *44*(4), 545-553. https://doi.org/10.1080/0020739X.2012.756553

Cabo, A., & Klaassen, R. (2018). Active learning in redesigning mathematics courses for engineering students. *The14th International CDIO Conference.*

Campbell, J. L., Quincy, C., Osserman, J., & Pedersen, O. K. (2013). Coding in-depth semistructured interviews: Problems of unitization and intercoder reliability and agreement. *Sociological Methods & Research, 42*(3), 294–320. https://doi.org/10.1177/0049124113500475

Capone, R. (2022). Blended learning and student-centered active learning environment: A case study with STEM undergraduate students. *Canadian Journal of Science, Mathematics and Technology Education, 22*(1), 210–236. https://doi.org/10.1007/s42330-022-00195-5

Capone, R., & Lepore, M. (2022). From distance learning to integrated digital learning: A fuzzy cognitive analysis focused on engagement, motivation, and participation during covid-19 pandemic. *Technology, Knowledge and Learning, 27*(4), 1259–1289. https://doi.org/10.1007/s10758-021-09571-w

Carbonneau, K. J., Wong, R. M., & Borysenko, N. (2020). The influence of perceptually rich manipulatives and collaboration on mathematic problem-solving and perseverance. *Contemporary Educational Psychology, 61*, 101846. https://doi.org/10.1016/j.cedpsych.2020.101846

Case, J. M. (2008). Alienation and engagement: Development of an alternative theoretical framework for understanding student learning. *Higher Education, 55*(3), 321–332. https://doi.org/10.1007/s10734-007-9057-5

Castro-Rodríguez, E., Mali, A., & Mesa, V. (2022). University students' engagement with digital mathematics textbooks: A case of linear algebra. *International Journal of Mathematical Education in Science and Technology, 55*(9), 2293–2315. https://doi.org/10.1080/0020739X.2022.2147104

Cevikbas, M., & Kaiser, G. (2022). Student engagement in a flipped secondary mathematics classroom. *International Journal of Science and Mathematics Education, 20*(7), 1455–1480. https://doi.org/10.1007/s10763-021-10213-x

Cleary, T. J., & Zimmerman, B. J. (2012). A cyclical self-regulatory account of student engagement: Theoretical foundations and applications. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), *Handbook of Research on Student Engagement* (pp. 237–257). Springer US. https://doi.org/10.1007/978-1-4614-2018-7_11

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement, 20*, 37–46. https://doi.org/10.1177/001316446002000104

Cohen, R., & Kelly, A. M. (2020). Mathematics as a factor in community college STEM performance, persistence, and degree attainment. *Journal of Research in Science Teaching, 57*(2), 279–307. https://doi.org/10.1002/tea.21594

Collie, R. J., Martin, A. J., Bobis, J., Way, J., & Anderson, J. (2019). How students switch on and switch off in mathematics: Exploring patterns and predictors of (dis)engagement across middle school and high school. *Educational Psychology, 39*(4), 489–509. https://doi.org/10.1080/01443410.2018.1537480

Csikszentmihalyi, M. (1990). *Flow: The Psychology of Optimal Experience*. Harper & Row.

Cumpston, M. S., McKenzie, J. E., Thomas, J., & Brennan, S. E. (2021). The use of 'PICO for synthesis' and methods for synthesis without meta-analysis: Protocol for a survey of current practice in systematic reviews of health interventions. *F1000Research, 9*, 678. https://doi.org/10.12688/f1000research.24469.2

D'Mello, S. K., Craig, S. D., Witherspoon, A., McDaniel, B., & Graesser, A. (2008). Automatic detection of learner's affect from conversational cues. *User Modeling and User-Adapted Interaction, 18*(1), 45–80. https://doi.org/10.1007/s11257-007-9037-6

Derr, K., Hübl, R., & Ahmed, M. Z. (2018). Prior knowledge in mathematics and study success in engineering: Informational value of learner data collected from a web-based pre-course. *European Journal of Engineering Education, 43*(6), 911–926. https://doi.org/10.1080/03043797.2018.1462765

Dibbs, R. (2019). Forged in failure: Engagement patterns for successful students repeating calculus. *Educational Studies in Mathematics, 101*(1), 35–50. https://doi.org/10.1007/s10649-019-9877-0

Engle, R. A., & Conant, F. R. (2002). Guiding principles for fostering productive disciplinary engagement: Explaining an emergent argument in a community of learners classroom. *Cognition and Instruction, 20*(4), 399–483. https://doi.org/10.1207/S1532690XCI2004_1

Evans, T., Kensington-Miller, B., & Novak, J. (2021). Effectiveness, efficiency, engagement: Mapping the impact of pre-lecture quizzes on educational exchange. *Australasian Journal of Educational Technology, 37*(1), 163–177. https://doi.org/10.14742/ajet.6258

Evans, T., Klymchuk, S., Murphy, P. E. L., Novak, J., Stephens, J., & Thomas, M. (2022). Engagement of undergraduate STEM students: The influence of non-routine problems. *Higher Education Research & Development, 41*(1), 146–162. https://doi.org/10.1080/07294360.2020.1835838

Finn, J. D. (1989). Withdrawing From School. *Review of Educational Research, 59*(2), 117–142. https://doi.org/10.3102/00346543059002117

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School Engagement: Potential of the concept, state of the evidence. *Review of Educational Research, 74*(1), 59–109. https://doi.org/10.3102/00346543074001059

Fredricks, J. A., Filsecker, M., & Lawson, M. A. (2016a). Student engagement, context, and adjustment: Addressing definitional, measurement, and methodological issues. *Learning and Instruction, 43*, 1–4. https://doi.org/10.1016/j.learninstruc.2016.02.002

Fredricks, J. A., Wang, M.-T., Schall Linn, J., Hofkens, T. L., Sung, H., Parr, A., & Allerton, J. (2016b). Using qualitative methods to develop a survey measure of math and science engagement. *Learning and Instruction, 43*, 5–15. https://doi.org/10.1016/j.learninstruc.2016.01.009

Galdas, P., Darwin, Z., Fell, J., Kidd, L., Bower, P., Blickem, C., McPherson, K., Hunt, K., Gilbody, S., & Richardson, G. (2015). A systematic review and metaethnography to identify how effective, cost-effective, accessible and acceptable self-management support interventions are for men with long-term conditions (SELF-MAN). *Health Serv Deliv Res, 3*(34). http://www.ncbi.nlm.nih.gov/books/NBK311083/

Geisler, S., Rolka, K., & Rach, S. (2023). Development of affect at the transition to university mathematics and its relation to dropout—Identifying related learning situations and deriving possible support measures. *Educational Studies in Mathematics, 113*(1), 35–56. https://doi.org/10.1007/s10649-022-10200-1

Gisev, N., Bell, J. S., & Chen, T. F. (2013). Interrater agreement and interrater reliability: Key concepts, approaches, and applications. *Research in Social and Administrative Pharmacy, 9*(3), 330–338. https://doi.org/10.1016/j.sapharm.2012.04.004

Gladstone, J. R., Wigfield, A., & Eccles, J. S. (2022). Situated expectancy-value theory, dimensions of engagement, and academic outcomes. In A. L. Reschly, & S. L. Christenson (Eds.), *Handbook of Research on Student Engagement* (pp. 57–76). Springer International Publishing. https://doi.org/10.1007/978-3-031-07853-8_3

Gleason, J. (2012). Using technology-assisted instruction and assessment to reduce the effect of class size on student outcomes in undergraduate mathematics courses. *College Teaching, 60*(3), 87–94. https://doi.org/10.1080/87567555.2011.637249

Gomes, S., Costa, L., Martinho, C., Dias, J., Xexéo, G., & Moura Santos, A. (2023). Modeling students' behavioral engagement through different in-class behavior styles. *International Journal of STEM Education, 10*(1), 21. https://doi.org/10.1186/s40594-023-00407-w

González, A., Rodríguez, Y., Faílde, J. M., & Carrera, M. V. (2016). Anxiety in the statistics class: Structural relations with self-concept, intrinsic value, and engagement in two samples of undergraduates. *Learning and Individual Differences, 45*, 214–221. https://doi.org/10.1016/j.lindif.2015.12.019

Gopal, K., Salim, N. R., & Ayub, A. F. M. (2019). Fuzzy conjoint model in describing Malaysian undergraduates' perceptions of statistics classroom engagement. *AIP Conference Proceedings, 2184*, 030002. https://doi.org/10.1063/1.5136370

Hart, S., Daucourt, M., & Ganley, C. (2017). Individual differences related to college students' course performance in calculus II. *Journal of Learning Analytics, 4*(2), 129–153. https://doi.org/10.18608/jla.2017.42.11

Henrie, C. R., Halverson, L. R., & Graham, C. R. (2015). Measuring student engagement in technology-mediated learning: A review. *Computers & Education, 90*, 36–53. https://doi.org/10.1016/j.compedu.2015.09.005

Heusel, L., Glaesser, J., Kilian, P., Merk, S., & Kelava, A. (2023). Comparing dropout intentions of math students on trainee teacher courses versus bachelor of science courses using intensive longitudinal data. *Frontiers in Education*, *8*. https://doi.org/10.3389/feduc.2023.1205949

Hiver, P., Al-Hoorie, A. H., Vitta, J. P., & Wu, J. (2024). Engagement in language learning: A systematic review of 20 years of research methods and definitions. *Language Teaching Research, 28*(1), 201–230. https://doi.org/10.1177/13621688211001289

Hochmuth, R. (2020). Service-Courses in university mathematics education. In S. Lerman (Ed.), *Encyclopedia of Mathematics Education* (pp. 770–774). Springer International Publishing. https://doi.org/10.1007/978-3-030-15789-0_100025

Hodds, M., Alcock, L., & Inglis, M. (2014). Self-explanation training improves proof comprehension. *Journal for Research in Mathematics Education, 45*(1), 62–101. https://doi.org/10.5951/jresematheduc.45.1.0062

Hong, Z.-Y., & Chien, C.-L. (2023). How does one's "mindset" contribute to statistical learning? A moderated mediation model of growth mindset of statistical ability on statistical learning outcomes. *Learning and Individual Differences, 107*, 102359. https://doi.org/10.1016/j.lindif.2023.102359

Hora, M. T., & Holden, J. (2013). Exploring the role of instructional technology in course planning and classroom teaching: Implications for pedagogical reform. *Journal of Computing in Higher Education, 25*(2), 68–92. https://doi.org/10.1007/s12528-013-9068-4

Hsieh, H.-F., & Shannon, S. E. (2005). Three approaches to qualitative content analysis. *Qualitative Health Research, 15*(9), 1277–1288. https://doi.org/10.1177/1049732305276687

Jack, E., Alexander, C., & Jones, E. M. (2024). Exploring the impact of gamification on engagement in a statistics classroom. *Teaching Mathematics and Its Applications, 00*, 1–14. https://doi.org/10.1093/teamat/hrae009

Jansen, R. S., van Leeuwen, A., Janssen, J., Jak, S., & Kester, L. (2019). Self-regulated learning partially mediates the effect of self-regulated learning interventions on achievement in higher education: A meta-analysis. *Educational Research Review, 28*, 100292. https://doi.org/10.1016/j.edurev.2019.100292

Jansen, A., Curtis, K., Mohammad Mirzaei, A., Cullicott, C. E., Smith, E. P., & Middleton, J. A. (2023). Secondary mathematics teachers' descriptions of student engagement. *Educational Studies in Mathematics, 113*(3), 425–442. https://doi.org/10.1007/s10649-023-10228-x

Järvinen, J., Ketonen, E. E., Hietajärvi, L., & Salmela-Aro, K. (2022). From high peaks to deep valleys: Using a situation- and person-oriented approach to assess within- and between-student variation in momentary engagement and disengagement. *Learning and Instruction, 82*, 101685. https://doi.org/10.1016/j.learninstruc.2022.101685

Jin, T. (2023). Online interactive face-to-face learning in mathematics in engineering education. *European Journal of Engineering Education, 48*(2), 300–320. https://doi.org/10.1080/03043797.2022.2117023

Juma, Z. O., Ayere, M. A., Oyengo, M. O., & Osang, G. (2022). Evaluating engagement and learning based on a student categorization using stack, exam data, key informant interviews, and focus group discussions. *International Journal of Emerging Technologies in Learning (iJET), 17*(23), 103–114. https://doi.org/10.3991/ijet.v17i23.36619

Kahu, E. R., & Nelson, K. (2018). Student engagement in the educational interface: Understanding the mechanisms of student success. *Higher Education Research & Development, 37*(1), 58–71. https://doi.org/10.1080/07294360.2017.1344197

Kang, B., LaViola, J. J., & Wisniewski, P. (2017). Examining interaction modality effects toward engagement in an interactive learning environment. In É. Lavoué, H. Drachsler, K. Verbert, J. Broisin, & M. Pérez-Sanagustín (Eds.), *Data Driven Approaches in Digital Education* (Vol. 10474, pp. 97–110). Springer International Publishing. https://doi.org/10.1007/978-3-319-66610-5_8

Kassab, S. E., El-Sayed, W., & Hamdy, H. (2022). Student engagement in undergraduate medical education: A scoping review. *Medical Education, 56*(7), 703–715. https://doi.org/10.1111/medu.14799

Kuh, G. D. (2003). What we're learning about student engagement from NSSE: Benchmarks for Effective Educational Practices. *Change: The Magazine of Higher Learning, 35*(2), 24–32. https://doi.org/10.1080/00091380309604090

Kuncoro, K. S., Kusumah, Y. S., Suryadi, D., Juandi, D., & Jupri, A. (2024). Augmented reality for supporting student's engagement in mathematics education: A systematic literature review. *The Eurasia Proceedings of Educational and Social Sciences*, 19–29. https://doi.org/10.55549/epess.797

Lavidas, K., Barkatsas, T., Manesis, D., & Gialamas, V. (2020). A structural equation model investigating the impact of tertiary students' attitudes toward statistics, perceived competence at mathematics, and engagement on statistics performance. *Statistics Education Research Journal, 19*(2), 27–41. https://doi.org/10.52041/serj.v19i2.108

Lee, J. Y., Pyon, C. U., & Woo, J. (2023). Digital twin for math education: A study on the utilization of games and gamification for university mathematics education. *Electronics, 12*(15), 3207. https://doi.org/10.3390/electronics12153207

Lei, H., Cui, Y., & Zhou, W. (2018). Relationships between student engagement and academic achievement: A meta-analysis. *Social Behavior and Personality: An International Journal, 46*(3), 517–528. https://doi.org/10.2224/sbp.7054

Li, L., Wang, X., & Wallace, M. P. (2022). I determine my learning path, or not? A study of different learner control conditions in online video-based learning. *Frontiers in Psychology, 13*, 973758. https://doi.org/10.3389/fpsyg.2022.973758

Liu, Q., & Khalil, M. (2023). Understanding privacy and data protection issues in learning analytics using a systematic review. *British Journal of Educational Technology, 54*(6), 1715–1747. https://doi.org/10.1111/bjet.13388

Lo, C. K., & Hew, K. F. (2021). Student engagement in mathematics flipped classrooms: Implications of journal publications from 2011 to 2020. *Frontiers in Psychology, 12*, 672610. https://doi.org/10.3389/fpsyg.2021.672610

Lowe, T., & Hakim, Y. E. (2020). An introduction to student engagement in higher education. In *A Handbook for Student Engagement in Higher Education*. Routledge.

Mandernach, B. J. (2015). Assessment of student engagement in higher education: A synthesis of literature and assessment tools. *International Journal of Learning, Teaching and Educational Research*, *12*(2), Article 2. https://www.ijlter.org/index.php/ijlter/article/view/367

Martin, A. J. (2023). Integrating motivation and instruction: Towards a unified approach in educational psychology. *Educational Psychology Review, 35*(2), 54. https://doi.org/10.1007/s10648-023-09774-w

Martins, J., Cunha, J., Lopes, S., Moreira, T., & Rosário, P. (2022). School engagement in elementary school: A systematic review of 35 years of research. *Educational Psychology Review, 34*(2), 793–849. https://doi.org/10.1007/s10648-021-09642-5

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine, 6*(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Murphy, S., & Ingram, N. (2023). A scoping review of research into mathematics classroom practices and affect. *Teaching and Teacher Education, 132*, 104235. https://doi.org/10.26181/25332520.v1

Newmann, F. M. (Ed.). (1992). *Student engagement and achievement in American secondary schools*. Teachers College Press.

Ní Shé, C., Ní Fhloinn, E., & Mac an Bhaird, C. (2023). Student engagement with technology-enhanced resources in mathematics in higher education: A review. *Mathematics*, *11*(3), Article 3. https://doi.org/10.3390/math11030787

Niss, M., & Højgaard, T. (2019). Mathematical competencies revisited. *Educational Studies in Mathematics, 102*(1), 9–28. https://doi.org/10.1007/s10649-019-09903-9

O'Connor, C., & Joffe, H. (2020). Intercoder reliability in qualitative research: Debates and practical guidelines. *International Journal of Qualitative Methods, 19*, 1609406919899220. https://doi.org/10.1177/1609406919899220

O'Sullivan, L., Casey, D., & Crowley, J. (2021). Asynchronous online mathematics learning support: An exploration of interaction data to inform future provision. *Teaching Mathematics and Its Applications: An International Journal of the IMA, 40*(4), 317–331. https://doi.org/10.1093/teamat/hrab016

Ouzzani, M., Hammady, H., Fedorowicz, Z., & Elmagarmid, A. (2016). Rayyan—A web and mobile app for systematic reviews. *Systematic Reviews, 5*(1), 210. https://doi.org/10.1186/s13643-016-0384-4

Paiva, R. C., Ferreira, M. S., & Frade, M. M. (2017). Intelligent tutorial system based on personalized system of instruction to teach or remind mathematical concepts. *Journal of Computer Assisted Learning, 33*(4), 370–381. https://doi.org/10.1111/jcal.12186

Plak, S., Van Klaveren, C., & Cornelisz, I. (2023). Raising student engagement using digital nudges tailored to students' motivation and perceived ability levels. *British Journal of Educational Technology, 54*(2), 554–580. https://doi.org/10.1111/bjet.13261

Rach, S. (2023). Motivational states in an undergraduate mathematics course: Relations between facets of individual interest, task values, basic needs, and effort. *ZDM – Mathematics Education, 55*(2), 461–476. https://doi.org/10.1007/s11858-022-01406-x

Raza, S. H., & Reddy, E. (2021). Intentionality and players of effective online courses in mathematics. *Frontiers in Applied Mathematics and Statistics, 7*, 612327. https://doi.org/10.3389/fams.2021.612327

Reeve, J. (2013). How students create motivationally supportive learning environments for themselves: The concept of agentic engagement. *Journal of Educational Psychology, 105*(3), 579–595. https://doi.org/10.1037/a0032690

Reschly, A. L., & Christenson, S. L. (2022). Jingle-jangle revisited: History and further evolution of the student engagement construct. In A. L. Reschly, & S. L. Christenson (Eds.), *Handbook of Research on Student Engagement* (pp. 3–24). Springer International Publishing. https://doi.org/10.1007/978-3-031-07853-8_1

Rienties, B., Tempelaar, D., Nguyen, Q., & Littlejohn, A. (2019). Unpacking the intertemporal impact of self-regulation in a blended mathematics environment. *Computers in Human Behavior, 100*, 345–357. https://doi.org/10.1016/j.chb.2019.07.007

Salmela-Aro, K., & Upadaya, K. (2012). The Schoolwork Engagement Inventory: Energy, dedication, and absorption (EDA). *European Journal of Psychological Assessment, 28*(1), 60–67. https://doi.org/10.1027/1015-5759/a000091

Sancho-Vinuesa, T., Escudero-Viladoms, N., & Masià, R. (2013). Continuous activity with immediate feedback: A good strategy to guarantee student engagement with the course. *Open Learning: The Journal of Open, Distance and e-Learning, 28*(1), 51–66. https://doi.org/10.1080/02680513.2013.776479

Saqr, M., López-Pernas, S., Helske, S., & Hrastinski, S. (2023). The longitudinal association between engagement and achievement varies by time, students' profiles, and achievement state: A full program study. *Computers & Education, 199*, 104787. https://doi.org/10.1016/j.compedu.2023.104787

Schoenfeld, A. H. (2022). Why are learning and teaching mathematics so difficult? In M. Danesi (Ed.), *Handbook of Cognitive Mathematics* (pp. 763–797). Springer International Publishing. https://doi.org/10.1007/978-3-031-03945-4_10

Schukajlow, S., Rakoczy, K., & Pekrun, R. (2023). Emotions and motivation in mathematics education: Where we are today and where we need to go. *ZDM – Mathematics Education, 55*(2), 249–267. https://doi.org/10.1007/s11858-022-01463-2

Shaker, A. J., Brignell, C., & Pugh, M. (2023). The effect of incentivising pre-class reading on engagement and student performance. *International journal of mathematical education in science and technology, 56*(2), 258–274. https://doi.org/10.1080/0020739X.2023.2214562

Shernoff, D. J., & Schmidt, J. A. (2008). Further evidence of an engagement-achievement paradox among U.S. high school students. *Journal of Youth and Adolescence, 37*(5), 564–580. https://doi.org/10.1007/s10964-007-9241-z

Sidekerskienė, T., & Damaševičius, R. (2023). Out-of-the-box learning: Digital escape rooms as a metaphor for breaking down barriers in STEM education. *Sustainability, 15*(9), 7393. https://doi.org/10.3390/su15097393

Sinatra, G., Heddy, B., & Lombardi, D. (2015). The Challenges of defining and measuring student engagement in science. *Educational Psychologist, 50*, 1–13. https://doi.org/10.1080/00461520.2014.1002924

Skinner, E., Furrer, C., Marchand, G., & Kindermann, T. (2008). Engagement and disaffection in the classroom: Part of a larger motivational dynamic? *Journal of Educational Psychology, 100*(4), 765–781. https://doi.org/10.1037/a0012840

Slavich, G. M., & Zimbardo, P. G. (2012). Transformational teaching: Theoretical underpinnings, basic principles, and core methods. *Educational Psychology Review, 24*(4), 569–608. https://doi.org/10.1007/s10648-012-9199-6

Smith, W. M., Voigt, M., Ström, A., Webb, D. C., & Martin, W. G. (2021). *Transformational change efforts: Student engagement in mathematics through an institutional network for active learning*. American Mathematical Soc.

Sutter, C. C., Hulleman, C. S., Givvin, K. B., & Tucker, M. (2022). Utility value trajectories and their relationship with behavioral engagement and performance in introductory statistics. *Learning and Individual Differences, 93*, 102095. https://doi.org/10.1016/j.lindif.2021.102095

Syarifuddin, H., & Atweh, B. (2021). The use of activity, classroom discussion, and exercise (ACE) teaching cycle for improving students' engagement in learning elementary linear algebra. *European Journal of Science and Mathematics Education, 10*(1), 104–138. https://doi.org/10.30935/scimath/11405

Symonds, J. E., Kaplan, A., Upadyaya, K., Aro, K. S., Torsney, B. M., Skinner, E., & Eccles, J. S. (2024). Momentary student engagement as a dynamic developmental system. *Journal of Theoretical and Philosophical Psychology*. Advance online publication. https://doi.org/10.1037/teo0000288

Tempelaar, D., Rienties, B., & Giesbers, B. (2024). Dispositional learning analytics and formative assessment: An inseparable twinship. *International Journal of Educational Technology in Higher Education, 21*(1), 57. https://doi.org/10.1186/s41239-024-00489-8

Thorson, K. R., Forbes, C. E., Magerman, A. B., & West, T. V. (2019). Under threat but engaged: Stereotype threat leads women to engage with female but not male partners in math. *Contemporary Educational Psychology, 58*, 243–259. https://doi.org/10.1016/j.cedpsych.2019.03.012

Ting, F. S. T., Shroff, R. H., Lam, W. H., & Chin, D. C. W. (2020). Examining the effect of flipped instruction on students' learning approaches in a STEM learning context. *Journal on Excellence in College Teaching, 31*(4), 41–68.

Tinto, V. (2022). Exploring the character of student persistence in higher education: The impact of perception, motivation, and engagement. In A. L. Reschly spsampsps S. L. Christenson (Eds.), *Handbook of Research on Student Engagement* (pp. 357–379). Springer International Publishing. https://doi.org/10.1007/978-3-031-07853-8_17

Tucker, M. C., Shaw, S. T., Son, J. Y., & Stigler, J. W. (2023). Teaching statistics and data analysis with R. *Journal of Statistics and Data Science Education, 31*(1), 18–32. https://doi.org/10.1080/26939169.2022.2089410
Wang, M.-T., & Hofkens, T. L. (2020). Beyond classroom academics: A school-wide and multi-contextual perspective on student engagement in school. *Adolescent Research Review, 5*(4), 419–433. https://doi.org/10.1007/s40894-019-00115-z
Wang, M.-T., Binning, K. R., Del Toro, J., Qin, X., & Zepeda, C. D. (2021). Skill, thrill, and will: The role of metacognition, interest, and self-control in predicting student engagement in mathematics learning over time. *Child Development, 92*(4), 1369–1387. https://doi.org/10.1111/cdev.13531
Wiedbusch, M., Dever, D., Li, S., Amon, M. J., Lajoie, S., & Azevedo, R. (2023). Measuring multidimensional facets of SRL engagement with multimodal data. In V. Kovanovic, R. Azevedo, D. C. Gibson, & D. lfenthaler (Eds.), *Unobtrusive Observations of Learning in Digital Environments: Examining Behavior, Cognition, Emotion, Metacognition and Social Processes Using Learning Analytics* (pp. 141–173). Springer International Publishing. https://doi.org/10.1007/978-3-031-30992-2_10
Wong, J., Bayoumy, S., Freke, A., & Cabo, A. (2022a). Augmented reality for learning mathematics: A pilot study with WebXR as an accessible tool. *Towards a New Future in Engineering Education, New Scenarios That European Alliances of Tech Universities Open Up*, 1805–1814. https://doi.org/10.5821/conference-9788412322262.1216
Wong, S. F., Mahmud, M. M., & Wong, S. S. (2022b). Students' performance and engagement in discrete mathematics online learning during COVID-19 pandemic. In Y. Maleh, M. Alazab, N. Gherabi, L. Tawalbeh, & A. A. Abd El-Latif (Eds.), *Advances in Information, Communication and Cybersecurity* (Vol. 357, pp. 354–365). Springer International Publishing. https://doi.org/10.1007/978-3-030-91738-8_33
Wong, Z. Y., & Liem, G. A. D. (2022). Student engagement: Current state of the construct, conceptual refinement, and future research directions. *Educational Psychology Review, 34*(1), 107–138. https://doi.org/10.1007/s10648-021-09628-3
Wong, Z. Y., Liem, G. A. D., Chan, M., & Datu, J. A. D. (2024). Student engagement and its association with academic achievement and subjective well-being: A systematic review and meta-analysis. *Journal of Educational Psychology, 116*(1), 48–75. https://doi.org/10.1037/edu0000833
Wu, J.-Y. (2021). Learning analytics on structured and unstructured heterogeneous data sources: Perspectives from procrastination, help-seeking, and machine-learning defined cognitive engagement. *Computers & Education, 163*, 104066. https://doi.org/10.1016/j.compedu.2020.104066
Yu, H., Gupta, A., Lee, W., Arroyo, I., Betke, M., Allesio, D., Murray, T., Magee, J., & Woolf, B. P. (2021). Measuring and integrating facial expressions and head pose as indicators of engagement and affect in tutoring systems. In R. A. Sottilare, & J. Schwarz (Eds.), *Adaptive Instructional Systems. Adaptation Strategies and Methods* (Vol. 12793, pp. 219–233). Springer International Publishing. https://doi.org/10.1007/978-3-030-77873-6_16

Authors and Affiliations

Elissavet Papageorgiou[1] · Jacqueline Wong[2] · Qinyi Liu[3] · Mohammad Khalil[3] · Annoesjka J. Cabo[1]

✉ Elissavet Papageorgiou
E.Papageorgiou@tudelft.nl

[1] Delft Institute of Applied Mathematics, Delft University of Technology, Mekelweg 4, 2628, CD, Delft, The Netherlands

[2] Department Of Education, Utrecht University, Heidelberglaan 8, 3584 CS Utrecht, the Netherlands

[3] Centre for the Science of Learning & Technology (SLATE), University of Bergen, Postboks 7807, NO-5020 Bergen, Norway