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Exploring the Link Between Motivational Regulation and Learning Design with Learning Analytics: A Systematic Literature Review

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Abstract

Effective learning design (LD) grounded in sound pedagogy is a critical driver of student success. Therefore, it is important to explore how LD of online learning environments influences student ability to manage their own learning. This understanding can inform the development of online programs that prioritize student-driven learning. Research increasingly shows that students can monitor and regulate their own motivation, significantly impacting their academic achievement. Based on the concept of motivational regulation (MR) as a context-dependent process, this systematic review aims to identify existing learning analytics research that examines the link between MR and LD as a key contextual factor. The findings reveal that: 1) there is a lack of consistency in how motivation is measured, operationalized, and applied within the learning analytics literature; 2) self-reporting through surveys remains the most common approach for measuring and operationalizing MR; 3) LD is primarily operationalized at the session and learning activity level, with descriptions focusing on pedagogical principles and strategies; and 4) most studies address the relation between motivational constructs and persistence or academic achievements by looking at variables such as performance or/and outcomes rather than the processes that influence motivational changes and the relationship between MR and LD.

Notes for Practice

- Students monitor and regulate their motivation or the processes responsible for their motivation, therefore this aspect of self-regulation can have an impact on their learning and achievement.
- The paper presents a systematic literature review of 21 peer-reviewed empirical studies within the research field of learning analytics to identify which measures and elements of the MR construct have been used to describe a potential association between LD and MR.
- Knowledge of how the various aspects of LD affect student MR throughout the learning process can be leveraged to support MR skills and facilitate student success in online learning.

Keywords: Motivation, self-regulated learning (SRL), learning analytics (LA), learning design (LD), technology-enhanced learning

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1. Introduction

Regulation of motivation helps students overcome potential obstacles such as boredom, difficulty in making progress, or environmental distractions (Wolters, 2003). Motivational regulation (MR) is an integral part of self-regulated learning (SRL), which involves the enhancement or maintenance of one's motivation in different phases of the learning process. A long-standing and central topic in educational psychology, SRL is recognized as a key competence for academic performance and persistence (Dent & Koenka, 2016; Donker et al., 2014; van Eekelen et al., 2005). Over the past decade, research evidence has emerged suggesting that many students struggle with SRL in the context of online and distance education (Baticulon et al., 2021; Jansen et al., 2020; Jung & Lee, 2018). Characterized by non-linear structures, limited external support, and reduced teacher presence, online and distance learning formats put more of an onus on the student to drive, manage, and reflect on their own learning process (Broadbent, 2017; Duffy & Azevedo, 2015; Schnaubert & Herold, 2020; Wong et al., 2019). This is even more pronounced in higher education, where students meet increased academic demands and are required to be more competent in self-organizing their studies (Broadbent & Poon, 2015; Pintrich & Zusho, 2007). Prompted by this, there is a growing body of empirical studies examining how to support and foster student SRL in online higher education (Devolder et al., 2012; Kizilcec et al., 2017; Theobald, 2021).

Research into supporting SRL in university-level online learning predominantly concerns explicit, targeted interventions, teaching students what SRL strategies are appropriate, and when and how to apply them. Examples include providing various types of prompts (Sonnenberg & Bannert, 2015; Wong, Baars, de Koning, & Paas, 2021), learning analytics dashboards (Matcha, Uzir et al., 2020), digital training modules and study materials (Bernacki et al., 2020; Jansen et al., 2020), intelligent tutoring systems (Azevedo & Cromley, 2004), and artificial intelligence applications (Jin et al., 2023). Recent research syntheses by Theobald (2021) and Edisherashvili et al. (2022) have provided a more nuanced understanding of the efficacy of targeted interventions. The effectiveness and precision of interventions are influenced by contextual factors, including learning environment and individual differences in learners. Other factors that appear to have an impact are the intensity and duration of interventions (Heikkinen et al., 2023). The interaction between the cognitive, metacognitive, and affective domains of SRL and the multiphase, cyclical nature of SRL processes complicates the design and implementation of precise, targeted interventions.

Edisherashvili et al. (2022) noted that there is a bias in the literature towards exploring a few domains and phases of SRL, more specifically the metacognitive domain and the performance phase, whereas the area of affect and motivational regulation and preparatory and appraisal phases have received comparatively less attention. Reviews of the literature on applying learning analytics (LA) methods to create SRL interventions in online learning (Heikkinen et al., 2023; Viberg et al., 2020), showed a similar bias towards the performance phase. The interest in what is often referred to as the "warm" aspects of SRL (Tinajero et al., 2024), i.e., the regulation of emotion and motivation during learning is, however, growing. MR in self-regulated learning can be defined as "the more or less conscious control over one's own motivation" (Wolters, 2003). Wolters and Benzon (2013) describe it as student efforts to manage their own level of motivation or to purposefully sustain or improve their effort or persistence for academic tasks. The emphasis here is on the active role students play in regulating their motivation, involving knowledge of motivation, monitoring of motivational states, and purposeful actions to control motivation. Earlier studies have shown that MR has a direct effect on student success in terms of academic performance and attrition. Students who are more skilled at MR are more likely to use adaptive, cognitive, and metacognitive strategies, which in turn is conducive to improved academic performance. More recent studies have made a clearer case for the importance of MR in learning, showing that MR is essential for maintaining task-related effort and persistence, which in turn leads to better academic performance, persistence, and positive learning outcomes (e.g. Artino & Ioannou, 2008; Kryshko et al., 2020; Ljubin-Golub et al., 2019). The present study is the outcome of a systematic review examining how literature conceptualizes university students' motivational regulation within the context of learning design, with a specific focus on studies in the field of learning analytics.

2. Background

2.1. The Complexities of SRL

Research on facilitating student SRL in online environments has been extensive (Viberg et al., 2020). However, differences in theoretical approaches, as well as varying understandings and applications of these approaches, make interpreting the findings challenging. Consequently, generalizing these findings to inform teaching and learning practices beyond specific tools, approaches, or training protocols is difficult. The multidisciplinary nature of the research and the resulting variation in methodological approaches contribute to this complexity. SRL theories are continually evolving, giving rise to multiple theoretical perspectives and models (Panadero, 2017; Tinajero et al., 2024). This evolution has led to a proliferation of terms and overlapping conceptualizations and operationalizations of the construct. Widely used models include cognitive, metacognitive, and affective/emotional components of learning. There is also consensus that SRL involves a cyclical, recursive sequence of processes where learners transition through phases of planning, performance/monitoring, and appraisal (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2008).

The availability of increasingly sophisticated technology and software (Rovers et al., 2019) has enabled researchers to study the dynamic and cyclical nature of SRL in greater detail. While these detailed studies provide valuable insights into the microprocesses of SRL as they occur in individual learners, there is a risk of focusing too narrowly on specific interventions and losing sight of the broader learning process. Edisherashvili et al. (2022) caution that while it may be tempting to create more complex interventions targeting specific SRL domains and sub-processes, this approach can overcomplicate the systems and designs, ultimately neglecting learner needs and the full nature of the learning process.

2.2. Motivational Regulation: Further Complexities

Described as student efforts to manage their own level of motivation or to purposefully sustain or improve their effort or persistence for academic tasks (Wolters & Benzon, 2013), MR is recognized as an important aspect of SRL and features in most of the frequently used SRL models (Boekaerts, 1999; Pintrich, 2000; Winne & Hadwin, 2008; Zimmerman, 2008). Although the emphasis varies between the different models, MR concerns the active role students play in regulating their motivation, involving metamotivational monitoring, metamotivational knowledge, and the use of purposeful strategies to control motivation (Wolters, 2011).

All the components of SRL, including cognitive, metacognitive, and affective processes, interact to facilitate effective learning. Consequently, MR is often mixed with other aspects and dimensions of SRL, leading to conceptual overlaps and confusion (Wolters & Benzon, 2013). While cognitive and metacognitive strategies focus on the regulation of knowledge and thinking processes, motivational regulation specifically targets the management of motivational states. However, the distinct boundaries between these components are not always clear in the literature, resulting in an overlap that complicates the understanding and study of MR.

Further contributing to the confusion, research often mixes motivation as a broader theoretical concept with motivational regulation. As noted by Kryshko et al. (2020) and Schwinger and Stiensmeier-Pelster (2012), the fields of motivation and MR are deeply intertwined, as both address aspects of why and how students engage in learning activities. Motivation, as a broader theoretical concept, can, according to Wolters (2003), be viewed as a student's state or level of willingness to engage in and persist in a task. While motivation provides the initial drive to act, MR involves specific strategies to manage and sustain this motivation. Empirical research often does not clearly differentiate between the two, leading to a conflation that gets in the way of a precise understanding of MR.

Wolters (2003) further proposes that motivation can be viewed as a process influenced by various beliefs and attitudes. Constructs such as self-efficacy, task value, and achievement goals are integral to motivation but also play a role in MR. Pintrich (2000) conceived of motivational beliefs as a set of internal convictions that influence a learner's approach to learning tasks. In his SRL model, motivational beliefs encompass three main categories: 1) expectancy beliefs, reflecting student perceptions of their ability to succeed in a task or self-efficacy; 2) value beliefs, including intrinsic motivation (interest and enjoyment derived from the task), extrinsic motivation (external rewards or consequences), and utility value (perceived usefulness of the task for personal goals); and 3) affect beliefs, which involve students' emotional responses and attitudes towards the task, e.g., anxiety, interest, boredom, and enjoyment. These beliefs collectively shape student motivational orientations and guide their self-regulatory processes in learning. All these constructs, whether they pertain to the student's perceptions of a learning task or to their belief in their ability to succeed, can affect their motivation as well as the effort and strategies they use to regulate it (Zimmerman & Schunk, 2008). These overlaps with broader motivational theories and constructs make it challenging to isolate MR as a distinct construct.

As the SRL field has matured, models place more emphasis on the dynamic, temporal, and situated qualities of SRL, as well as going into more detailed levels of specificity in describing motivational processes and potentially making it easier to differentiate between motivation and its regulation. For example, in Schwinger and Stiensmeier-Pelster's (2012) model, MR occurs at a micro-strategic level as a response to perceiving a task deficit and consequently making appropriate adjustments. Miele and Scholer (2018) have proposed a metamotivational model that offers a nuanced framework for understanding MR within the context of goal pursuit. The model posits bidirectional associations between motivational components and the processing mode used during task engagement, modulated by anticipated costs and obstacles. The initial motivation to engage in a task stems from a well-defined objective, often representing a broader aspiration or goal. This motivation is intricately linked to individual self-efficacy beliefs and perceptions of the task's value, which are continually monitored and controlled throughout task execution. In combination with Pintrich's (2000) categorization of motivational beliefs, Miele and Scholer's (2018) model provides a comprehensive, dynamic, and context-sensitive framework that aligns well with the needs and gaps identified in the current literature on motivational regulation. While Pintrich's categories will function as the basis for our literature search and analysis, Miele and Scholer's model can serve as a valuable tool for highlighting conceptual overlaps between motivational constructs and regulatory strategies and efforts.

When reviewing the literature and searching for studies examining MR, it is essential to adopt a broad approach that accounts for the lack of conceptual clarity. In the present study, we have chosen to be open to various definitions and operationalizations of MR, recognizing that it may be studied under different labels and frameworks. This broad approach involves considering studies that address related constructs and strategies, such as self-efficacy, task value, and motivational beliefs, which may overlap with or encompass aspects of MR. By doing so, we aim to gain a more comprehensive understanding of how students regulate their motivation and identify commonalities and differences across different theoretical and methodological perspectives.

2.3. Learning Design as a Context

In a 2015 paper, Roll and Winne (2015) stated, “Whether by design or not, a learner’s environment constrains the possibility of achieving particular goals and of taking particular steps to approach a goal” (p. 7). The underlying argument is that SRL interventions alone do not shape student SRL; rather, they do so as an integral part of the rest of the learning context. Boekaerts (1999) discussed the reciprocal relationship between learning environments and SRL. On one hand, learning environments can facilitate the development of self-regulatory skills; on the other, self-regulatory skills are important in making effective use of resources available within a learning environment. In short, whether an individual possesses an adaptive set of regulatory skills or not influences how they perceive the learning environment and whether they deem it conducive to achieving their learning objectives.

In their paper, Miele and Scholer (2018) emphasize the critical role of context in the regulation of motivation. They argue that student motivation is not only influenced by internal factors such as their beliefs and attitudes but also significantly shaped by external contextual elements. Since the early days of SRL research, context — conceptualized as “task in context,” “learning task,” or “environment” — has been considered a key factor in SRL frameworks (Ben-Eliyahu & Bernacki, 2015; de la Fuente-Arias, 2017). SRL skills may not transfer from one context or domain to the other, i.e., a student who is able to self-regulate during one learning task may not be able to do this as effectively in a different type of task. Contextual features such as task type, academic discipline, social interactions, physical environment, teaching methods, and technologies each contribute to shaping how regulation processes are enacted in specific situations. The link between context and SRL is inherent in online measures, however, interpreting the data is problematic in terms of making inferences about which underlying constructs the observed behaviour may be attributed to (Rovers et al., 2019).

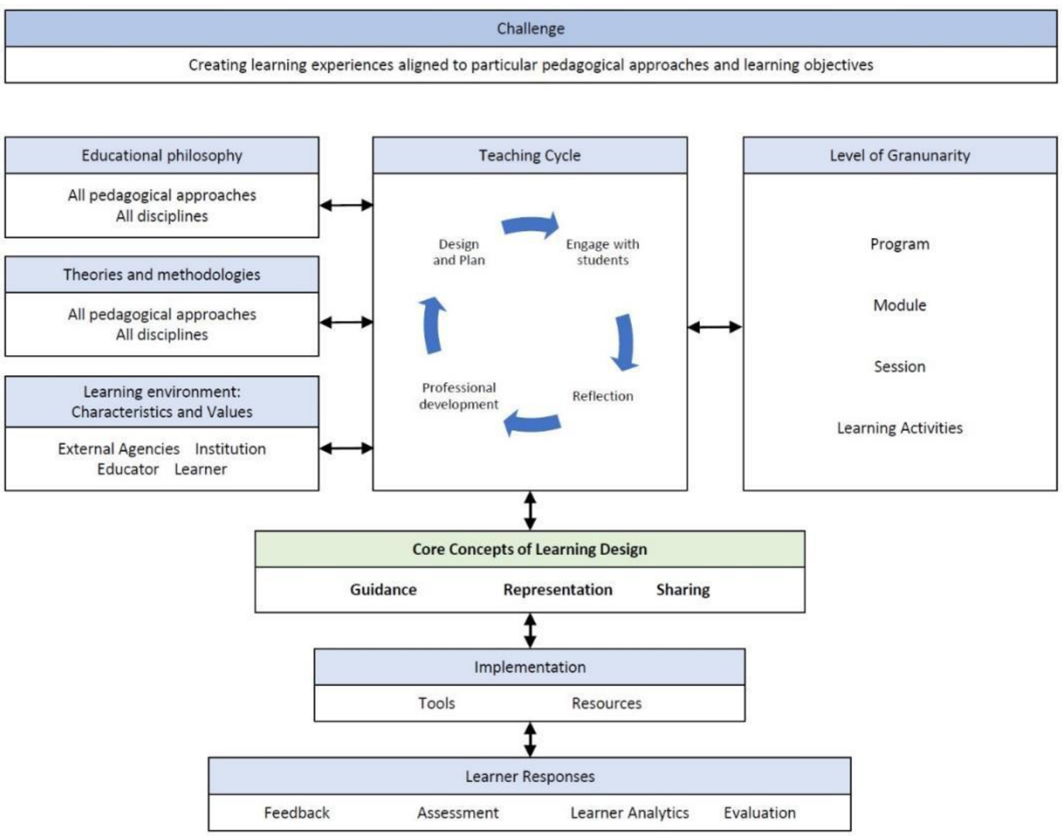

Figure 1. A learning design conceptual map (LD–CM); Dalziel et al., 2016, p. 10.

Learning design (LD) is a part of the pedagogical context, which in turn is a part of the learning environment. Over recent years, the research field of LD, also called “design for learning” (Conole, 2013), has gained a lot of attention among researchers and educators. Research has shown that LD is of significance for how students regulate their motivation (Gabriel et al., 2022;

Hood et al., 2015; Schumacher & Ifenthaler, 2018). Due to the ontological and conceptual duality of LD — i.e., "learning" and "design" — there have been numerous attempts to provide an overarching understanding of the field capturing such diversity. For example, Dobozy (2011) suggests classifying LD into three types: 1) learning design as a concept that is a standardized representation of learning sequences and design-based procedures underpinned by learning theories, e.g., cognitive constructivism, social constructivism, and social learning; 2) learning design as a process that illustrates the learning intent, planning, and enacting of a particular learning sequence in a context, and 3) learning design as a product of the methods, tools, and resources, referring to artefacts such as models, templates, and lesson plans. The second and third approaches to LD are typically used in learning analytics literature. For example, Mangaroska and Giannakos (2019) refer to LD as a process of designing effective learning experiences with the use of technological innovations and resources. While Bakharia et al. (2016) approach LD both as a process "of creating and adapting pedagogical ideas" and as a product "of a formalised description of a sequence of learning tasks, resources and support that a teacher constructs for students for an entire, or part of, an academic semester" (p. 330). The Larnaca Declaration goes a step further and attempts to provide an overarching theoretical foundation for the field (Dalziel et al., 2016). In addition to ontological and conceptual diversity, it also considers the wider educational context and its impact on learning design decisions. Moreover, it captures and summarizes the core concepts of LD in the Learning Design Conceptual Map (LD-CM; Figure 1). Additionally, all elements in the conceptual map can be interpreted based on Dobozy's classification of LD, i.e., as a concept, as a process, and as a product.

Whatever approach or concept one uses, there is an agreement in the research that LD plays an important role in structuring the pedagogical context where learning occurs, and it plays an important role in providing a framework for analyzing and interpreting data about learner behaviour (Mangaroska & Giannakos, 2019; Matcha, Uzir et al., 2020; Pardo et al., 2019; Rienties et al., 2017). As motivational processes are the drivers of learning, and thus influence learning behaviour, such as engagement, perseverance, and performance of learning tasks (Wolters, 2003; Zimmerman, 2008), there is a need to increase understanding of the relationship between LD and MR, i.e., understanding what and how elements/components of LD can alter or trigger student MR processes.

2.4. Learning Analytics

In the data for her meta-analysis, Theobald (2021) found that the predominant method for measuring SRL is retrospective self-reports. In addition to concerns about validity issues and response biases typically associated with this type of data (e.g., Winne, 2010), relying solely on self-report measures reflects an outdated conceptualization of SRL as a static disposition, not considering the dynamic, temporal aspects of the construct. To capture this, alternative or additional assessment methods such as behavioural measures are needed.

Learning analytics (LA) is an interdisciplinary field, relying on research, methods, and techniques from numerous fields such as educational data mining, educational and learning sciences, psychology, and data/information visualization (Gašević et al., 2016). The general definition of LA was coined at the first Learning Analytics and Knowledge (LAK) conference in 2011 as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and environments in which it occurs" (Ferguson & Clow, 2017, p. 56). Thus, LA approaches are leveraged to monitor and track student behaviour related to the learning environment and LD (e.g., use of different resources and learning activities, viewing, downloading, number of attempts, submissions, posting messages, etc.), and applying data mining techniques to identify patterns in traces (Khalil et al., 2022). LA features in the LD-CM under the rubric "learner response," suggesting that Dalziel et al. (2016) view LA as one of the available measures for gaining insight into LD. Further, grounded in theory, LA involves interpreting these patterns to help improve the understanding of learning and teaching processes (e.g., recommend, provide feedback, aid decisions on resource allocation) and predict the achievement of learning outcomes (Aldowah et al., 2019; Gašević et al., 2016; Viberg et al., 2018). There is currently a consensus within the LA field that research has often prioritized analytical approaches and methodological innovations over direct interventions in learning processes (Ferguson et al., 2023). This has led to a situation where, despite the wealth of data and analytical tools available, the impact on actual learning outcomes has been somewhat limited. In line with Reimann (2016), Ferguson and colleagues highlight the importance of grounding LA research in robust learning theories and addressing the misalignment between the goals of LA and its research scholarship.

Over the last 10–15 years, leveraging LA has primarily explored SRL behaviours related to cognitive (or metacognitive) and behavioural domains, identifying learning tactics and strategies (Fincham et al., 2019; Jovanović et al., 2017; Jovanović et al., 2019; Kizilcec et al., 2017; Matcha, Gašević et al., 2020). Several tools and methods have been developed to support and foster SRL, including predicting performance, identifying at-risk students, providing data-driven student feedback, suggesting interventions, and revising learning design (Chen et al., 2019; Davis et al., 2017; Jovanović et al., 2021; Persico & Pozzi, 2015; Wong, Baars, de Koning, & Paas, 2021).

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Literature shows that there is also a growing trend in leveraging multimodal learning analytics (MMLA). Techniques such as eye tracking, facial monitoring, and psychophysiological indicators are applied to measure dynamic states of SRL such as emotions and affect (Ahn & Harley, 2020; Chen et al., 2022; Gabriel et al., 2022; Taub & Azevedo, 2018; Taub et al., 2021). For example, Chen et al. (2022) used the self-regulated learning tool Mirror to detect learners' affective states in video-based learning. The researchers leveraged MMLA to inform learners of their affective states on self-regulated learning and then explored how learners perceived and used the tool for reflection. In the study by Taub et al. (2021), the researchers examined student emotions through facial expressions while engaging in cognitive and metacognitive SRL processes such as taking notes, summarizing, judgment of learning, and feeling of knowing. Then, the relationship between cognitive, metacognitive, and affective SRL processes was examined and assessed.

Despite leveraging the potential of MMLA, the researchers emphasize that most of those studies have focused on cognitive and meta-cognitive aspects of SRL and considerably less attention has been given to the affective domain of the construct, with only very few studies addressing motivation and MR directly (Gabriel et al., 2022; Littlejohn et al., 2016; Talbi & Ouared, 2022) in the context of online learning in higher education.

2.5. The Current Study

Based on the notion that MR is a context-dependent process, this systematic review aims to identify LA research addressing the link between MR and LD as an important contextual factor. Doing so will involve summarizing and discussing methods used to link different understandings of MR and LD constructs. More specifically, which measures and elements of the MR construct have been used to describe a potential association between LD and MR. To address this aim we pose the following research questions:

RQ1: a) How does LA research understand or conceptualize MR; b) how is LA used to operationalize and measure MR?
RQ2: How does LA research understand or conceptualize LD?
RQ3: How does this LA research link LD and MR?

3. Methods

The present review was conducted in accordance with the Preferred Reporting Items for Systematic reviews and Meta-Analysis (PRISMA 2020) extended checklist (Page et al., 2021). Following the PRISMA guidelines, the review process was conducted in four phases: 1) identifying information sources, 2) title and abstract screening, 3) assessing the full text for eligibility, and 4) qualitatively synthesizing the included research.

3.1. Search Strategy and Information Sources

The first phase involved searching the following databases and libraries: ACM DL, ERIC, IEEE, ScienceDirect, and Web of Science. These databases/libraries cover the most relevant papers within the interdisciplinary fields of computer science and computer science information systems, including learning analytics and educational data mining, educational research, psychology, and a combination of those. Using the first LAK conference in 2011 and the 2013 Horizon Report (Johnson et al., 2013) as a chronological starting point for LA as a research field, the search was limited to articles published from January 2012 to September 2023.

Table 1. Key Search Terms

Concept 1	Concept 2	Concept 3
Learning Analytics Educational data mining	SRL Self-regulated learning Learning strateg* Motivation Motivational belief* Task value* Task interest* Self-efficac*	Learning Design Design for learning Instructional design Course design Module design

The search was conducted in September 2023 by combining the keywords shown in Table 1. The combination of the terms should capture a large scale of research within the literature of LA about motivation, i.e., MR, LD, and any intersection or relationship between those. The key terms had to contain at least one keyword from each concept (Table 1) in the title, abstract, and/or keywords. In addition, inclusion criteria from items 8, 9, and 11 from Table 2 was applied to filter the search, which resulted in a total of 255 hits with the following database distribution:

- ACM DL — 19 hits
- ERIC — 9 hits
- IEEE — 13 hits
- ScienceDirect — 212 hits. Since the database is limited to a maximum of eight search terms, the following search string was used: ((“learning analytics”) AND (“learning design” OR “instructional design”) AND (“SRL” OR “motivation” OR “motivational belief” OR “self-efficacy” OR “task value”))
- Web of Science — 43 hits

Table 2. Inclusion/Exclusion Criteria

Criteria	Inclusion	Exclusion
Topic and focus	1. The study should be empirical	The research is not an empirical study
	2. Within the fields of learning analytics and educational data mining	Outside the fields of learning analytics and educational data mining
	3. Includes/describes a learning design as a whole (framework and concepts) or component parts (module/session, particular learning activity, e.g., assessment, discussion)	The research does not describe learning design
	4. Measures observed motivation regulation during the learning process or situation (so-called online behavioural measures)	Measures SRL behaviour using offline measures, outcome measures (e.g., performance, persistence, satisfaction), or non-observable behaviour (e.g., self-report measures)
	5. Attempts to link motivational regulation and learning design, e.g., in-depth discussions, measures, and/or analyses relationships/effects	Papers that merely mention potential links and/or are not specifically themed on learning design and SRL behaviour in online education
	6. Clearly addresses the research problem — includes descriptions of research questions and objectives, participants, methods, and results. Uses appropriate research design to address the aim of the research/study	The research has no clear description of the research problem, the participants, methods, and results of studies
Participants	7. Higher education (HE) students	Outside of the HE student population
Publication status	8. Peer-reviewed published works	Non-peer reviewed and articles in press
Publication type	9. Journal articles, conference proceedings papers	Dissertations, books, book chapters, workshops papers, posters, editorials, and reports
Publication date	10. January 2012 – September 2023	Outside the specified timeframe
Language	11. English	Other languages

From the pool of retrieved records, we identified 10 duplicates. Thus, the initial search resulted in 286 records. These were further filtered using different sets of criteria (Table 2).

3.2. Selection Strategy

In the second phase, the first author went through the records by scanning titles, abstracts, metadata, and keywords to determine their relevance according to selection criteria 1–7 in Table 2. In cases where it was not obvious whether the given record would be relevant, the first author examined it in detail by reading the method and result sections. From the pool of 286 records, only 106 met those inclusion criteria.

Next, the first author assessed the remaining papers by reading and examining the full text to determine whether they met the eligibility criteria and coded those accordingly (see Section 3.3). A search in the reference section for each selected paper was also included to uncover any additional relevant papers for the final sample (the snowball technique). In this stage of the screening, the corpus of papers was reduced to 45. In the next stage, to ensure reliability, the remaining papers were screened and coded independently by all three authors, leaving a final corpus of 21 papers (see Figure 2).

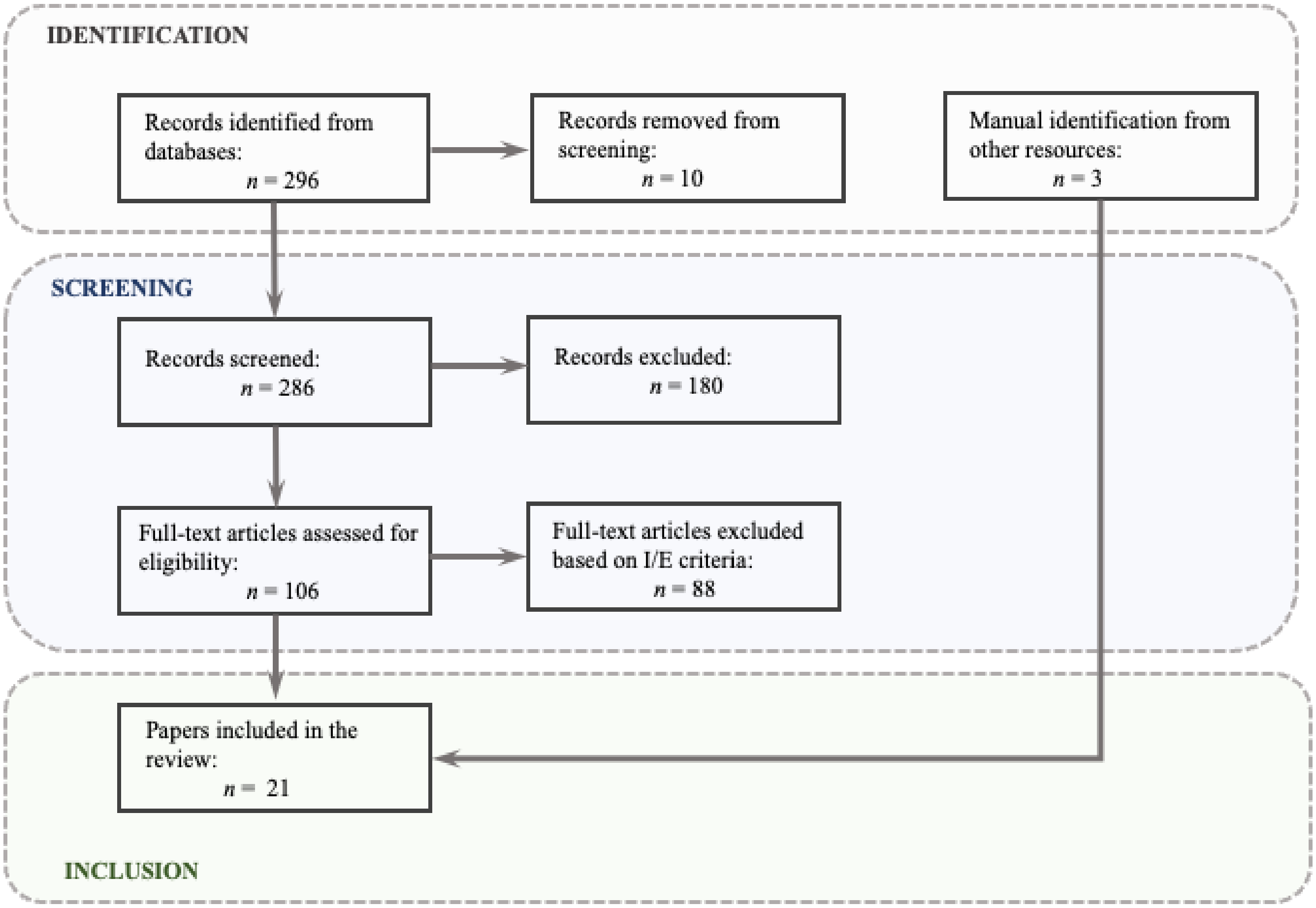

Figure 2: The review process according to PRISMA 2020.

3.3. Coding Scheme

To ensure that assessed papers met the eligibility criteria, the authors composed the coding scheme (a condensed version of which is available in Appendix 1). Parameters included in the coding scheme were developed according to the inclusion criteria in Table 2, thus helping to reduce the bias in selecting papers. Since most of the papers did not directly address MR, interpretation relied on the authors' knowledge of relevant literature. Thus, rather than measuring inter-rater reliability with, e.g., Cohen's Kappa, the authors discussed and resolved any uncertainties and disagreements through consensus meetings.

After the coding process, papers were analyzed to explore the current status of how MR and LD are understood and conceptualized in the learning analytics literature, which aspects of motivational behaviour are observed and how the relationship between MR and LD is understood.

4. Results and Discussion

The final corpus consisted of 15 journal articles and six conference proceeding papers (n = 21). The corpus was distributed across different conferences and journals, as shown in Table 3. The highest number of retrieved papers came from the ACM LAK conference proceedings (n = 6), followed by the journals *Computers in Human Behaviour* (n = 5) and *IEEE* (n = 4). The remaining two journal articles were retrieved from the *Journal of Educational Data Mining* (Taub & Azevedo, 2018) and the *Journal of Computer Assisted Learning* (de Barba et al., 2016).

Table 3. Distribution of Published Work by Journal/Conference

ScienceDirect:	Computers in Human Behaviour	5
	Computers and Education	3
	The Internet and Higher Education	1
IEEE		4
ACM Conference proceedings		6
Other		2

According to criteria 1 and 7 in Table 2, selected papers have described empirical studies only within higher education. Ten of the 21 papers presented studies of more than just one course. A range of student sample sizes per course varied between 59 and 4,831 learners, with the largest sample size belonging to a MOOC. Papers that reported the education level of offered courses predominantly consisted of undergraduate students (n = 13). One paper reported case studies of both undergraduate and graduate course levels. Of eight papers that did not report educational level, four were MOOC studies, three were performed in the context of blended learning, and one paper collected aggregated course data from 11 online study programs.

4.1. Response to RQ1

4.1.1. How Does LA Research Understand or Conceptualize MR?

To answer RQ1a, the authors initially looked at how the selected papers conceptualized MR. Most did not address MR explicitly; thus, conceptualization was based on the authors' understanding and interpretation of the theoretical construct. To organize and communicate findings about MR within the LA literature, the current study adopted the categories of motivational beliefs outlined in Pintrich's SRL model (2000, 2004).

The reviewed papers showed a range of approaches to understanding and conceptualizing MR and motivation, reflecting the conceptual conflation we described in the introduction. Figure 3 visualizes the distribution and co-appearance of motivational constructs across the reviewed papers. For example, de Barba et al. (2016) and Wong, Baars, He, et al. (2021) addressed motivation differently in their research, drawing on distinct theoretical frameworks. de Barba et al. (2016) used Pintrich's (2004) model, incorporating constructs like interest, achievement goals, and value beliefs, and specifically examined intrinsic motivation by combining individual interest, mastery-approach goals, and utility value beliefs to represent student general learning motivation, while situational interest reflected their state-level motivation. In contrast, Wong, Baars, He, et al. (2021) conceptualized motivation more narrowly, focusing on self-efficacy and task value beliefs, suggesting an emphasis on student confidence in their learning ability and the perceived relevance and value of tasks.

Using Miele and Scholer's (2018) metamotivational model as a lens, we do see that some studies touch on aspects of MR, such as metamotivational feelings. Although their terminology did not align with established theoretical frameworks, Srivastava et al. (2022) address concepts such as the "importance of performing well." This may be seen as being related to value beliefs; however, it can also be an expression of a metamotivational process. In other words, a phenomenological experience that indicates the status of different motivational components in the metamotivational model. Zamecnik et al. (2022) conceptualized motivation as the student's reason for enrolling in a course. This can conceivably be placed under the category of intrinsic motivation, or it can be seen in a metamotivational light as a feeling that helps students monitor and assess their motivation, signalling when regulation is needed.

We found little evidence of attempts to capture the dynamic nature of MR, except for two studies. In Jovanović et al. (2019), students evaluated pre-class activities by scoring them along two dimensions: difficulty and self-efficacy. These were conceptualized as motivation. Then, the fluctuations in motivational state were captured by the association between student use of online learning activities and the perceived effect of those activities on the student self-efficacy towards the corresponding course unit, i.e., capturing how students regulate their motivation in relation to different activities. Wong, Baars, He, et al. (2021) describe two studies in their paper. The first study is conducted in the context of online video-based learning. The second study examines five MOOCs. For the purposes of this article, the first study is of primary relevance. In Wong, Baars, He, et al.'s (2021) first study, the researchers examined whether prompting influences student self-motivational beliefs, SRL-related behaviour, course engagement and performance, and goal attainment in online video-based learning environment. Self-motivational beliefs (self-efficacy and task value) were measured with a self-report at three different time slots: after a course introduction, after a writing activity, and after a learning phase with three of the course`s content videos.

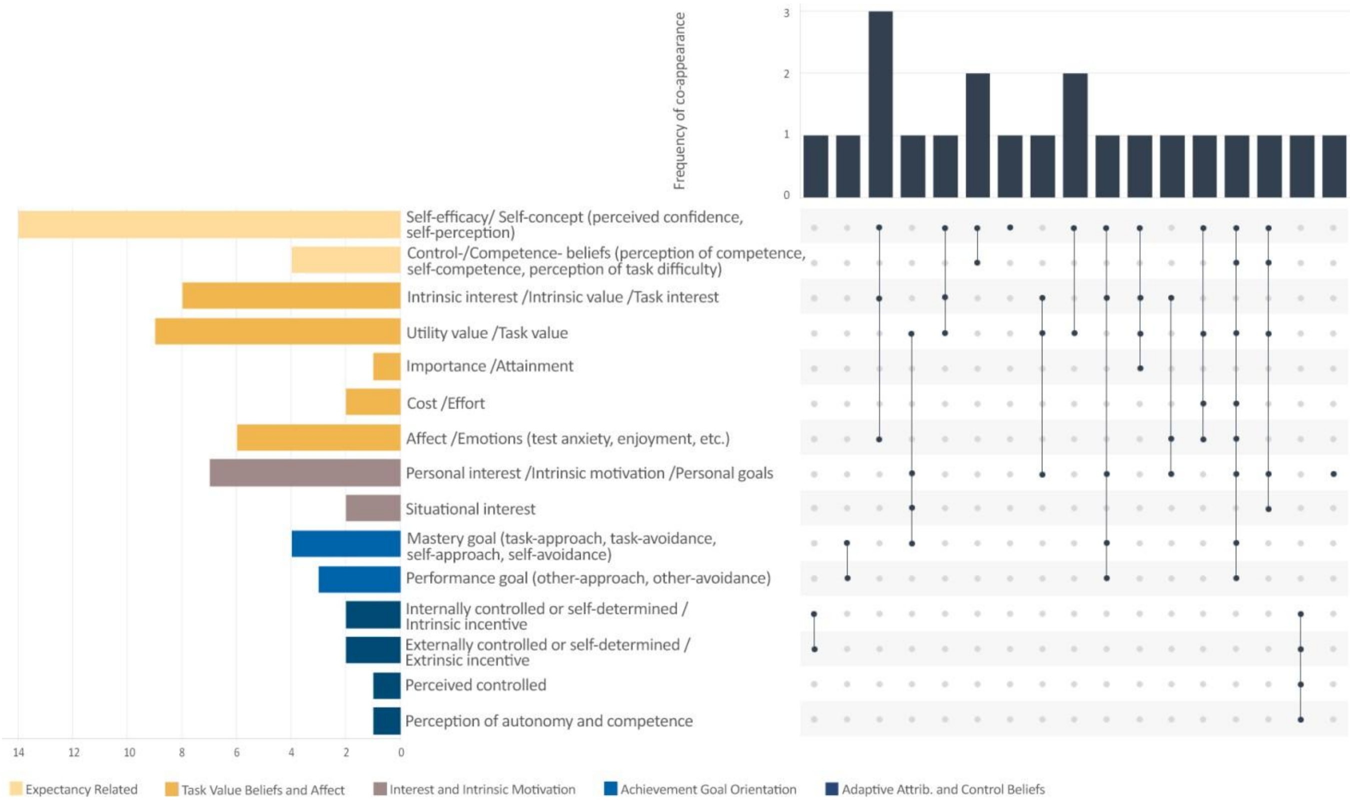

Figure 3. Distribution of motivational constructs and their co-appearance in the reviewed papers considering Pintrich's (2004) social-cognitive motivational constructs.

While most papers did not directly address MR, inferences were drawn from relevant literature (Miele & Scholer, 2018; Panadero, 2017; Pintrich, 2004; Schwinger et al., 2012; Wolters, 2003; Wolters & Benzon, 2013) to answer RQ1a. As shown in Figure 3, many studies (n = 18) examined MR through the combination of expectancy, task value beliefs, and intrinsic motivation. Others explored goal orientations (de Barba et al., 2016; Milikić et al., 2020; Tempelaar et al., 2018). Beheshitha et al. (2016) considered goal achievement constructs, while Al-Shabandar et al. (2018) investigated internal/external incentives and amotivation grounded in Expectancy-Value Theory (EVT). Finally, another study by Wong, Baars, de Koning, and Paas (2021) examined motivational constructs based on Self-Determination Theory.

4.1.2 How is LA Used to Operationalize and Measure MR?

Table 4 summarizes the distribution of operationalizations and measures used for the MR construct families, as shown in Figure 3. The focus of this section is RQ1b, which explores how the reviewed papers operationalized and measured these constructs.

The primary method for measuring and operationalizing MR was self-report via survey instruments (n = 18). Common examples included the use of the Motivated Strategies for Learning Questionnaire (MSLQ)/Motivational Beliefs Self-Regulation Scale (MBSRS) in six papers, the Achievement Emotions Questionnaire (AEQ) in two papers (Tempelaar et al., 2018; Tempelaar et al., 2015), and instruments like self-reported evaluation scores (Jovanović et al., 2019) and SRL prompts (Schumacher & Ifenthaler, 2021). Notably, four papers investigated achievement goal orientation, while only two focused on adaptive attributions and control beliefs. As shown in Figure 3, several studies measured more than one MR construct family.

Only two studies used trace data or log data to capture and measure MR. Taub and Azevedo (2018) employed facial expression logs to measure student emotions during gameplay, while Al-Shabandar et al. (2018) operationalized motivational regulation based on student behavioural data (traces). Their approach involved first conceptualizing motivation according to EVT, which categorizes motivation as intrinsic incentive, extrinsic incentive, and amotivation. Subsequently, the motivational dimension was identified based on the value of student records, including grades, course launch and completion dates, and course end dates.

Table 4. Operationalization and Measurement Instruments of MR

MR construct family Number of papers	**Operationalization/ Measurement instruments**	**Author(s)**
Expectancy, task value beliefs and intrinsic motivation N= 18	MSLQ/MBSRS = 6	Chen et al. (2019); Cicchinelli et al. (2018); Kia et al. (2021); Larmuseau et al. (2018); Pardo et al. (2017); Wang (2021)
	Other self-report (e.g., AEQ, OLVSES, OLEI, EV, PIQ, evaluation tool, prompts, etc.) = 12	de Barba et al. (2016); Dietrich et al. (2021); Jovanović et al. (2019); Kizilcec et al. (2017); Milikić et al. (2020); Schumacher & Ifenthaler (2018); Srivastava et al. (2022); Taub & Azevedo (2018); Tempelaar et al. (2015); Tempelaar et al. (2018); Wong, Baars, He, et al. (2021); Zamecnik et al. (2022)
	Log data (facial expressions) = 1	Taub & Azevedo (2018)
Achievement goal orientation N = 4	AGQ = 2 Other self-report = 2	de Barba et al. (2016); Milikić et al. (2020); Taub & Azevedo (2018); Beheshitha et al. (2016)
Adaptive attributions and control beliefs N = 2	Trace data = 1 Prompts = 1	Al-Shabandar et al. (2018); Wong, Baars, de Koning, & Paas (2021)

Note: MSLQ = Motivated Strategies for Learning Questionnaire; *MBSRS* = Motivational Beliefs and Self-Regulation Strategies; *AEQ* = Achievement Emotion Questionnaire; *AGQ* = Achievement Goal Questionnaire.

Motivation, being a dynamic construct, exhibits both temporal and context dependence. One approach to capturing this dynamism, including that of MR, involves taking snapshots of motivation as a state at various points in time.

As summarized in Table 5, the reviewed papers employed various strategies to capture the temporal nature of the motivational state. *Pre*, *post,* and *during* refer to when motivational data have been collected relative to a course, activity, or task. *Longitudinal* refers to studies collecting data at more than one time point between the start and end of a course/activity/task. For example, Tempelaar et al. (2015; 2018) measured motivational constructs such as self-beliefs and task value beliefs at the start of a course, in addition to measuring affect/emotions at time points during the course. Taub and Azevedo (2018) collected data about motivation and task interest before and after gameplay, while emotions were collected by facial expressions during gameplay.

Among the 21 reviewed papers, only two studies explicitly captured motivation as a dynamic state using longitudinal designs. Jovanović et al. (2019) collected trace data on student engagement with pre-class activities across two years of a 12-week flipped classroom course. They also used an evaluation tool (2D Canvas) to assess students' perceived self-efficacy, as well as their level of difficulty relative to the various course units. In the first study, Wong, Baars, He, et al. (2021) conducted controlled experiments in an online video-based learning environment, using the Online Learning Value and Self-Efficacy Scale (OLVSES) to measure self-motivational beliefs (self-efficacy and task value) at three points: after a course introduction, after a writing activity, and after a learning phase.

Table 5. Strategies for Capturing Motivation Temporality

Time point	Number of papers	Author(s)
Pre	5	Cicchinelli et al. (2018); Kizilcec et al. (2017); Milikić et al. (2020); Taub & Azevedo (2018); Tempelaar et al. (2015); Tempelaar et al. (2018)
Post	2	de Barba et al. (2016); Kia et al. (2021)
Pre and Post	7	Chen et al. (2019); Dietrich et al. (2021); Larmuseau et al. (2018); Wong, Baars, de Koning, & Paars (2021); Schumacher & Ifenthaler (2018); Srivastava et al. (2022); Taub & Azevedo (2018)
During course/ activity/task	3	Tempelaar et al. (2015); Tempelaar et al. (2018); Wang (2021)
Undefined	4	Al-Shabandar et al. (2018); Pardo et al. (2017); Beheshitha et al. (2016); Zamecnik et al. (2022)
Longitudinal	3	Jovanović et al. (2019); Taub & Azevedo (2018); Wong, Baars, He, et al. (2021)

4.2. Response to RQ2

Despite attempts to achieve an overarching understanding of LD, whether through classification or conceptualization, there is considerable diversity in how researchers and practitioners understand and approach it. This diversity is evident in the use of different terms and concepts such as “course design,” “instructional design,” “design for learning,” “curriculum design,” and “educational design” (Conole, 2013; Dobozy, 2011; Matcha, Gašević, et al., 2020). It also manifests in the descriptions, which range from applying different learning theories and educational principles and concepts (e.g., flipped classroom, problem-based learning, case-based learning) to descriptions of specific learning activities based on educational ideas like assessment-driven approaches, feedback interventions, or problem-solving tasks.

To address this diversity of understanding and approaches to LD, the authors adopted the LD-CM framework (Figure 1) and Dobozy’s (2011) classification to organize, describe, and communicate findings. Within the context of this review, the learning environment, description of pedagogical approaches, and granularity level of the LD-CM are considered part of the pedagogical context. This aligns with Dobozy’s (2011) classification of LD as a concept. Most reviewed studies focused primarily on describing the course setup or structure within a particular learning environment. This setup typically included a set of resources for students to access and tools to conduct learning activities or interactions. This aligns with the Engagement component of the Teaching Cycle and Implementation, which Dobozy (2011) classifies as an LD product. Finally, the Learner Response component of the LD-CM framework corresponds to assessment outcomes and feedback mechanisms.

4.2.1. Pedagogical Context: LD as a Concept

Learning and/or pedagogical theories were rarely explicitly referenced as the basis for LD. Instead, the reviewed papers more typically described pedagogical principles and strategies, or a combination of both, as the key elements for promoting student learning. In this context, pedagogical principles are understood as general guidelines for educators regarding specific considerations during instructional planning, adaptation, and delivery to enhance learning. Examples include flipped classrooms, problem-based learning, and case-based learning. The application of these principles often coincides with the use of pedagogical concepts and strategies (Ambrose et al., 2010), which can be viewed as the practical manifestations of chosen principles. These concepts and strategies, such as assessment-driven approaches, feedback interventions, or problem-solving activities, are typically applied at the level of specific teaching and learning tasks.

Only two papers explicitly mentioned learning theory alongside pedagogical principles and strategies as the basis for course design. Dietrich et al. (2021) clearly described the LD instructions to support cognitive learning processes. Tempelaar et al. (2018) opted for learning disposition instruments grounded in social-constructivist learning theories. Table 6 shows the distribution of published papers by pedagogical approach, and Figure 4 also visualizes the co-appearance of those.

We can further categorize the reviewed papers based on the reported pedagogical approaches used. Some studies employed both pedagogical principles and specific concepts or strategies (n = 7). Conversely, other studies focused solely on broader pedagogical principles without mentioning specific concepts or strategies (n = 4) — examples include works by Chen et al. (2019), Pardo et al. (2017), and Taub and Azevedo (2018). Another group of studies described specific teaching and learning approaches without referencing broader pedagogical principles (n = 5). Finally, five studies did not report any specific pedagogical approaches used. These include three MOOC studies (Al-Shabandar et al., 2018; de Barba et al., 2016; Kizilcec et al., 2017), a blended learning study (Cicchinelli et al., 2018), and a study using aggregated data from online programs (Zamecnik et al., 2022).

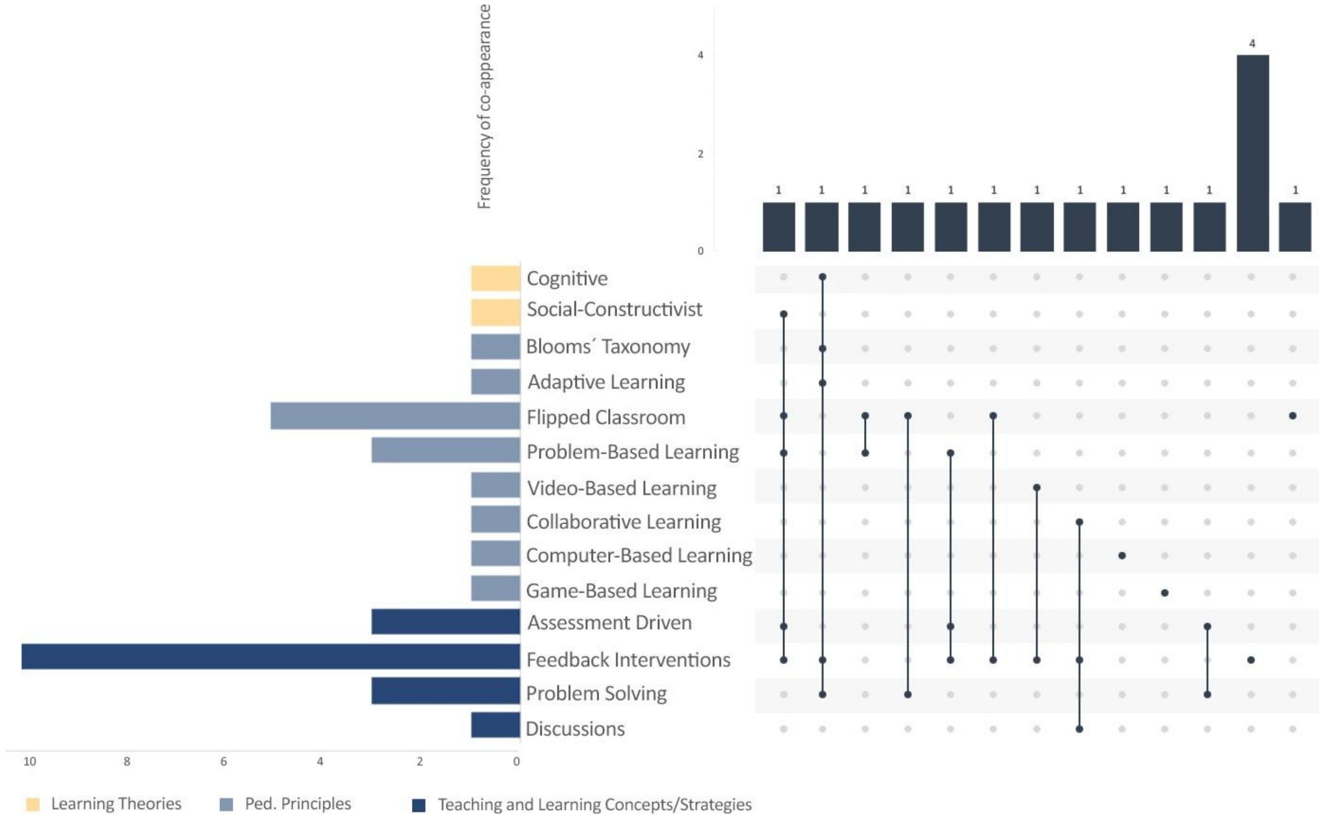

Figure 4. Distribution of pedagogical approaches and their co-appearance in reviewed papers.

The most frequent pedagogical principle employed was the flipped classroom (n = 5), followed by problem-based learning (n = 3). The most reported teaching and learning concept/strategy was feedback interventions (n = 10), including system-generated feedback and scaffolding. Assessment-driven approaches (n = 3) and problem-solving tasks (n = 3) were also prevalent. Group discussion was another reported strategy (Beheshitha et al., 2016). Figure 4 summarizes the distribution of pedagogical approaches (theories, principles, and concepts) and illustrates their co-occurrence in the studies.

The concept of "granularity level" refers to the scale of detail employed in a learning experience. It can range from a broad curriculum or entire study program down to a specific learning activity. As a rule, the chosen level of granularity reflects the course delivery method. Nine papers examined student learning behaviour at the session level, primarily corresponding to blended and online learning delivery methods. Seven papers described LD at the learning activity level, with most lacking a specified delivery method (undefined). Finally, five papers described LD at the course level, all of which were MOOCs. One exception to this was the two studies by Wong, Baars, He, et al. (2021), which investigated student self-regulation at both the course and session/learning activity levels. Table 6 summarizes the distribution of the granularity level in the reviewed papers with corresponding delivery methods.

Table 6. Level of Granularity with Corresponding Delivery Methods

Granularity Level	Delivery Method	Number of papers
Session	BL = 8, O = 1	9
Learning Activity	MOOC = 1, BL = 1, UND = 5	7
Course	MOOC = 5	5

Note: BL = blended; O = online; UND = undefined.

4.2.2. LD as a Product

The design and configuration of a course is often a direct outcome of the planning, design, and engagement stages within the Teaching Cycle. It is also dependent on the specific level of granularity addressed by a particular study. In face-to-face settings, LD products might be physical tools like books, whiteboards, paper sheets, and pens. Conversely, online contexts might require virtual learning platforms (VLPs) with a range of functionalities and tools, such as online videos, discussion forums, quizzes, and more. All reviewed papers (n = 21) reported the use of VLPs equipped with a set of learning resources, activities, and various system responses made available to students.

4.2.3. Learner Response

According to the LD-CM, framework, the Learner Response component lists four aspects of student interaction. For the present review, only feedback and assessment are deemed relevant since these directly pertain to the student learning process. Assessment encompasses all aspects of student response to learning outcomes. Formative and summative assessments represent common methods for measuring such responses. Student feedback, on the other hand, aims to capture student reactions to teaching styles and methods through course evaluations and surveys. Learner analytics is the third aspect, which in this review is addressed as a method for data collection, analysis, and interpretation of student MR (see Section 2.4). The fourth aspect of the LD-CM is evaluation. This concerns teaching practice improvement and is, as such, beyond our scope of interest.

Most papers (n = 17) mentioned or described the use of assessment. Twelve of these reported the use of both formative and summative assessments, and five reported only the use of formative assessment. Four papers did not report any type of assessment: Beheshitha et al. (2016) examined the effect of visualization-based feedback on student engagement in a discussion forum; Milikić et al. (2020) explored the effect of scaffolding interventions on social awareness and social embeddedness of learners and the associations between the use of the interventions and microlevel self-regulated learning processes; Taub and Azevedo (2018) assessed student metacognitive monitoring and hypothesis testing behaviour with facial expressions of emotions during learning while students played a game; and Zamecnik et al. (2022) focused on the development of profiles of nontraditional learners enrolled in online learning programs.

Only one study, Schumacher and Ifenthaler (2018), reported learner responses as student feedback. In this quasi-experimental study, students were introduced to cognitive, metacognitive, motivational, or a combination of these plus resource-related prompts. Students rated the prompts to indicate their usefulness.

See Appendix 1 for a full view of selected papers in relation to LD-CM components addressed for the review.

4.3. Response to RQ3

In answering RQ3, the authors aligned the interpretation and operationalization of MR and LD in the reviewed papers according to RQ1 and RQ2 (Appendix 1).

The systematic literature review of the 19 selected papers also showed the differences in statistical approaches in exploring the association/link between MR and LD. Two papers were excluded from this part of the systematic review. In the study by Kia et al. (2021), self-efficacy was measured as a part of SRL construct by MSLQ, but there was no clear role of motivation in the study. In the experimental study described by Wong, Baars, de Koning, and Paars (2021), a survey was used to check differences in students' intrinsic, identified, introjected, and extrinsic regulation of motivation at the beginning of the course in the different experimental conditions. As illustrated in Figure 5, in the remaining papers (n = 19), two groups of analysis emerge.

Eleven papers used linear models with or without regression and/or additional correlation analysis to examine the association between different variables and/or their significance and changes while manipulating different variables. Three studies used motivation as an outcome (Chen et al., 2019; Jovanović et al., 2019; Pardo et al., 2017), while the rest (n = 7) used motivation as a predictor, mostly of outcomes or performance (Cicchinelli et al., 2018; Kizilcec et al., 2017; Schumacher & Ifenthaler, 2018; Beheshitha et al., 2016; Tempelaar et al., 2018; Tempelaar et al., 2015; Wang, 2021).

The second group (n = 5) belongs to effect analysis using ANOVA/MANOVA, where three papers described experimental (Srivastava et al., 2022; Wong, Baars, He, et al., 2021) or quasi-experimental (Schumacher & Ifenthaler, 2018) studies examining differences between groups. Such as in the experimental study by Srivastava et al. (2022), the researchers assigned students to three prompt conditions — Generalized, Personalized, and Control — and used ANOVA to measure the effect of student motivational status on SRL strategies used in the essay-writing task. Motivation status was measured by pre- and post-surveys and was referred to as a part of "internal condition," not as a part of SRL strategies. Results revealed the differences between different SRL strategy groups and learner motivation, i.e., perception regarding task performance and self-efficacy, but no discussion about how motivation might be regulated.

Figure 5. Distribution of the reported statistical approaches and their co-appearance in the reviewed papers.

In the quasi-experimental study, Schumacher and Ifenthaler (2018) assigned students to different prompt conditions — Cognitive, Meta-Cognitive, All Prompt, and Control. The motivation was conceptualized as self-efficacy/perceived confidence and difficulty and was integrated into the "All Prompt" condition. Further, motivation was used as a predictor of student learning performance in a knowledge transfer (with regression analysis) and to examine whether cognitive, metacognitive, and a combination of these ("All prompt") affect learning performance, participant perceptions, i.e., task difficulty and confidence (with MANOVA). Results showed that the "All Prompt" group did better, but it was not possible to interpret whether this was due to the motivational aspects of the prompt or due to other conditions. In other words, the study design makes it difficult to identify the role of motivational constructs.

The first experimental study by Wong, Baars, He, et al. (2021) used ANOVA to measure the effect of motivational dynamics in the context of online video-based learning. Students were assigned to four conditions: 1) Mental Contrasting and Implementation Intention (MCII) prompt, 2) SRL prompt, 3) MCII and SRL prompt, and 4) Control, where motivational beliefs were measured at three different time points during a course. Results showed that learners in the MCII-only condition perceived significantly higher task value measures at Time 2 (after completing the MCII activity) than learners in the prompt-only condition. However, no significant differences in task value and self-efficacy were found between the conditions.

Another analysis approach to measure motivational dynamics was applied in the study by Jovanović et al. (2019). The researchers used a mixed-effect linear model to measure the association between the way students engaged with individual learning activities and how they perceived those activities in terms of difficulty and effect on their self-efficacy towards the course units. Then, correlational analyses between the students' final exam scores and indicators of their overall evaluation of pre-class learning activities, i.e., if/how the students' course performance was associated with their overall perception of difficulty and self-efficacy effect of various learning activities they engaged with during the course.

As Figure 5 illustrates, two reviewed papers used machine learning approaches with the goal of building prediction models. In the study by Al-Shabandar et al. (2018), the researchers used a set of machine learning algorithms (Decision Tree, Neural Networks, and Regularized Discriminant Analysis) to test which gave the best prediction of learner motivation (intrinsic, extrinsic, and amotivation), i.e., motivation is an outcome variable, while grade is a predictor. The study did not explicitly investigate the link between LD and motivation, but rather different levels of motivation connected to student achievement (retention, completion, and attrition), and then examines the difference between failure and success with respect to student demographics and per course, i.e., engagement with (reading/watching etc.) course materials. In the study by Zamecnik et al. (2022), the motivation construct was placed oppositely, i.e., as the predictor, while dropout was an outcome variable. The researchers used the machine learning method to examine the different motivational factors and engagement of students in online settings. Latent class analysis approach was used to calculate the probability membership of factors for each cluster and examine connections between the clusters from the survey model. A chi-square test was conducted to assess the statistical significance between each of the features.

5. Discussion

The aim of the review was twofold. First, we explored how the LA literature conceptualizes or understands MR and LD. Second, we looked at how the literature links different understandings of MR and LD, more specifically, which measures and elements of the MR construct have been used to describe a potential association between LD and MR. The findings related to each research question are discussed in this section.

5.1. Research Questions

MR is important for student success and part of a complex system of interdependently connected SRL processes. While motivation drives initial engagement, the regulation of motivational states influences what, how, whether, and when students learn on different levels underway in the learning process (Winne, 2020; Wolters, 2003; Zimmerman, 2008). Especially in the online context, motivation and its subsequent regulation play a key role due to the autonomous nature of the online learning context (Artino & Ioannou, 2008; de Barba et al., 2016; Park & Yun, 2018). Research shows that highly motivated students are more adept at self-regulating, more likely to achieve set goals, and less prone to dropping out of their studies (e.g., Al-Shabandar et al., 2018; Artino & Ioannou, 2008; Kryshko et al., 2020; Littlejohn et al., 2016; Ljubin-Golub et al., 2019). However, motivation does not occur in a vacuum. Context matters greatly, be it internal, such as personal goals, interests, and values, i.e., motivational beliefs (Pintrich, 2000), or external, such as learning environment, such as an LD, with its particular structure of learning resources and learning activities. Levels of motivation can fluctuate over the course of a learning task (Ainley & Ainley, 2019). Research is emerging, indicating that, albeit indirectly, MR plays a part in student success in terms of academic performance and attrition (e.g., Artino & Ioannou, 2008; Kryshko et al., 2020; Ljubin-Golub et al., 2019). Students may act to monitor and regulate their motivational states or the factors influencing these, and this can ultimately have an impact on their learning and achievement (Artino & Ioannou, 2008; Pintrich, 2000; Wolters, 2003). It follows that motivation, and thus motivational regulation, is a dynamic, temporal, context-dependent construct. Therefore, when exploring student motivational behaviour in real-time, there is a need to capture dynamic states.

For RQ1, our review shows that there is a lack of consistency in how motivation and MR is measured, operationalized, and applied within the reviewed literature. Typically, studies address MR on the motivational construct level (Wolters, 2003), e.g., self-efficacy or task value. Yet, in the study designs, as seen in Jovanović et al. (2019) and Wong, Baars, He, et al. (2021), constructs are treated in line with what Wolters defines as motivational regulation, i.e., activities that students use to initiate, maintain, and increase a certain level of motivation during learning.

Further, the review also shows that the predominant method of measuring and operationalizing MR is through self-reporting using survey instruments. From 21 reviewed papers, only the study by Al-Shabandar et al. (2018) has fully operationalized MR based on student behavioural data, i.e., traces. In the study by Taub and Azevedo (2018), the researchers used facial expression log data to measure student emotions while students were playing a game, yet the role of MR in relation to gameplay was not examined.

In terms of RQ2, LD, like motivation, does not appear in a vacuum. Factors such as teachers' practical skills and knowledge about learning theories, pedagogical principles, and strategies play a crucial role in how LD is approached and shaped (Ambrose et al., 2010; Conole, 2013; Dalziel et al., 2016). The research reveals that the structure and approach of LD has become even more important in online and distance education. VLP context puts more of an onus on students to drive, manage, and reflect on their own learning process as the dynamic of a physical classroom is absent (Broadbent, 2017; Duffy & Azevedo, 2015; Schnaubert & Herold, 2020; Wong et al., 2019). The literature shows that online learners are at a much greater risk of losing motivation (de Barba et al., 2016; Jung & Lee, 2018; Littlejohn et al., 2016) and therefore at a much higher risk of dropout (Davis et al., 2017; de Barba et al., 2016; de Barba et al., 2020; Gašević et al., 2016).

However, the review shows that the studies primarily operationalized LD at the session and learning activity level, with little mention of learning and/or pedagogical theories as a basis for the chosen approach. Rather, the reviewed papers typically described pedagogical principles and strategies or a mix of those as a foundation for student learning. The most reported teaching and learning concept/strategy was feedback interventions (e.g., system-generated feedback based on LA, scaffolding), followed by an assessment-driven approach and problem-solving tasks. For example, Beheshitha et al. (2016) examined the effect of visualization-based feedback on student engagement in a discussion forum. The study by Milikić et al. (2020) explored the effect of scaffolding interventions on social awareness and social embeddedness of learners and the associations between the use of the interventions and microlevel self-regulated learning processes. Taub and Azevedo (2018) assessed student metacognitive monitoring and hypothesis testing behaviour with facial expressions of emotions during learning while students played a game. This finding is in alignment with the research that predominantly concerns explicit interventions to support a few domains and phases of SRL (Azevedo & Cromley, 2004; Bernacki et al., 2020; Jansen et al., 2020; Jin et al., 2023; Matcha, Uzir et al., 2020; Sonnenberg & Bannert, 2015; Wong, Baars, de Koning, & Paas, 2021), whereas the area of affect and MR had comparatively received limited attention (Edisherashvili et al., 2022).

When it comes to RQ3, it is important to understand how LD influences MR processes and hence SRL, e.g., what learning activity/task to choose and when to start, level of engagement/involvement and persistence, and regulation of the effort. As the results reveal, most studies (n = 11) address the relationship between motivational constructs and persistence or academic achievements by looking at variables such as performance and/or outcomes rather than the processes that influence motivational changes and the relationship between MR and LD. This indicates that there is a lack in the literature of explicit understanding of learning behaviour as a direct response to the relationship between MR and LD. As an example, in the experimental study by Srivastava et al. (2022), the researchers measured the effect of student motivational status on SRL strategies used in the essay-writing task. Results revealed the differences between different SRL strategy groups and learner motivation, i.e., perception regarding task performance and self-efficacy, but no direct link between motivation and the essay-writing task. In another study by Jovanović et al. (2019), the researchers measured the association between the way students engaged with individual learning activities and how they perceived those activities in terms of difficulty and effect on their self-efficacy towards the course units. Then, the student's course performance was associated with their overall perception of difficulty and self-efficacy effect of various learning activities they engaged with during the course, but no direct association between the context of the learning activities and changes in perceived difficulty and effect.

5.2. Limitations

The current study has limitations due to the nature of systematic reviews and methods that were applied. First, chosen search terms/queries and particular inclusion criteria, such as empirical studies within higher education, might have left out relevant papers. Second, the filtering process and manual filtering of papers are limited to the reviewers' subjective views. To minimize subjectivity, the authors separately coded all selected papers. To ensure reliability, the final corpus of 21 papers was screened independently by all three authors. To discuss and resolve any uncertainties and disagreements, the researchers held consensus meetings. Third, as MR processes are not treated explicitly in the research field of LA, their interpretation relies on author understanding of the literature.

6. Conclusion

The paper presents a systematic literature review of 21 peer-reviewed empirical studies within the research field of learning analytics to identify which measures and elements of the MR construct have been used to describe a potential association between LD and MR. There is a need for LA research to understand the drives of student learning; more specifically, the role of MR in the context of self-regulation, how LD, as a part of the external context, influences motivation, and how students regulate their motivation (Gabriel et al., 2022; Littlejohn et al., 2016; Talbi & Ouared, 2022). In trying to foster SRL, we know from the literature that targeted interventions are complex and may have limited overall effects (Edisherashvili et al., 2022; Heikkinen et al., 2023; Theobald, 2021). This suggests that we need to look further back because student motivation and ability to regulate motivation have an impact on what, how, whether, and when students learn. As our review shows, the research focuses on isolated elements of the two concepts, thereby missing the forest for the trees. Moreover, despite leveraging the potential of LA and MMLA, the research looking at MR is still in its infancy. Most of the reviewed studies still rely on surveys/self-report instruments to measure motivation and MR.

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References

Ahn, B., & Harley, J. M. (2020). Facial expressions when learning with a queer history app: Application of the control value theory of achievement emotions. *British Journal of Educational Technology*, *51*(5), 1563–1576. https://doi.org/10.1111/bjet.12989

Ainley, M., & Ainley, J. (2019). Motivation and learning: Measures and methods. In K. A. Renninger & S. E. Hidi (Eds.), *The Cambridge handbook of motivation and learning* (pp. 665–688). Cambridge University Press. https://doi.org/10.1017/9781316823279.028

Al-Shabandar, R., Hussain, A. J., Liatsis, P., & Keight, R. (2018). Analyzing learners behavior in MOOCs: An examination of performance and motivation using a data-driven approach. *IEEE Access*, *6*, 73669–73685. https://doi.org/10.1109/ACCESS.2018.2876755

Aldowah, H., Al-Samarraie, H., & Fauzy, W. M. (2019). Educational data mining and learning analytics for 21st century higher education: A review and synthesis. *Telematics and Informatics*, *37*, 13–49. https://doi.org/10.1016/j.tele.2019.01.007

Ambrose, S. A., Bridges, M. W., DiPietro, M., Lovett, M. C., & Norman, M. K. (2010). *How learning works: Seven research-based principles for smart teaching*. Jossey-Bass.

Artino, A., & Ioannou, A. (2008). Promoting academic motivation and self-regulation: Practical guidelines for online instructors. *Proceedings of the Society for Information Technology & Teacher Education International Conference* (SITE 2008), 3 March 2008, Las Vegas, NV, USA (pp. 208–212). Association for the Advancement of Computing in Education (AACE). https://www.learntechlib.org/primary/p/27160/

Azevedo, R., & Cromley, J. G. (2004). Does training on self-regulated learning facilitate students' learning with hypermedia? *Journal of Educational Psychology*, *96*(3), 523–535. https://doi.org/10.1037/0022-0663.96.3.523

Bakharia, A., Corrin, L., de Barba, P., Kennedy, G., Gašević, D., Mulder, R., Williams, D., Dawson, S., & Lockyer, L. (2016). A conceptual framework linking learning design with learning analytics. *Proceedings of the 6th International Conference on Learning Analytics and Knowledge* (LAK '16), 25–29 April 2016, Edinburgh, UK (pp. 329–338). ACM Press. https://doi.org/10.1145/2883851.2883944

Baticulon, R. E., Sy, J. J., Alberto, N. R. I., Baron, M. B. C., Mabulay, R. E. C., Rizada, L. G. T., Tiu, C. J. S., Clarion, C. A., & Reyes, J. C. B. (2021). Barriers to online learning in the time of COVID-19: A national survey of medical students in the Philippines. *Medical Science Educator*, *31*(2), 615–626. https://doi.org/10.1007/s40670-021-01231-z

Beheshitha, S. S., Hatala, M., Gašević, D., & Joksimović, S. (2016). The role of achievement goal orientations when studying effect of learning analytics visualizations. *Proceedings of the 6th International Conference on Learning Analytics and Knowledge* (LAK '16), 25–29 April 2016, Edinburgh, UK (pp. 54–63). ACM Press. https://doi.org/10.1145/2883851.2883904

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

Bernacki, M. L., Vosicka, L., & Utz, J. C. (2020). Can a brief, digital skill training intervention help undergraduates "learn to learn" and improve their STEM achievement? *Journal of Educational Psychology*, *112*(4), 765–781. https://doi.org/10.1037/edu0000405

Boekaerts, M. (1999). Self-regulated learning: Where we are today. *International Journal of Educational Research*, *31*(6), 445–457. https://doi.org/10.1016/S0883-0355(99)00014-2

Broadbent, J. (2017). Comparing online and blended learner's self-regulated learning strategies and academic performance. *The Internet and Higher Education*, *33*, 24–32. https://doi.org/10.1016/j.iheduc.2017.01.004

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

Chen, L., Goda, Y., Shimada, A., & Yamada, M. (2019). Factors investigation of learning behaviors affecting learning performance and self-regulated learning. *Proceedings of the 2019 IEEE International Conference on Engineering, Technology and Education* (TALE 20), 10–13 December 2019, Yogyakarta, Indonesia. IEEE. https://doi.org/10.1109/TALE48000.2019.9225926

Chen, S., Liu, Y., Lu, R., Zhou, Y., Lee, Y.-C., & Huang, Y. (2022). "Mirror, mirror, on the wall": Promoting self-regulated learning using affective states recognition via facial movements. *Proceedings of the 2022 ACM Designing Interactive Systems Conference* (DIS '22), 13–17 June 2022, Virtual, Australia (pp. 1300–1314). ACM Press. https://doi.org/10.1145/3532106.3533500

Cicchinelli, A., Veas, E., Pardo, A., Pammer-Schindler, V., Fessl, A., Barreiros, C., & Lindstädt, S. (2018). Finding traces of self-regulated learning in activity streams. *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (LAK '18), 7–9 March 2018, Sydney, NSW, Australia (pp. 191–200). ACM Press. https://doi.org/10.1145/3170358.3170381

Conole, G. (2013). *Designing for learning in an open world*. Springer. https://doi.org/10.1007/978-1-4419-8517-0

Dalziel, J., Conole, G., Wills, S., Walker, S., Bennett, S., Dobozy, E., Cameron, L., Badilescu-Buga, E., & Bower, M. (2016). The Larnaca declaration on learning design. *Journal of Interactive Media in Education, 2016*(1), 7. https://doi.org/10.5334/jime.407

Davis, D., Jivet, I., Kizilcec, R. F., Chen, G., Hauff, C., & Houben, G.-J. (2017). Follow the successful crowd: Raising MOOC completion rates through social comparison at scale. *Proceedings of the 7th International Conference on Learning Analytics and Knowledge* (LAK '17), 13–17 March 2017, Vancouver, BC, Canada (pp. 454–463). ACM Press. https://doi.org/10.1145/3027385.3027411

de Barba, P. G., Kennedy, G. E., & Ainley, M. D. (2016). The role of students' motivation and participation in predicting performance in a MOOC. *Journal of Computer Assisted Learning*, *32*(3), 218–231. https://doi.org/10.1111/jcal.12130

de Barba, P. G., Malekian, D., Oliveira, E. A., Bailey, J., Ryan, T., & Kennedy, G. (2020). The importance and meaning of session behaviour in a MOOC. *Computers & Education*, *146*, 103772. https://doi.org/10.1016/j.compedu.2019.103772

de la Fuente-Arias, J. (2017). Theory of self- vs. externally-regulated learning™: Fundamentals, evidence, and applicability. *Frontiers in Psychology*, *8*, 1675. https://doi.org/10.3389/fpsyg.2017.01675

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

Devolder, A., van Braak, J., & Tondeur, J. (2012). Supporting self-regulated learning in computer-based learning environments: Systematic review of effects of scaffolding in the domain of science education. *Journal of Computer Assisted Learning*, *28*(6), 557–573.

Dietrich, J., Greiner, F., Weber-Liel, D., Berweger, B., Kämpfe, N., & Kracke, B. (2021). Does an individualized learning design improve university student online learning? A randomized field experiment. *Computers in Human Behavior*, *122*, 106819. https://doi.org/10.1016/j.chb.2021.106819

Dobozy, E. (2011). Typologies of learning design and the introduction of a "LD-Type 2" case example. *eLearning Papers*, *27*, 1–11. http://hdl.handle.net/20.500.11937/22874

Donker, A. S., de Boer, H., Kostons, D., Dignath van Ewijk, C. C., & van der Werf, M. P. C. (2014). Effectiveness of learning strategy instruction on academic performance: A meta-analysis. *Educational Research Review*, *11*, 1–26. https://doi.org/10.1016/j.edurev.2013.11.002

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

Edisherashvili, N., Saks, K., Pedaste, M., & Leijen, Ä. (2022). Supporting self-regulated learning in distance learning contexts at higher education level: Systematic literature review. *Frontiers in Psychology*, *12*, 792422. https://doi.org/10.3389/fpsyg.2021.792422

Ferguson, R., & Clow, D. (2017). Where is the evidence? A call to action for learning analytics. *Proceedings of the 7th International Conference on Learning Analytics and Knowledge* (LAK '17), 13–17 March 2017, Vancouver, BC, Canada (pp. 56–65). ACM Press. https://doi.org/10.1145/3027385.3027396

Ferguson, R., Khosravi, H., Kovanović, V., Viberg, O., Aggarwal, A., Brinkhuis, M., Buckingham Shum, S., Chen, L. K., Drachsler, H., Guerrero, V. A., Hanses, M., Hayward, C., Hicks, B., Jivet, I., Kitto, K., Kizilcec, R., Lodge, J. M., Manly, C. A., Matz, R. L., … Yan, V. X. (2023). Aligning the goals of learning analytics with its research scholarship: An open peer commentary approach. *Journal of Learning Analytics*, *10*(2), 14–50. https://doi.org/10.18608/jla.2023.8197

Fincham, E., Whitelock-Wainwright, A., Kovanović, V., Joksimović, S., van Staalduinen, J.-P., & Gašević, D. (2019). Counting clicks is not enough: Validating a theorized model of engagement in learning analytics. *Proceedings of the 9th International Conference on Learning Analytics and Knowledge* (LAK '19), 4–8 March 2019, Tempe, AZ, USA (pp. 501–510). ACM Press. https://doi.org/10.1145/3303772.3303775

Gabriel, F., Cloude, E. B., & Azevedo, R. (2022). Using learning analytics to measure motivational and affective processes during self-regulated learning with advanced learning technologies. In Y. Wang, S. Joksimović, M. O. Z. San Pedro, J. D. Way, & J. Whitmer (Eds.), *Social and emotional learning and complex skills assessment: An inclusive learning analytics perspective* (pp. 93–108). Springer. https://doi.org/10.1007/978-3-031-06333-6_6

Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, *28*, 68–84. https://doi.org/10.1016/j.iheduc.2015.10.002

Heikkinen, S., Saqr, M., Malmberg, J., & Tedre, M. (2023). Supporting self-regulated learning with learning analytics interventions: A systematic literature review. *Education and Information Technologies*, *28*(3), 3059–3088. https://doi.org/10.1007/s10639-022-11281-4

Hood, N., Littlejohn, A., & Milligan, C. (2015). Context counts: How learners' contexts influence learning in a MOOC. *Computers & Education*, *91*, 83–91. https://doi.org/10.1016/j.compedu.2015.10.019

Jansen, R. S., van Leeuwen, A., Janssen, J., Conijn, R., & Kester, L. (2020). Supporting learners' self-regulated learning in massive open online courses. *Computers & Education*, *146*, 103771. https://doi.org/10.1016/j.compedu.2019.103771

Jin, S.-H., Im, K., Yoo, M., Roll, I., & Seo, K. (2023). Supporting students' self-regulated learning in online learning using artificial intelligence applications. *International Journal of Educational Technology in Higher Education*, *20*(1), 37. https://doi.org/10.1186/s41239-023-00406-5

Johnson, L., Adams Becker, S., Cummins, M., Estrada, V., Freeman, A., & Ludgate, H. (2013). *NMC horizon report: 2013 higher education edition*. The New Media Consortium. https://files.eric.ed.gov/fulltext/ED559358.pdf

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

Jovanović, J., Gašević, D., Pardo, A., Dawson, S., & Whitelock-Wainwright, A. (2019). Introducing meaning to clicks: Towards traced-measures of self-efficacy and cognitive load. *Proceedings of the 9th International Conference on Learning Analytics and Knowledge* (LAK '19), 4–8 March 2019, Tempe, AZ, USA (pp. 511–520). https://doi.org/10.1145/3303772.3303782

Jovanović, J., Saqr, M., Joksimović, S., & Gašević, D. (2021). Students matter the most in learning analytics: The effects of internal and instructional conditions in predicting academic success. *Computers & Education*, *172*, 104251. https://doi.org/10.1016/j.compedu.2021.104251

Jung, Y., & Lee, J. (2018). Learning engagement and persistence in massive open online courses (MOOCs). *Computers & Education*, *122*, 9–22. https://doi.org/10.1016/j.compedu.2018.02.013

Khalil, M., Prinsloo, P., & Slade, S. (2022). A comparison of learning analytics frameworks: A systematic review. *Proceedings of the 12th International Conference on Learning Analytics and Knowledge* (LAK '22), 21–25 March 2022, Online USA (pp. 152–163). ACM Press https://doi.org/10.1145/3506860.3506878

Kia, F. S., Hatala, M., Baker, R. S., & Teasley, S. D. (2021). Measuring students' self-regulatory phases in LMS with behavior and real-time self report. *Proceedings of the 11th International Conference on Learning Analytics and Knowledge* (LAK '21), 12–16 April 2021, Irvine, CA, USA (pp. 259–268). ACM Press. https://doi.org/10.1145/3448139.3448164

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in massive open online courses. *Computers & Education*, *104*, 18–33. https://doi.org/10.1016/j.compedu.2016.10.001

Kryshko, O., Fleischer, J., Waldeyer, J., Wirth, J., & Leutner, D. (2020). Do motivational regulation strategies contribute to university students' academic success? *Learning and Individual Differences*, *82*, 101912. https://doi.org/10.1016/j.lindif.2020.101912

Larmuseau, C., Elen, J., & Depaepe, F. (2018). The influence of students' cognitive and motivational characteristics on students' use of a 4C/ID-based online learning environment and their learning gain. *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (LAK '18), 7–9 March 2018, Sydney, NSW, Australia (pp. 171–180). ACM Press. https://doi.org/10.1145/3170358.3170363

Littlejohn, A., Hood, N., Milligan, C., & Mustain, P. (2016). Learning in MOOCs: Motivations and self-regulated learning in MOOCs. *The Internet and Higher Education*, *29*, 40–48. https://doi.org/10.1016/j.iheduc.2015.12.003

Ljubin-Golub, T., Petričević, E., & Rovan, D. (2019). The role of personality in motivational regulation and academic procrastination. *Educational Psychology*, *39*(4), 550–568. https://doi.org/10.1080/01443410.2018.1537479

Mangaroska, K., & Giannakos, M. (2019). Learning analytics for learning design: A systematic literature review of analytics-driven design to enhance learning. *IEEE Transactions on Learning Technologies*, *12*(4), 516–534. http://dx.doi.org/10.1109/TLT.2018.2868673

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

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

Miele, D. B., & Scholer, A. A. (2018). The role of metamotivational monitoring in motivation regulation. *Educational Psychologist*, *53*(1), 1–21. https://doi.org/10.1080/00461520.2017.1371601

Milikić, N., Gašević, D., & Jovanović, J. (2020). Measuring effects of technology-enabled mirroring scaffolds on self-regulated learning. *IEEE Transactions on Learning Technologies*, *13*(1), 150–163. https://doi.org/10.1109/TLT.2018.2885743

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *International Journal of Surgery*, *88*, 105906. https://doi.org/10.1016/j.ijsu.2021.105906

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, *8*, 422. https://doi.org/10.3389/fpsyg.2017.00422

Pardo, A., Gašević, D., Jovanović, J., Dawson, S., & Mirriahi, N. (2019). Exploring student interactions with preparation activities in a flipped classroom experience. *IEEE Transactions on Learning Technologies*, *12*(3), 333–346. https://doi.org/10.1109/TLT.2018.2858790

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

Park, S., & Yun, H. (2018). The influence of motivational regulation strategies on online students' behavioral, emotional, and cognitive engagement. *American Journal of Distance Education, 32*(1), 43–56. https://doi.org/10.1080/08923647.2018.1412738

Persico, D., & Pozzi, F. (2015). Informing learning design with learning analytics to improve teacher inquiry. *British Journal of Educational Technology*, *46*(2), 230–248. https://doi.org/10.1111/bjet.12207

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451–502). Academic Press. https://doi.org/10.1016/B978-012109890-2/50043-3

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

Pintrich, P. R., & Zusho, A. (2007). Student motivation and self-regulated learning in the college classroom. In R. P. Perry & J. C. Smart (Eds.), *The scholarship of teaching and learning in higher education: An evidence-based perspective* (pp. 731–810). Springer. https://doi.org/10.1007/1-4020-5742-3_16

Reimann, P. (2016). Connecting learning analytics with learning research: The role of design-based research. *Learning: Research and Practice*, *2*(2), 130–142. https://doi.org/10.1080/23735082.2016.1210198

Rienties, B., Nguyen, Q., Holmes, W., & Reedy, K. (2017). A review of ten years of implementation and research in aligning learning design with learning analytics at the Open University UK. *Interaction Design & Architecture(s) Journal, 33*, 134–154. https://doi.org/10.55612/s-5002-033-007

Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *Journal of Learning Analytics*, *2*(1), 7–12. https://doi.org/10.18608/jla.2015.21.2

Rovers, S. F. E., Clarebout, G., Savelberg, H. H. C. M., de Bruin, A. B. H., & van Merriënboer, J. J. G. (2019). Granularity matters: Comparing different ways of measuring self-regulated learning. *Metacognition and Learning*, *14*(1), 1–19. https://doi.org/10.1007/s11409-019-09188-6

Schnaubert, L., & Herold, B. (2020). Social-distance education: Struggling with cognition, emotion or motivation during SRL? *28th International Conference on Computers in Education* (ICCE 2020), 23–27 November 2020, Online.

Schumacher, C., & Ifenthaler, D. (2018). The importance of students' motivational dispositions for designing learning analytics. *Journal of Computing in Higher Education*, *30*(3), 599–619. https://doi.org/10.1007/s12528-018-9188-y

Schumacher, C., & Ifenthaler, D. (2021). Investigating prompts for supporting students' self-regulation: A remaining challenge for learning analytics approaches? *The Internet and Higher Education*, *49*, 100791. https://doi.org/10.1016/j.iheduc.2020.100791

Schwinger, M., Steinmayr, R., & Spinath, B. (2012). Not all roads lead to Rome: Comparing different types of motivational regulation profiles. *Learning and Individual Differences*, *22*(3), 269–279. https://doi.org/10.1016/j.lindif.2011.12.006

Schwinger, M., & Stiensmeier-Pelster, J. (2012). Effects of motivational regulation on effort and achievement: A mediation model. *International Journal of Educational Research*, *56*, 35–47. https://doi.org/10.1016/j.ijer.2012.07.005

Sonnenberg, C., & Bannert, M. (2015). Discovering the effects of metacognitive prompts on the sequential structure of SRL-processes using process mining techniques. *Journal of Learning Analytics*, *2*(1), 72–100. https://doi.org/10.18608/jla.2015.21.5

Srivastava, N., Fan, Y., Rakovic, M., Singh, S., Jovanović, J., van der Graaf, J., Lim, L., Surendrannair, S., Kilgour, J., Molenaar, I., Bannert, M., Moore, J., & Gašević, D. (2022). Effects of internal and external conditions on strategies of self-regulated learning: A learning analytics study. *Proceedings of the 12th International Conference on Learning Analytics and Knowledge* (LAK '22), 21–25 March 2022, Online USA (pp. 392–403). ACM Press. https://doi.org/10.1145/3506860.3506972

Talbi, O., & Ouared, A. (2022). Goal-oriented student motivation in learning analytics: How can a requirements-driven approach help? *Education and Information Technologies*, *27*(9), 12083–12121. https://doi.org/10.1007/s10639-022-11091-8

Taub, M., & Azevedo, R. (2018). Using sequence mining to analyze metacognitive monitoring and scientific inquiry based on levels of efficiency and emotions during game-based learning. *Journal of Educational Data Mining*, *10*(3), 1–26.

Taub, M., Azevedo, R., Rajendran, R., Cloude, E. B., Biswas, G., & Price, M. J. (2021). How are students' emotions related to the accuracy of cognitive and metacognitive processes during learning with an intelligent tutoring system? *Learning and Instruction*, *72*, 101200. https://doi.org/10.1016/j.learninstruc.2019.04.001

Tempelaar, D., Rienties, B., Mittelmeier, J., & Nguyen, Q. (2018). Student profiling in a dispositional learning analytics application using formative assessment. *Computers in Human Behavior*, *78*, 408–420. https://doi.org/10.1016/j.chb.2017.08.010

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior*, *47*, 157–167. https://doi.org/10.1016/j.chb.2014.05.038

Theobald, M. (2021). Self-regulated learning training programs enhance university students' academic performance, self-regulated learning strategies, and motivation: A meta-analysis. *Contemporary Educational Psychology*, *66*, 101976. https://doi.org/10.1016/j.cedpsych.2021.101976

Tinajero, C., Mayo, M. E., Villar, E., & Martínez-López, Z. (2024). Classic and modern models of self-regulated learning: Integrative and componential analysis. *Frontiers in Psychology*, *15*, 1307574. https://doi.org/10.3389/fpsyg.2024.1307574

van Eekelen, I. M., Boshuizen, H. P. A., & Vermunt, J. D. (2005). Self-regulation in higher education teacher learning. *Higher Education*, *50*(3), 447–471. https://doi.org/10.1007/s10734-004-6362-0

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior*, *89*, 98–110. https://doi.org/10.1016/j.chb.2018.07.027

Viberg, O., Khalil, M., & Baars, M. (2020). Self-regulated learning and learning analytics in online learning environments: A review of empirical research. *Proceedings of the 10th International Conference on Learning Analytics and Knowledge* (LAK '20), 23–27 March 2020, Frankfurt, Germany (pp. 524–533). ACM Press. https://doi.org/10.1145/3375462.3375483

Wang, F. H. (2021). Interpreting log data through the lens of learning design: Second-order predictors and their relations with learning outcomes in flipped classrooms. *Computers & Education*, *168*, 104209. https://doi.org/10.1016/j.compedu.2021.104209

Winne, P. H. (2010). Improving measurements of self-regulated learning. *Educational Psychologist*, *45*(4), 267–276. https://doi.org/10.1080/00461520.2010.517150

Winne, P. H. (2020). Construct and consequential validity for learning analytics based on trace data. *Computers in Human Behavior*, *112*, 106457. https://doi.org/10.1016/j.chb.2020.106457

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

Winne, P. H., & Hadwin, A. F. (2008). The weave of motivation and self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and applications* (pp. 297–314). Lawrence Erlbaum.

Wolters, C. A. (2003). Regulation of motivation: Evaluating an underemphasized aspect of self-regulated learning. *Educational Psychologist*, *38*(4), 189–205. https://doi.org/10.1207/S15326985EP3804_1

Wolters, C. A. (2011). Regulation of motivation: Contextual and social aspects. *Teachers College Record*, *113*(2), 265–283. https://doi.org/10.1177/016146811111300202

Wolters, C. A., & Benzon, M. B. (2013). Assessing and predicting college students' use of strategies for the self-regulation of motivation. *The Journal of Experimental Education*, *81*(2), 199–221. https://doi.org/10.1080/00220973.2012.699901

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

Wong, J., Baars, M., de Koning, B. B., & Paas, F. (2021). Examining the use of prompts to facilitate self-regulated learning in massive open online courses. *Computers in Human Behavior*, *115*, 106596. https://doi.org/10.1016/j.chb.2020.106596

Wong, J., Baars, M., He, M., de Koning, B. B., & Paas, F. (2021). Facilitating goal setting and planning to enhance online self-regulation of learning. *Computers in Human Behavior*, *124*, 106913. https://doi.org/10.1016/j.chb.2021.106913

Zamecnik, A., Kovanović, V., Joksimović, S., & Liu, L. (2022). Exploring non-traditional learner motivations and characteristics in online learning: A learner profile study. *Computers and Education: Artificial Intelligence*, *3*, 100051. https://doi.org/10.1016/j.caeai.2022.100051

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

Zimmerman, B. J., & Schunk, D. H. (2008). Motivation: An essential dimension of self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and applications* (pp. 1–30). Lawrence Erlbaum.

Appendix 1: Overview of the Studies Included in the Systematic Review

Table A1: Reduced version of coding schema for the reviewed papers
GL = Granularity Level: P = Study program; C = Course; S = Session; LA = Learning Activity; 0 = Undefined
PA = Pedagogical Approach: LT = Learning Theory; PP = Ped. Principle; TLC = Teaching and Learning Concept/Strategies; 0 = Undefined
TC = Teaching Cycle: D&P = Design and Planning; E = Engagement; TPD = Teacher Professional Development; F = Feedback; 0 = Undefined
R&T = Resources and Tools
A = Assessment: F = Formative; S = Summative; 0 = Undefined

Study/ authors	Conceptualization LD	Learning environm.	Conceptualization motivation and/or MR	Measure/operation. of motivation and/or MR	Temporality	Statistical analysis	Link between MR and LD
1. Al-Shabandar et al. (2018)	**GL:** C **PA:** 0 **R&TLA:** video, pages, quiz, **VLE**: EdX **A:** F, S	MOOC	intrinsic incentive, extrinsic incentive, amotivation	Motivation = [traces; grade; course start day; course launch day; course wrap date; course end day]	0	**Chi-square:** examine the difference between failure and success groups per course with respect to the learners' academic achievement. **DT, NN and RDA** algorithms tested to predict learner motivation.	**LD: A** and **MR: Incentive Motivational Theory** (trait) Prediction of motivation based on outcomes.
2.Beheshitha et al. (2016)	**GL:** LA **PA:** PP, TLC **TC:** D&P, E **R&T:** online discussion, LA tool in Canvas LMS **A:** 0	BL	task-approach, task-avoidance, self-approach, self-avoidance, other-approach, other-avoidance	AGQ	0	**Exp. study design** (two groups: condition and control) **Hierarchical linear model**: measure association between the use of LA-tool (to monitor participation in discussion) and the quantity of posted messages, after controlling for self-reported AGOs.	**LD: R&T** and **Motivation: AGO** (trait)
3.Chen et al. (2019)	**GL:** S **PA:** PP **TC:** D&P, E **R&T:** reading materials in BookRoll, assignment **A:** F, S	BL	self-efficacy, intrinsic value, test anxiety	MSLQ	Pre- & Post-	**Stepwise multiple regression analysis:** determine which of the learning behaviour (independent) variables predicted students' final scores and changes in the MSLQ (by calculating the number of learning behaviours in each lecture and investigating the effect of these behaviours on learning performance and MSQL changes as SRL awareness).	**LD: R&T, A and MR: Motivational beliefs** (trait) Prediction of outcomes.
4.Cicchinelli et al. (2018)	**GL:** S **PA:** 0 **TC:** D&P, E **R&T:** course materials and quizzes in LMS (version of Sphinx-doc) **A:** F, S	BL	self-efficacy, intrinsic value, test anxiety	MBSRS	Before	**Correlation analysis**: measure the association between self-reported motivation and SRL; the relation between performance and motivational belief. **Regression analysis:** assess if the results in control (responses to quizzes) and performance (points obtained in the final exam) can be explained from the scores in MBSRS (independent variable).	**LD: R&T** (as SRL behaviour), **A** and **MR: Motivational beliefs** (trait) Motivation is connected to SRL behaviour, both self-reported and as interactions with course elements in LMS.

5.De Barba et al. (2016)	**GL:** LA **PA:** 0 **TC:** D&P, E **R&T:** video, course materials, quiz, peer assessment essay, discussion forum in Coursera LMS **A:** F, S	MOOC	individual interest, mastery-approach goals, utility value beliefs, situational interest	Survey	After	**Correlational anal.** between intrinsic motivation scores and participation (video hits and quiz attempts) **SEM:** investigate the relationship between intrinsic motivation, participation, situational interest and performance of persistent students.	**LD: R&T, A** and **MR: Motivational beliefs & AGO** (trait) Prediction of performance.
6.Dietrich et al. (2021)	**GL:** S **PA:** LT, PP, TLC **TC:** D&P, E, R, TPD **R&T:** video, course content, quiz, progress bar in Moodle LMS **A:** F, S	BL	self-concept, self-efficacy, intrinsic value, utility value	Self-report	Pre- and post-	**SEM**: examine students' learning behaviour linked to the covariates measured at pre- and post-test; computed separate models for course-specific motivation, for course performance, and for teacher professional development.	**LD: R&T, A** and **MR: Motivational beliefs** (trait)
7.Jovanović et al (2019)	**GL:** S **PA:** PP, TLC **TC:** D&P, E **R&T:** video, readings, quiz, problem sequences, preparatory learning activities, evaluation tool in Canvas LMS **A:** F, S	BL	self-efficacy, task difficulty	Trace-based self-report: scores from evaluation tool.	Evaluated at least 35 activities in 2016, and 31 or more activities in 2017.	**Mixed effect linear model:** measure association between the way the students engaged with individual learning activities and how they perceived those activities in terms of difficulty and effect on their self-efficacy towards the course units. **Correlational analyses:** measure relationship between students' final exam scores and indicators of their overall evaluation of pre-class learning activities, i.e., if / how the students' course performance was associated with their overall perception of difficulty and self-efficacy effect of various learning activities they engaged with during the course.	**LD: R&T** and **MR: state Motivational beliefs** (state)
8.Kia et al. 2021	**GL:** LA **PA:** TLC **TC:** D&P, E **R&T:** assign. related recourses in Canvas LMS (discussions, handouts, examples) **A:** F	0	self-efficacy	MSLQ	Before	**Agglomerative hierarchical clustering** students into high, moderate groups based on measures of scores form the survey and engagement **Cohen´s kappa:** measure agreement between self-reported and observed SRL tags.	**No** Not clear the role of self-efficacy in the study.
9.Kizilcec et al. (2017)	**GL:** C **PA:** 0 **TC:** D&P, E **R&T:** video, readings, quiz, peer review in Coursera LMS **A:** F	MOOC	personal goal for the course, general interest, task value beliefs	OLEI	Before	**Penalized regression:** assess differences in SRL examined by demographics, prior experience, time commitment, goals and motivations by relevance values (predictors), e.g., job relevance, school, earn certificate, and interest (e.g., meet new people, personal growth, improvement, career, general interest).	**LD: R&T** and **SRL strategies** and **MR: Motivational beliefs** (trait)

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10.Larmuseau et al. (2018)	**GL:** S **PA:** TLC **TC:** D&P, E **R&T:** video, audio, curse recourses, quiz, peer-review activities in Moodle LMS **A:** F	O	self-efficacy, task value	MSLQ	Pre- and post	**SEM** and **correlation analysis:** measure influence of students' cognitive (i.e., prior knowledge) and motivational (i.e., task value and self-efficacy) characteristics on the use of the different LD components; and influence of the use of the different LD components on students' learning gain, taken into account students' cognitive and motivational characteristics (i.e., task value and self-efficacy).	**LD: R&T** and **MR: Motivational beliefs** (trait)
11.Milikić et al. (2020)	**GL:** Course **PA:** TLC **TC:** D&P, E **R&T:** video, readings, scaffolding intervent. In edX LMS and ProSolo (to support SRL) **A:** 0	MOOC	individual interest/ intrinsic motivation, self-efficacy, task interest, mastery goal orientation, performance approach, goal orientation, academic efficacy	questionary and PALS	Before	**Mixed effect model:** examine if motivational variables moderate the associations between the employed mirroring scaffolds and learners' self-regulation processes.	**LD: R&T** and **MR: Motivational beliefs and AGO** (trait)
12.Pardo et al. (2017)	**GL:** S **PA:** PP **TC:** D&P, E **R&T:** video, course resourses, quiz, exercises, dashboard in LMS **A:** F, S	BL	self-efficacy, intrinsic value, test anxiety	MSLQ	0	**Correlation anal.:** explore the relationship between the scales from the questionnaire, the aggregated scores of frequencies of all the engagement with events, and the academic performance results. **Hierarchical cluster analysis:** group students based on motivational and self-regulated variables, and students' academic performance. **Hierarchical multiple regression:** calculate which of the motivation, self-regulation, and engagement contributed to the academic performance.	**LD: R&T, A** and **MR: Motivational beliefs** (trait)
13.Schumacher & Ifenthaler (2021)	**GL:** LA **PA:** PP, TLC **TC:** D&P, E, Feedback **R&T:** video, readings, prompts in LMS **A:** F	0	task perception, self-efficacy	Prompt-based self-report: motivation included in the «All prompts» condition (combination of cogn., metacogn., motiv. & resource prompts).	T1 (after session1) and T2 (after session 2)	**Quasi-expm.:** Cognitive (CP), Meta-Cognitive (MP), C, M, Motivational and Resource related (AP), Control Group (CG). **Correlation and regression analyses:** examine (a) students' study related characteristics (perceived difficulty and confidence of the learning unit) and (b) their online learning behavior could significantly predict their learning performance in the knowledge transfer test. **MANOVA:** test whether the experimental groups differ in their perceptions of the prompts with regard to perceived learning support, perceived usefulness. **MANOVA:** determine whether the different experimental conditions vary regarding their online behavior within the learning unit.	**LD: R&T, A** and **MR: Motivational beliefs** (trait) Testing perceived confidence and difficulty as a predictor of participants' learning performance in a knowledge transfer.

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14.Srivastava et al. (2022)	**GL:** LA **PA:** TLC **TC:** D&P, E **R&T:** instruction and readings, writing task in Moodle LMS **A:** F	0	value importance/ attainment, task interest, task value utility, self-efficacy	Survey	Pre- and post	**Expm. study:** three. random. groups CG (Control), GE (Generalised) and PL (Personalised) general vs. individualised needs. **EM clustering:** detect SRL strategies based on the behavioural/ navigation patterns. **ANOVA:** measure effect of student's motivational status on SRL strategies used in the essay-writing task.	**LD: R&T** and **MR: Motivational beliefs** (trait)
15.Taub & Azevedo (2018)	**GL:** LA **PA:** PP **TC:** D&P, E **R&T:** game environment **A:** 0	0	intrinsic/personal motivation, task interest, emotion (facial expressions)	Self-report: EV, AGQ, PIQ (level of emotions, motivation and task interest).	Pre- and post, real-time	Grouped students in low- and high efficiency-emotion groups based on how efficiently they solved the task and how emotionally expressive they were during learning. **MANOVA**: measure effect between the groups (differences in these efficiency-emotion groups based on their behavioural patterns). **Chi-square**: significance of differences in behavioural sequences between emotion groups.	**LD: R&T** and **MR: Emotions** (state) and **Motivational beliefs** (trait)
16.Tempelaar et al. (2015)	**GL:** S **PA:** PP, TLC **TC:** D&P, E **R&T:** course materials, video, e-tutorials, LMS (BlackBoard) & e-tutorials MyLabs with feedback func. **A:** F,S	BL	adaptive thoughts, i.e., self-belief, value of school and learning focus; maladaptive thoughts, i.e., anxiety, failure avoidance, and uncertain control, emotions, i.e., enjoyment, anxiety, boredom and hopeless	Self-report on week 0 (learning motivation and engagement) and AEQ; week 4 (learning emotions)	Week 0 and Week 4	**Linear and hierarchic regression:** predict performance modeling by learning dispositions data, separate model for motivation and engagement, learning emotions and by all combining all available data.	**LD : R&T, A** and **MR : Motivational beliefs** (trait) Prediction performance.
17.Tempelaar et al. (2018)	**GL:** S **PA:** LT, PP, TLC **TC:** D&P, E **R&T:** video, readings, quiz, assign.SOWISO and MyStatLa, Blackboard LMS **A:** F, S	BL	**Based on EVT**: self-perception, task value, self-competence, individual interest, effort, affect **Based on CVTAE**: surprise, curiosity, confusion, anxiety, frustration, enjoyment, boredom **Other**: mastery- and performance approach	AEQ: academic control (enjoyment, anxiety, boredom, hopelessness, academic control); SATS instrument: affect, value, perception difficulty, interest, effort.	Dispositions: start of the course; Affect/Emotions: halfway in the course.	**Stepwise regression analysis:** test prediction models based on different constructs, including motivation and engagement. **K-means cluster**: build student profiles based on trace data, outcomes and survey data.	**LD : R&T, A** and **MR : Motivational beliefs, AGO** (trait)
18.Wang (2021)	**GL:** Course **PA:** PP **TC:** D&P, E **R&T:** video, text, discussion, quiz, peer review in Moodle LMS **A:** F, S	MOOC	self-efficacy, control of learning beliefs, intrinsic/extrinsic motivation, task value	MSQL	Week 4	**Multiple regression model:** examine if personal learning dispositions and students' past assessment data can help improve prediction ability for the various learning outcomes.	**LD: R&T, A** and **MR: Motivational beliefs** (trait) Prediction learning outcomes.

19. Wong, Baars, de Koning, Paas (2021)	**GL:** Course **PA:** TLC **TC:** D&P, E **R&T:** video, texts, pages, discussions, quizzes, and peer review assignment in Coursera **A:** F, S	MOOC	**Self-Determination Theory (SDT):** identified (intrinsic, extrinsic); controlled (introjected and extrinsic);	Prompt-based	Pre- and post-survey (week 2 and last week).	**Experimental study** (three randomised groups SRL-Q, SRL-QR, CG). **ANOVA**: examine effect of prompting SRL in MOOC by differences in any of the four SRL-related activities, course engagement, and performance across the three conditions (SRL-Q, SRL-QR, control group).	**No** Motivation was used to check that the three conditions did not differ significantly in their motivation at the beginning of the course.
20. Wong, Baars, He, et al. (2021)	**GL:** LA **PA:** PP, TLC **TC:** D&P, E **R&T:** video, prompt in Coursera **A:** F, S	MOOC and 0	task value, self-efficacy	Prompt-based self-report: OLVSES (Online Learning Value and Self-Efficacy Scale).	T1 (after introduction), T2 (after writing activity), T3 (after learning phase).	**Experimental study:** Study 1 with 1) MCII only, 2) prompt only, 3) MCII and prompt, and 4) control condition without MCII and prompt, **Study 2:** MCII only, goal only and control. **ANOVA:** compare task value and self-efficacy scores of the conditions measured at each of the three time points. **Kruskal-Wallis:** test assumption of normality was violated.	**LD: R&T** and **MR: Motivational beliefs** (state)
21.Zamecnik et al. (2022)	**GL**: 0 **PA**: 0 **TC**: E **R&T**: video, weblinks in Moodle LMS **A:** 0	P	intrinsic motivation (motivation for enrolling the course)	Survey	0	**LCA:** examine the different motivational factors and engagement of students in online settings. **Two-step approach**: models based on i) motivation survey data and ii) demographics, engagement and performance. **Chi-square:** test the statistical significance between each of the features.	**LD: R&T, A** and **MR: Motivational beliefs** (trait) Prediction of dropout based on the learner´ profile.

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