When Practice Meets Theory: From Trace and Self-Reported Data to Self-Regulated Learning Model

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Abstract

Self-regulated learning (SRL) –understood as the process whereby individuals activate and sustain cognitions and behaviours toward the attainment of their learning goals– is highly relevant because it gives learners independence and fosters lifelong learning. SRL has been widely explored and supported by technology-enhanced learning and learning analytics communities, as evidenced by the number of systematic literature reviews that can be found in these domains. Those reviews often highlight the scarcity of theoretical grounding and framing in specific SRL models. While numerous automatic data gathering and self-reported strategies have been proposed, it is still unexplored how existing trace-data indicators and self-reported data instruments for measuring SRL cover the aspects of the theoretical models. To address this gap, this study presents an analysis of 206 indicators extracted from three systematic literature reviews on traced data and SRL, and six instruments identified in one review on SRL self-reported data, mapping them towards the COPES model. The insights derived from this work can support researchers and tool developers to inform the selection of indicators and data sources, and raise awareness about the already covered and still missing SRL dimensions and phases.

Keywords

Self-Regulated Learning, Learning Analytics, Indicators, Trace data, Self-reported instruments, COPES model,

1. Introduction

Self-regulated learning (SRL) is highlighted as an essential skill for lifelong learning [1] or when facing technology-enhanced learning [2], where learners usually face situation which they have to manage autonomously [3]. While several authors have defined SRL (e.g., [4, 5, 6]), highlighting different nuances, there is something in common: SLR is understood as a process towards a learning goal. Also, there have been several attempts to model SRL. As illustrated in a recent meta-analysis by Panadero [7], these models differ in where the authors place the focus. For instance, some models emphasise emotions [8], while others highlight the role of the context [6, 4] or external evaluations [4].

SRL has gathered considerable attention during the last few decades in the Learning Analytics (LA) field, as illustrated by the number of studies and systematic literature reviews examining SRL through different educational contexts, such as flipped classroom [9], online learning [10], collaborative learning [11] or higher education [12, 13]. Interestingly, different reviews noticed that most of the studies do not justify their research regarding the underlying SRL theory [11, 14], nor do they relate the tool functionalities with the SRL processes [10].

To address this gap between theory and practice, this paper reflects on how existing trace-data indicators and self-reported data instruments cover the aspects elicited in SRL theoretical models. For that goal, first, we have taken as a starting point systematic reviews that identify LA indicators based

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on trace data [12, 2, 15] and self-reporting instruments [16] for SRL. Then, we have analysed each indicator and instrument, mapping them against an SRL model, specifically the one proposed by Winne and Hadwin since it covers not only the SRL phases but also other aspects such as the contextual and cognitive conditions [4]. The resulting mapping raises awareness about the coverage of SRL dimensions and phases by the studied indicators and instruments, and may guide tool providers and researchers in their selection of indicators as well as guide future research towards existing gaps in the literature.

2. Related Work

2.1. SRL Models

Several models have been proposed to describe SRL, as reported in the meta-analysis by Panadero [7]. Some models focus on the SRL process and its phases (e.g., forethought, performance, and self-reflection [5]). Others also identify additional dimensions to be considered, such as cognition and meta-cognition[8, 4], motivation/affect [17, 8, 4, 6], behaviour and context [6, 4, 8], or external evaluation [4].

While existing reviews in the LA field report that a minority of studies state and justify the SRL model they build upon (see, for instance, [13]), the most cited ones models according to [18, 11, 13] are those proposed by Zimmerman and Moylan [5] and Pintrich's [8].

For the context of this paper, we have selected the COPES model [4] to guide our analysis of trace-data indicators and self-reported data. This decision is triggered by two reasons: first, its holistic nature allows us not only to reflect on the process and phases that the learners go through, but also on related factors which are usually of interest when using self-reported data (e.g., task and cognitive conditions as well as the operations, standards or cognitive evaluations, or even external factors that affects the conditions and the process such as external evaluations). Secondly, it is grounded in a well-known synthesis of the literature on learning feedback [19].

2.2. SRL Indicators in Learning Analytics

Several reviews have extracted trace-data indicators used to analyse SRL. Peréz-Álvarez et al. [10] selected 42 papers on tools that support SRL, and identified 15 groups of indicators, classifying them according to their thematic (whether they were action, content, results, social, context, or learner related) and related SRL phases (namely, goal setting, monitoring, self-evaluation, help seeking, organization, strategic planning, time management, and self-reflection). The main finding in terms of indicators was that most of them were content-related (i.e., based on traces of the learners' interaction with the content). It should be noticed that the authors did not find indicators related to the social context (i.e., about how the learner interacts with others) or describing the learner in the tools, and only one was related to the context (more concretely, about the learner's location). The SRL phases were identified bottom-up, and the authors found indicators for all phases except for help seeking.

Du et al. [2] analysed 38 empirical papers about SRL in online or blended learning, extracting 70 indicators that used online trace data about SRL and classified them according to three processes (preparatory, performance, and appraisal) and subprocesses inspired by the models of Zimmerman and Moylan [5] and Pintrich [8]. The SRL category in which these authors found more indicators was evaluation, followed by time management. The authors highlighted that the same indicator was interpreted differently in distinct papers; thus, the study context cannot be forgotten in order to understand what indicators mean.

Alhazbi et al. [12], in a review of 25 empirical studies using trace data for measuring SRL, identified 101 indicators used in LA to inform SRL [12]. The authors categorized them into eight categories: engagement, study regularity, anti-procrastination, help-seeking, monitoring, planning, motivation, and environment structuring. Nevertheless, these authors did not reflect on the mapping of these indicators towards specific existing SRL models. The authors realised that some indicators misrepresented the complex SRL process, and the majority of the studies focused on just a course. They also highlighted the missing validation of indicators with SRL models.

Boulahmel et al. [15] identified 41 groups of indicators in their 53 selected studies on measuring SRL, both in LA and educational data mining. The authors grouped the indicators following the model proposed by Siadaty et al. [20], in which SRL is described around three main phases (planning, engagement, evaluation/reflection) and seven specific microprocesses (task analysis, goal setting, making personal plans, working on the task, applying strategy changes, evaluation, reflection). Each indicator of the review was interpreted as an observable manifestation of one of those microprocesses in the student interaction data. Their results reveal that indicators were used for behavioural analysis and student profiling, with little adoption for scaffolding SRL.

Among these reviews, some map the indicators against emerging SRL categories [10] or existing models [15, 2]. However, in these cases, the authors mainly reflect on the related SRL phases. On the other hand, while the remaining review [12] pays attention not only to the SRL phases but also to other aspects such as cognitive conditions (e.g., motivation), the authors picked the categories based on their interest, not attending to a model that tries to identify ”all” potential factors surrounding the SRL phases. Thus, there is a need for a mapping that employs a more holistic model to reflect on the coverage of LA indicators.

2.3. Self-reported Instruments of SRL

Roth et al. [16] carried out a systematic review of self-report instruments that measure SRL in higher education, identifying nine instruments: seven questionnaires, one interview, and one think-aloud technique [21]. Out of these instruments, we have selected the questionnaires for our study since they are more scalable for data gathering and processing. Table 1 presents an overview of each instrument. In addition, we have focused on the ones shared by their creators, therefore excluding LASSI as an

Table 1
Overview of questionnaire instruments for self-reported data in SRL identified in [16]. Those not selected for this study, since they were not open and accessible, are marked with (*).

Instrument name	Number of items	Item type	Thematics
Motivated Strategies for Learning Questionnaire (MSLQ) [22]	81 / 44	7-pt Likert	Self-efficacy, intrinsic value, test anxiety, self-regulation, cognition
(*) Learning & Study Strategies Inventory (LASSI)	80	5-pt Likert	Skill: Information processing, test strategies, selecting main ideas; Will: Anxiety, attitude, motivation; Self-regulation: Concentration, self-testing, study aids, time management
Inventory of learning styles (ILS) [23, 24]	120 / 60	5-pt Likert	Learning opinions, learning motivations, and learning activities
Academic Self-Regulated Learning Scale (A-SRL-S) [25]	55	4-pt Likert	Goal setting, seeking assistance, learning responsibility, organizing, self-evaluation, memory strategy, and environment structuring
Online Self-regulated Learning Questionnaire (OSLQ) [26]	24	5-pt Likert	Environment structuring, goal setting, time management, help-seeking, task strategies, and self-evaluation
Self-Efficacy for Learning Form (SELF) [27]	57	100-pt scale	Self-efficacy for learning
Self-Efficacy for Self-Regulated Learning Scale (SESRL) [28]	24	7-pt Likert	General organization and planning, task preparation strategies, environmental restructuring, recall ability, typical study strategies

ad-hoc payment is required to access the instrument.

3. Methods

This study adopts a bottom-up perspective, starting from concrete examples of indicators and instruments, going up to an SRL model. To select the indicators, we used as a starting point the reviews mentioned in Section 2.2 where the full list of indicators was provided by the authors [2, 12, 15]. Regarding the model, as justified in Section 2.1, we used the COPES[4] to guide the classification of the indicators. More concretely, we considered the following dimensions and subdimensions, as depicted in Figure 1:

- Task conditions: the external features of the studying situation. They define the environment and structure within which the learner works.
  - Resources: the materials and tools available for studying.
  - Instructional cues: the given instructions and information about the task.
  - Time: the temporal constraints.
  - Social context: the social surroundings of the task, including the presence or influence of peers, teachers, or other people relevant to the study situation.
- Cognitive conditions: the internal conditions of the learner that shape how the task is interpreted and how studying proceeds. These conditions may be changed during the task.
  - Beliefs, dispositions, and styles: the learner's ways of thinking or approaching learning, including assumptions about knowledge, learning, and her own capacities.
  - Motivational factors and orientations: the learner's goals, interests, incentives, and orientations.
  - Domain knowledge: the field's contents that the student has acquired previously.
  - Knowledge of task: the understanding of what is expected to be done.
  - Knowledge of study tactics and strategies: the awareness of the different study tactics and strategies a person has.
- Operations: the strategies the learner uses in order to complete the task.
- Products: the outputs of operations.
- Phases:
  - Task definition: The learner constructs a personal interpretation of the task. It involves identifying the task objectives, constraints, and resources.
  - Goals and plans: after defining the task, the student sets goals and develops a plan to address the task.
  - Enactment: The learner carries out the plan. It includes applying tactics and monitoring progress.
  - Adaptation: The learner reflects and adapts for future situations, leading to changes in knowledge, beliefs, and strategies.
- Standards: the expectations the student has about their development of the task and their products.
- Cognitive evaluations: when the learner compares the product with their standards and assesses what has been achieved.
- Performance: refers to what the student creates that others can observe.
- External evaluation: the products' feedback that could be received, e.g., from the teacher, a system or a peer.

Throughout the analysis, the triangulation of researchers was employed to cross-validate data and ensure the quality and rigour of the analysis and its findings [29]. The process was carried out by an interdisciplinary team composed of experts in education and computer science. To categorise indicators and instruments, the main author applied deductive coding, using [4] as a reference framework. Second, all dubious cases were discussed among the four authors. Third, taking into account the decisions from the previous step, the main author reviewed the codification again to ensure the same criteria were applied in all cases. Fourth, two authors went through all indicators and instruments, verifying the coding and raising potential disagreements, which were finally discussed and solved. Finally, each dimension was computed to measure the number of indicators and instruments informing them. The results of the coding process are openly available under Section 7.

4. Results

Figure 1 summarises the main outcomes from our analysis of 206 indicators and six questionnaires of self-reported data. In some cases, the indicators were not directly linked to elements of the model, but they could be potentially related depending on the situation (see asterics in Figure 1).

Regarding the indicators, we can observe that most of them refer to the *phases* (183), *task conditions* (174), *operations* (147 but 111 only potentially), and *products* (73). Regarding the phases, the enactment is by far the most analysed phase (133), while the rest of the phases vary between 21 and 27 indicators. The imbalanced attention to the different phases may be caused by the technological contexts where the trace data are collected. All reviews report that, in most cases, the data is collected from learning management systems or MOOCs (e.g., 67,5% of the papers in the review by [2]) in opposition to a few studies taking place in SRL platforms (e.g., 16,3% of the papers in [2]). While the former settings are mainly focused on supporting the distribution and interaction with the learning resources, they do not necessarily support the rest of the phases. On the contrary, the indicators referring to task definition, goals and plans, or adaptations are commonly associated with platforms specifically developed to support SRL. Then, among the task conditions, most indicators refer to resources (135), a few to time and social context (48 and 33, respectively), and a minority to instructional cues (4). This distribution could also be expected since most traces are generated while interacting with learning resources. It is noteworthy the scarcity of trace data indicators about cognitive conditions (2), which may be caused by difficulty in inferring the cognitive background of the learners' interactions with the systems.

On the other hand, analysing the instruments, we have detected that the six of them relate to the *cognitive conditions*, the *task conditions*, and *products*. This is explained because the instruments especially ask about the strategies and tactics that learners tend to use while facing different tasks, how they deal with the task conditions (e.g., with resources, time constraints, or other stakeholders), and the generated outcomes. Regarding the phases, all questionnaires cover the enactment, four of them the goals and plans, two the adaptation, and only one the task definition. As it could be expected, the *operations* dimension only appears in one instrument, since instruments are oriented to assess the learners' trends (in general), not the specific tasks they have just carried out.

One of the elements less explored both with *indicators* and *instruments* is external evaluations, with just 18 indicators and one instrument (A-SLR-S). This may be due to the fact that external evaluations are not considered in other SRL models, maybe triggering less attention. Nevertheless, external evaluations are quite important in Winne and Hadwin's model [4] as they might influence the conditions and standards of the learner.

5. Discussion

Our analysis reveals uncovered SRL aspects of the model. The scarce attention to the external evaluations and the adaptation phase is especially critical because they will affect the following SRL cycles, as well as the cognitive conditions of the learners. Thus, future research could explore alternative indicators or data sources that could inform the aforementioned gaps. Also, longitudinal studies that cover several SRL cycles would enable the understanding of how learners modify their studying tactics.

Also, the social context could gather further attention. While teasing out the social context without invasive and costly measurement could be challenging, insights from the computer-supported

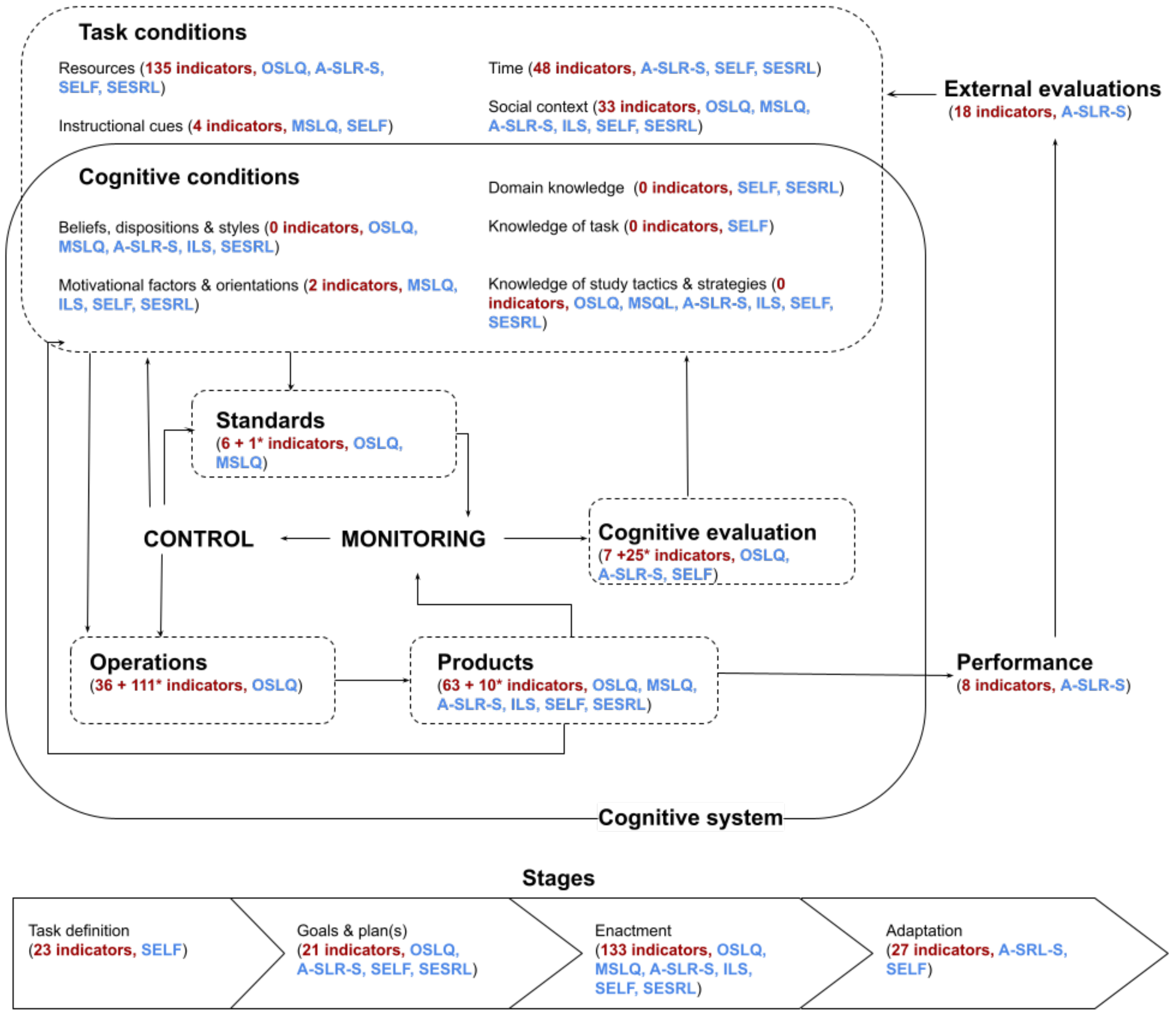

Figure 1: Number of trace data indicators and self-reported instruments (in red and blue) found per dimension and subdimension of the COPES SRL model as described in [4] (in black). The number of indicators is split between those referring directly to the (sub)dimensions and those potentially related (marked with *).

collaborative learning domain could be of great help in this regard (see e.g., [30]), contributing to a better understanding of how learners interact with their peers or instructors, as well as help-seeking behaviours.

As we have seen, while trace data indicators and self-reported questionnaires sometimes tackle the same elements enabling triangulation and cross-validation [12], the former primarily relate to SRL phases, whereas the latter mainly focus on task and cognitive conditions. Thus, combining both would be advisable so that they can complement each other, contributing to a better understanding of the relation between traces and learners' behaviours from a higher-level perspective.

It should also be noticed that the reviewed indicators and instruments focus on quantitative measures of SRL. Therefore, it would be advisable to also involve other data gathering approaches that could offer qualitative details and further insights about the SRL process, such as learning diaries. However, according to Roth et al. [16], structured SRL learning diaries have not been found. This fact opens a window to explore how to structure learning diaries so that learners can express their SRL process according to their conditions by adapting the reviewed questionnaires to reflect on the current learning tasks.

5.1. Limitations

Since our analysis builds on existing reviews on SRL trace data indicators and self-reported instruments, it is conditioned by the filtering criteria and periods covered in those works. In fact, in the case of self-reported data, our search was limited to one review about SRL instruments [16], but we acknowledge that instruments exist beyond those found in that review (e.g., SLQ and SRQ). Furthermore, we have not extracted the unique indicators among the three reviews, since in some reviews they were grouped, but not in others. Last but not least, our coding may lack accuracy since relevant details from the original papers have been potentially missed.

6. Conclusions and Future Work

Through this study, trace data indicators and self-reported instruments have been mapped against SRL theory, through the use of the COPES model by [4]. This mapping may help tool developers and researchers decide and reflect on the sources and data gathered about the different SRL dimensions (e.g., when designing learning analytics or scaffolding tools), contributing to having a more complete picture of the complex SRL phenomena.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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7. Online Resources

The coding of the indicators and instruments based on COPES model is available at: https://doi.org/10.5281/zenodo.20023381