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Citation for published version:
Siadaty, M, Gasevic, D & Hatala, M 2016, 'Trace-based micro-analytic measurement of self-regulated learning processes', *Journal of Learning Analytics*, vol. 3, no. 1, pp. 183-214. https://doi.org/10.18608/jla.2016.31.11

Digital Object Identifier (DOI):
10.18608/jla.2016.31.11

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Publisher's PDF, also known as Version of record

Published In:
Journal of Learning Analytics

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Download date: 27. Jul. 2024

(2016). Trace-based microanalytic measurement of self-regulated learning processes. *Journal of Learning Analytics, 3*(1), 183-214. http://dx.doi.org/10.18608/jla.2016.31.11

Trace-Based Microanalytic Measurement of Self-Regulated Learning Processes

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ABSTRACT: To keep pace with today's rapidly growing knowledge-driven society, productive self-regulation of one's learning processes are essential. We introduce and discuss a trace-based measurement protocol to measure the effects of scaffolding interventions on self-regulated learning (SRL) processes. It guides tracing of learners' actions in a learning environment on the fly and translates these data into indicators of engagement in SRL processes that reflect learners' use of scaffolding interventions and contingencies between those events. Graphs of users' learning actions in a learning environment are produced. Our trace-based protocol offers a new methodological approach to investigating SRL and new ways to examine factors that affect learners' use of self-regulatory processes in technology-enhanced learning environments. Our application of the protocol was described in a study about Learn-B, a learning environment for SRL in the workplace. The findings of the work presented in this paper indicate that future research can gain substantially by using learning analytics based on users' trace data and merging them with other quantitative and qualitative techniques for researching SRL beliefs and processes.

Keywords: Self-regulated learning, micro-level process, trace-based methodologies, learning analytics, graph theory, learning technology

1 INTRODUCTION

Self-regulated learning (SRL) is acknowledged as an essential skill for lifelong learning in today's knowledge-driven society (Klug, Ogrin, & Keller, 2011). It is often characterized as a process in which learners take initiative to identify their learning goals; and choose and regulate their learning strategies, cognitive resources, motivation, and behaviour to optimize their learning outcomes (Boekaerts, 1997; Winne, 2010a; Zimmerman, 1990). Several research studies show that, in various learning contexts, learners often sub-optimally regulate their learning processes or simply have inadequate models of their learning process that leads them to misevaluating their learning (Bjork, Dunlosky, & Kornell, 2013; Margaryan, Milligan, & Littlejohn, 2009; Winne, 2005).

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To address this challenge, self-regulatory scaffolds and pedagogical affordances have recently become of interest to researchers as a means to support learners' engagement in SRL processes (see, for example, Dabbagh & Kitsantas, 2005; Hadwin, Oshige, Gress, & Winne, 2010; McLoughlin & Lee, 2007; Zhou & Winne, 2012). Although empirical research has shown that scaffolding can foster learners' engagement in some of the main elements of metacognition and SRL — such as self-observation, self-reflection, or goal-orientation (Greene & Azevedo, 2010) — no methodological framework has yet been developed that can measure the impact of individual scaffolds, embedded tools, or different elements of SRL in the context in which they are used. The context also plays an important role in the effect of a given scaffold. Current research has shown that SRL is highly context dependent and specific features of a learning environment can influence whether learners engage in SRL processes and the extent of their engagement (Boekaerts & Cascallar, 2006; Whipp & Chiarelli, 2004; Winne, 2010a, 2010b). In most research studies, however, learner engagement in SRL processes is measured via self-reports that represent learners' perceptions of their own beliefs and abilities, statically and outside of the actual learning environment, rather than indicating their dynamic cognitive processes and responses in the immediate temporal context of scaffolding interventions. Although recent research has begun to pay more attention to methods for collecting data about learning as it happens through so-called trace data (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007; Winne, 2014), more work is needed showing how trace data are 1) integrated into research methods and 2) aligned with theoretical models of SRL in which effects of technological scaffolds for SRL are studied.

To be able to investigate whether, and to what extent, certain theorized SRL elements can be enhanced through scaffolds provided by software tools and interventions in a learning environment, in this paper, we introduce a trace-based methodology to measure use of SRL processes at both macro and micro levels, as well as the effect of tool components on certain theorized SRL elements. Macro-level processes indicate categories or phases of SRL as defined in the underlying theory such as planning, monitoring or evaluation, whilst micro-level processes indicate more specific activities within each of those phases or categories such as goal setting within the planning phase (Greene & Azevedo, 2009). In our research, we pursue an *event*-based conceptualization of SRL processes (Winne, 2014). We developed and applied a trace-based microanalytic measurement protocol methodology to investigate users' deployment of SRL processes in the authentic, dynamic context of learning. Via this methodology, learners' actions are captured on the fly and in the authentic context of occurrence. One of the greatest advantages of trace-based methodologies is that they allow for grounding analyses and inferences drawn from analyses on accurate and authentic data that proximally identify learning events in their very own context (Azevedo, Moos, Johnson, & Chauncey, 2010; Greene & Azevedo, 2010; Winne, 2010a, 2010b; Winne & Perry, 2000; Zhou, Xu, Nesbit, & Winne, 2010).

This paper does not aim to report on the findings of any specific study or introduce a theoretical model. Rather, it aims to introduce a novel measurement protocol for use in different studies that look at the effects of technological scaffolding interventions to support SRL. The protocol has been applied to two

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different studies (Siadaty, Gašević, & Hatala, 2016a, 2016b) that offer 1) theoretical details for the adopted SRL model and the choice and design of technological interventions, 2) hypothesized effects of the technological interventions on specific SRL phases, and 3) findings regarding the proposed protocol to both test the validity of the hypothesized effects and detect and explore which interventions had the strongest effects on specific SRL processes.

We organize this paper as follows: Models conceptualizing self-regulated learning processes and various methods used in the literature to measure these processes are introduced in Section 0. Section 0 describes our measurement protocol, starting with a discussion of the prerequisites for applying it, namely, formulating the underlying SRL model and the intended scaffolding interventions, followed by a detailed explanation of the steps in the protocol and examples of how we applied them in our research. Section 0 discusses the implications of the proposed protocol for both research and practice and Section 0 concludes by offering directions for future research.

2 ASSESSMENT OF SRL PROCESSES

In this section, we provide an overview of existing perspectives and models of SRL, and describe methods commonly applied in current empirical research for measuring SRL according to these perspectives.

2.1 Self-Regulated Learning: Conceptualization

The concept of SRL emerged from within educational psychology research in the 1980s and became increasingly popular as the concept of *learning to learn* found its way through educational environments. Since then, it has been a subject of extensive study in different disciplines, such as training, academic education, medical education, and educational psychology (Carmen & Torres, 2004; Karoly, 1993; Schunk & Zimmerman, 1994; Winne & Perry, 2000; Zimmerman, 2001).

Different models posit alternative views on how learning is self-regulated (Boekaerts, 1997; Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman & Schunk, 1989). SRL models in general aim to describe how learners take control of and manage their learning processes (Wolters, 2010). One way to differentiate these models is through different conceptualizations of SRL. One perspective offers an *aptitude* or *component* conceptualization, while another conceptualizes SRL in terms of *events* or *processes* (Dettori & Persico, 2008; Klug et al., 2011; Puustinen & Pulkkinen, 2001; Steffens, 2006; Winne, 2010b). The models using the *component* or *aptitude* perspective are more *trait*-oriented (Klug et al., 2011); they characterize SRL in terms of relatively stable, decontextualized individual differences (e.g., attitudes and beliefs) and identify cognitive, meta-cognitive, motivational, and emotional aspects of (self-regulated) learning. An important commonality within this category is that aptitudes, although relatively enduring, are considered *adjustable*, in that learners can be taught to develop the desired aptitudes, or transfer

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the level or nature of an aptitude as they progress through learning events (Winne, 2010a, 2010b). On the other hand, the *event* or *process* perspective is more concerned with the way learners approach problems and apply their learning strategies (Steffens, 2006) *in situ*. These models view SRL as proactive, goal-oriented processes that learners deploy to acquire academic skills and competencies (Klug et al., 2011; Steffens, 2006). Such processes are typically organized as a set of learning phases within which learners perform learning activities, e.g., tactics and strategies. These phases typically repeat during learning activities and may influence one another.

Another way to differentiate the existing models is by their theoretical underpinnings (Greene & Azevedo, 2007; Puustinen & Pulkkinen, 2001). The models proposed by Pintrich (2000), Winne and Hadwin (1998), and Zimmerman and Schunk (1989) are most empirically supported in the current literature. While these models share some overlapping conceptualizations, discussed in Section 0, the biggest differential is the theoretical background in which they are grounded.

Pintrich's (2000) and Zimmerman and Schunk's (1989) models are based on social-cognitive theory (Bandura, 1989), in that learning is shaped in terms of interactions between individual capacities, behaviours, and the environment. Although there is no universal, single definition for SRL, many recent works cite the definition provided by Pintrich (2000, p. 453): "*an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behaviour, guided and constrained by their goals and the contextual features in the environment.*" This definition reflects a goal-oriented perspective. Consistent with this perspective, in Zimmerman's view, "*students can be described as self-regulated to the degree that they are meta-cognitively, motivationally, and behaviourally active participants in their own learning process*" (Zimmerman, 2001, p. 15). Self-regulation in Zimmerman's social cognitive model is cyclic over three phases: forethought, performance, and self-reflection. Pintrich's framework of self-regulation is denoted via a four-by-four grid of *phases* and *areas*. The four phases include forethought, monitoring, control, and reflection. The self-regulatory activities related to each phase occur in four different *areas*, including the categories of 1) cognitive, 2) motivational and affective, 3) behavioural, and 4) contextual features of the environment.

Winne and Hadwin's (1998) model, on the other hand, is inspired by information processing theory (IPT). In this model, SRL is identified in terms of events, and unfolds over four loosely sequenced, potentially recursive stages. These stages include 1) task definition, 2) goal setting and planning, 3) studying tactics, and 4) meta-cognitively adapting studying techniques. The acronym COPES is used in this model to describe an IPT-based structure, in the form of *event units* common within the four phases (Winne, Jamieson-Noel, & Muis, 2002). It stands for Conditions, Operations, Products, Evaluations, and Standards. Except for operations, the other four elements represent information that learners take as input to, or produce as output of their learning process (Greene & Azevedo, 2007). *Conditions* include internal (i.e., cognitive conditions such as beliefs, domain knowledge, and motivation) and external (i.e., task conditions such as instructional cues and time available) information available to a learner that

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influences how the task will be engaged. *Operations* represent the cognitive processes, tactics, and strategies that learners perform to address the task. *Products* are the information generated as a result of *operations*, such as information recalled from memory. *Evaluations* are internal and external feedback about *products*, while *standards* are the criteria against which products and effectiveness of the operations used are monitored.

In line with the various models of SRL in the literature, there exist different approaches for measuring how learning is self-regulated. In the following, we discuss the measurement methods available, and mostly applied, in the current literature.

2.2 Self-Regulated Learning: Measurement

To provide a succinct yet inclusive overview of the available SRL measurement methods, we start with describing the taxonomy provided by Schraw (2010). This taxonomy is built upon the four articles in a special issue of *Educational Psychologist* dedicated to the topic of measuring SRL constructs (Greene & Azevedo, 2010). The taxonomy represents the big picture on this topic well since these articles forefront challenges and issues raised by pioneer researchers in this field.

In this taxonomy, Schraw (2010) divides applied measurement strategies into online and offline methods. Online methods are those to be applied during students' active learning episodes, while offline methods are taken before or after those episodes. Online methods can be either *obtrusive* or *unobtrusive*. Online, obtrusive methods require learners' "conscious attention." Such methods thus consume a portion of learners' "processing resources" and might interfere with their flow of cognition (not necessarily in a negative way). Among methods categorized under this label, *think-alouds* are perhaps the most frequently applied. Unobtrusive methods, on the other hand, are indicators that do not require learners' attention; they are gathered *in the background.* The most notable of these methods is *trace logs.* In general, traces can be any type of data collected from users' actions in a learning environment, such as their clicks on hyperlinks or options selected from a palette. Reading times and eye-tracking strategies are other examples of online, unobtrusive methods (Greene & Azevedo, 2010; Nesbit et al., 2006; Zhou et al., 2010).

Schraw (2010) categorizes offline methods into *self-reported beliefs*, *current abilities,* and *expected performance. Self-reported beliefs* represent learners' perceptions about their own beliefs and abilities. These reports may concern metacognition, epistemology, or self-efficacy, and might be measured in general or within a specific domain, e.g., self-efficacy for computer use. There exist a number of different self-report questionnaires in the literature that are often used in this regard (Carmen & Torres, 2004). For instance, the *Motivational Strategies for Learning Questionnaire* (MSLQ) is one of the most widely used self-report questionnaires (Credé & Phillips, 2011; Duncan & McKeachie, 2005). This questionnaire includes 81 items, and aims to assess learners' motivational orientation and use of different learning strategies relative to a specific course or subject matter (Pintrich, Smith, Garcia, &

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McKeachie, 1991). The *Learning and Study Strategy Inventory* (LASSI) is another frequently used self-report questionnaire designed mainly to assess the learning strategies that university students report using (Weinstein, Schulte, & Palmer, 1987). This questionnaire includes 77 items grouped according to ten scales, including attitude, motivation, time-organization, anxiety, concentration, information processing, selection of main ideas, use of techniques and support materials, and self-assessment and testing strategies.

Current abilities are existing abilities and skills that learners bring with them to a learning task (Schraw, 2010). These abilities might be general, such as students' intelligence or reasoning skills, or more domain-specific, such as their interest and past achievement in a given subject matter. *Expected performance* can be indicated through learners' pre-judgement of learning (JOL) regarding a learning task, as well as learners' verbal reports on their plans and intended strategies for successful learning. Such reports indicate how learners define and plan to carry out their learning goals, plus an articulation of their criteria for successful learning.

Another useful way to examine existing measurement methods is to look at how SRL constructs are conceptualized in the underlying model. Winne (2010b) and Winne and Perry (2000) describe protocols for measuring SRL categorized by whether they measure SRL as *events* or as *aptitudes*. *Inventories* and *think-alouds* are the main protocols used in the existing research to measure SRL as *aptitude*. In self-report inventories learners are usually asked about some characteristic of their learning strategies (e.g., frequency, likelihood, or difficulty), in a *loosely defined* context (e.g., when you study, in this course, or for exams). To answer such questions, learners rely on their memories and previous learning experiences in similar situations. Their responses are typically limited to a pre-defined set of options, e.g., a Likert-scale of 1–5. In *think-alouds*, learners are asked to speak about thoughts and decisions as they engage in learning. Contrary to self-reports, *think-alouds* do not require learners to *recall* from memory or think in a particular way as directed by instructions in self-reports. Think alouds have potential to indicate dynamic aspects of SRL (Winne, Zhou, & Egan, 2010). Nonetheless, these indicators are learners' *interpretations* about their "in-action" events, and who decides what events are taken into account when describing their choices and decisions. As well, think-alouds could activate cognitive and metacognitive processes that would not be triggered otherwise.

Unstructured interviews are another protocol used to measure SRL as aptitudes (Cleary & Zimmerman, 2012; Winne, 2010b). They are similar to *think-alouds* in that learner responses are not limited to pre-defined answers but different from think-alouds (and rather similar to self-reports) in that learners are asked about their SRL processes after the learning session has finished, or about *typical behaviour* that they foresee using in future learning situations (see, for example, Kitsantas & Zimmerman, 2002).

Traces (or trace-logs as phrased in Schraw's 2010 taxonomy) are the main protocol used (and suggested to be used) to measure SRL as events (Azevedo et al., 2010; Greene & Azevedo, 2010; Winne, 2010a, 2010b; Winne & Perry, 2000). Traces capture learners' actions *on the fly*, in the authentic context where

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they happen. They are defined as "observable indicators about cognition that students create as they engage with a task" (Winne & Perry, 2000, p. 551). For instance, a trace could be that the student highlights a text because he/she metacognitively monitors it as important, or clicks on a hyperlink based on a judgment that additional content would be useful at this moment. Although traces are the most suitable, available method to measure SRL "*as the dynamic, contextual and adaptive process it is theorized to be*" (Winne, 2010b, p. 275), they cannot and should not be considered the only method for measuring SRL constructs (Azevedo et al., 2010; Winne, 2010b). *Self-reports* and *think-alouds* still provide researchers with valuable information on learner perceptions about SRL, intentions, beliefs, and some motivational constructs. As noted to earlier, the underlying model of SRL affects how it should be measured. Besides clarifying their underlying model and conceptualization of SRL, it is important for researchers to decide which SRL constructs or processes are most important to their research, and then use measurement protocols most appropriate to measuring those processes/constructs.

Affordances of technology-enhanced learning environments provide opportunities to measure SRL processes based on learners' *traces* (Greene & Azevedo, 2010; Winne, 2010b; Zhou et al., 2010). Because traces are gathered within the learning environment and in their authentic context, they empower researchers to track learners' choices thoroughly and precisely, interactions with learning content, learning actions, and tactics applied on the fly. This method is often referred to as *Trace Methodology* in the contemporary research on measuring SRL features (Nesbit, Xu, Zhou, & Winne, 2007; Winne & Perry, 2000; Zhou et al., 2010). Winne (Winne & Perry, 2000; Winne, 2010b) defines traces as "records of behaviour, a form of performance assessment, that provide grounds for inferring a learner's cognitive and metacognitive activities." In other words, while the cognitive and metacognitive states of learners might not be visible to researchers, traces are the "observable indicators about cognition that students create as they engage with a task" (Winne & Perry, 2000, p. 551). Unlike inventories and think-aloud methods (see Section 0), trace methodologies enable researchers to unobtrusively track learners' experiences through actual, in-action evidence of their cognitive and metacognitive states rather than relying on learners' perceptions of their use of these processes, sampled from memory (e.g., in self-reports), or the portion that they decide to share with the researcher (e.g., in think-aloud or unstructured interviews).

Recently, several proposals have emerged for the use of traces (Molenaar & Järvelä, 2014; Winne, 2014) to study SRL based on sound theoretical principles and with a strong emphasis on advanced analysis methods such as process mining (Reimann, Markauskaite, & Bannert, 2014), graph theory (Hadwin et al., 2007), sequence mining (Zhou et al., 2010), and statistical discourse analysis (Molenaar & Chiu, 2014). However, much less attention has been paid to developing a protocol that would guide researchers in measuring and analyzing SRL processes concomitantly with the effects of technological interventions based on trace data collected by technology-enhanced learning environments.

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3 THE MEASUREMENT PROTOCOL

In this section, first we describe prerequisites to employing our proposed trace-based, microanalytic measurement protocol (summarized in Figure 1), and then provide a systematic process to assist researchers and practitioners in employing this protocol. We supplement each step with models from our previous research, illustrating comprehensive implementation and application cases of trace-based, microanalytic measurement protocols.

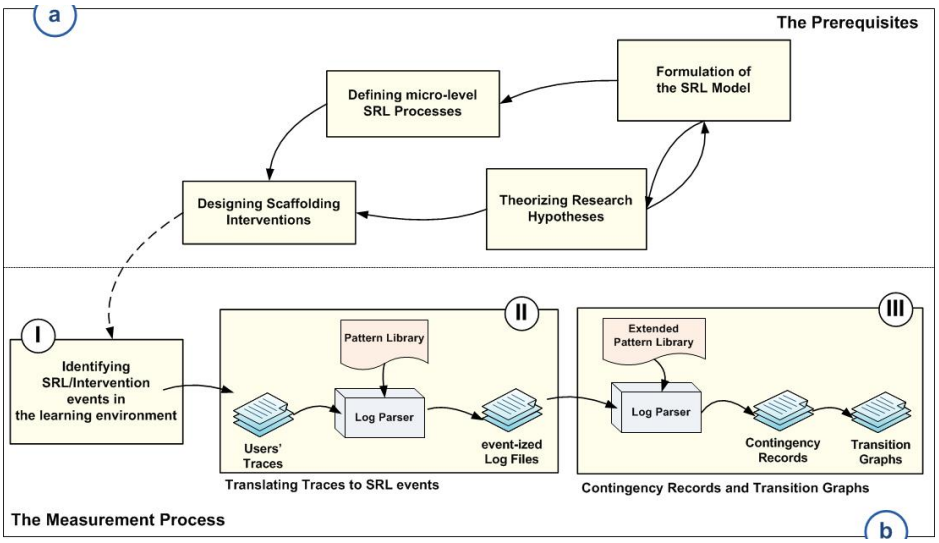

Figure 1:Trace-based microanalytic measurement protocol:
a) the prerequisites, b) the measurement process.

3.1 The Prerequisites

The measurement method applied reflects how SRL is theorized. To set the stage for valid interpretation of measurements and generalization, the selection, development, and deployment of a measurement method (or a combination of methods) should align with the underpinning SRL model or theory (Greene & Azevedo, 2010; Klug et al., 2011; Winne & Perry, 2000; Winne, 2010b). Thus, the first prerequisite for the application of this protocol is a precise and plain formulation of the SRL model underlying the research plus the type of conceptualization pursued (e.g., event, aptitude, or both), and the constructs and/or processes (e.g., the planning process or motivation constructs) of interest to the researcher(s) and intended to be operationalized in a scaffolding intervention. Once the underlying SRL model is identified, the second prerequisite is to theorize how scaffolding supports processes within this model, which lead to formulating the research questions and hypotheses. Accordingly, the first step in applying the measurement protocol is to define the processes/constructs included in the SRL model at a fine-grained, micro level — see Figure 1.a. This enables researchers to target highly specific self-regulatory beliefs and/or behaviours, supported via a theorized set of scaffolding interventions, as they occur in

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real time through individual engagement in specific (academic/non-academic) tasks across authentic contexts (Cleary, 2011).

We applied the proposed protocol in our research to investigate how a set of scaffolding interventions can support knowledge workers' SRL processes in the workplace (Siadaty, 2013; Siadaty, Gašević, et al., 2012). These interventions were tailored to their particular workplaces. In our related work, we provided a detailed description of the theoretical model along with the empirical and theoretical grounding for the SRL scaffolding interventions and how they are hypothesized to facilitated specific SRL processes (Siadaty et al., 2016a).

In the following subsections, we illustrate how the above prerequisites are met in the application of the protocol in the theorization, design, instrumentation, and measurement of the Learn-B tool. The section on the SRL model offers only an example of how it could be theorized and supported with the functionalities of a learning tool. The detailed theoretical underpinnings of the model discussed in the following subsection can be found in related work (Siadaty et al., 2016a).

3.1.1 The SRL Model

To meet the first prerequisite, in this section we illustrate and discuss the formulation of the underlying SRL model applied in our research. This model consists of three phases: 1) planning, 2) engagement, and 3) evaluation and reflection. They manifest the three common phases across the principal SRL models discussed in section 0, which, despite the terminology used, collectively characterize a number of phases proceeding from a forethought or preparatory phase, through a task performance or enactment phase, to a self-reflective and evaluation phase (Dettori & Persico, 2008; Puustinen & Pulkkinen, 2001; Winters, Greene, & Costich, 2008). The underlying SRL model applied in our research is grounded on these phases, as they encompass the need of contemporary knowledge workers to identify and plan their learning goals, apply strategies toward performing these goals, and reflect on their learning practices that would influence their subsequent preparatory processes. To define the fine-grained SRL processes in our model, a set of specific self-regulatory activities were identified per each phase based on the existing literature (Dettori & Persico, 2008; Greene & Azevedo, 2009; Puustinen & Pulkkinen, 2001). As coined by Greene & Azevedo (2009), the three common phases in our model are the "macro-level," and the specific activities within each are "micro-level" processes. These are discussed in the next sections.

3.1.2 Planning

This phase contains processes that precede acting and in particular includes activities related to analyzing a task at hand, setting related goals and planning strategies for achieving those goals (Dettori & Persico, 2008; Greene & Azevedo, 2009; Puustinen & Pulkkinen, 2001; Zimmerman, 2008). Entwined with task analysis, goal setting is often the premier step of a self-regulatory learning process. Learners vary significantly in the types and effectiveness of the goals they set for themselves (Valle et al., 2009; Zimmerman, 2008). Nevertheless, that there are differences in the nature and goals of learning processes between workplace context and formal education should be borne in mind. In educational

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settings, learning is a goal in itself; in workplace settings, it is mostly a by-product of work and task performance (Illeris, 2011; Ley, Kump, & Albert, 2010; Margaryan et al., 2009). Moreover, strategic planning is also closely associated with goal setting, whereby learners identify the appropriate strategies to perform in order to achieve their desired learning goals. In short, during this phase learners analyze a specific situation and/or identify the need to enhance their competencies, set their learning goals, select strategies to reach them, judge their perceived capability to reach the goals, and take the expected outcomes into their consideration. Table 1 describes the micro-level processes included in this phase.

3.1.3 Engagement

The Engagement phase refers to processes occurring during task effort. This phase facilitates a *feedback loop* (Zimmerman & Schunk, 1989) in that learners engage in their learning strategies, observe their performance, compare it with a standard benchmark (e.g., within the organization) or a goal, and apply appropriate strategy changes in order to respond to the perceived differences (Dabbagh & Kitsantas, 2004; see Table 1 for the micro-level processes included in this phase). This phase thus describes learners' efforts not only to enact their plans and strategies, but also to monitor and track their ongoing progress toward a learning goal and apply changes in their planned strategies if need be.

3.1.4 Evaluation and Reflection

This phase refers to processes occurring after a task ends or a goal is achieved. During this phase, learners compare their self-observed performance against some standard, such as prior performance, another person's performance, or an absolute standard of performance (e.g., some criteria established within their organization's culture). In addition, learners review and reflect on their learning experience. One key aspect of this phase is the generation of new meta-level knowledge about the whole learning process, strategies, or self, which in turn affects subsequent SRL processes (Winters et al., 2008). The two micro-level processes included in this phase are described in Table 1.

Table 1: Micro-level processes included in the SRL model and their descriptions (Siadaty, Gašević, et al., 2012).

Macro-level SRL process	Micro-level SRL process	Description
Planning	**Task Analysis**	To get familiar with the learning context and the definition and requirements of a (learning) task at hand
	Goal Setting	To explicitly set, define, or update learning goals
	Making Personal Plans	To create plans and select strategies for achieving a set learning goal
Engagement	**Working on the Task**	To consistently engage with a learning task, using tactics and strategies
	Applying Strategy Changes	To revise learning strategies, or apply a change in tactics
Evaluation & Reflection	**Evaluation**	Evaluating one's learning process and comparing one's work with the goal
	Applying Strategy Changes	Reflecting on individual learning and sharing learning experiences

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The theorized SRL model is supported by the scaffolding interventions described in the following subsection. The theoretical reasons for the use of specific scaffolds and the empirical results of their effects on each of the theorized SRL processes are reported elsewhere (Siadaty et al., 2016a).

3.1.5 Scaffolding Interventions

As alluded to earlier, existing research has shown that SRL is inherently contextual and the specific features of a learning environment can influence whether learners engage in SRL processes and the extent of their engagement (Boekaerts & Cascallar, 2006; Whipp & Chiarelli, 2004; Winne, 2010). Thus, to measure the effectiveness of certain scaffolding interventions on users' SRL processing, the second prerequisite to our proposed measurement protocol is to precisely formulate the context, i.e., how the designed interventions are expected to support the intended SRL processes. At a basic level, context can be modeled via a set of *Condition* (*If*)-*Action* (*Then/Else*) statements (Winne, 2010b). This model assists researchers to delineate the context of users' SRL processing via a theorized set of *If-Then* transitions, where *If*'s represent the specific intervention conditions in the learning environment (i.e., input information to users' learning process), upon which, i.e., *Then'*s, users could choose to operate an SRL action with respect to the applied SRL model.

According to the SRL model underlying our research, we have designed and implemented a set of scaffolding interventions to support users' SRL processes in the workplace. In particular, the design and implementation of the various functionalities of these interventions were enhanced with 1) social embeddedness elements to support the social nature of workplace learning and 2) support for the harmonization of individual learning goals with those of the organization to nurture the contextual dimension of learning in the workplace. These interventions were developed and integrated in Learn-B, a learning software we developed and applied in our research. The Learn-B environment aims to assist knowledge workers to create, maintain, and pursue their learning goals according to their competence gaps. In the following, we introduce these interventions and formulate the respective contextual hypotheses, as required in the second pre-requisite. Figure 2 depicts these interventions and their theorized supporting effect on users' SRL processing within the underlying SRL model. Greater detail about the development and implementation of these interventions are provided in Siadaty, Jovanović, et al. (2012) along with sample *events* from Siadaty, Gašević, et al. (2012).

The notion of context used in the definition of interventions builds on what Winne and Hadwin call international and external conditions. Conditions are not shown in the theoretical model used in the design of Learn-B, given in Table 1, as the model focuses on specific SRL micro-level processes. According to Winne and Hadwin (1998), external conditions are surrounding factors (e.g., instructional design and social networks) that influence learners' decisions associated with different micro-level SRL processes. For example, in the case of the study with Learn-B, social context was supported through different interventions that allow for social awareness, comparison, and co-operation in the following subsections. What Winne and Hadwin (1998) refer to as internal conditions (e.g., affective states, motivation, study skills) are not used in the studies with the Learn-B software (Siadaty et al., 2016a,

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2016b). Data about internal conditions can be obtained through self-reported measures, physiological measures, think-aloud protocols, video analysis, discourse analysis, and so on (Azevedo, 2015).

3.1.6 Usage Information

Derived from collective knowledge, this intervention informs users of various learning resources within the organization and supports the functionality of Recommendation interventions (described in a following section). In other words, this intervention was developed to inform users of the social context of their organization around a particular learning resource. Hence, the respective hypothesis on the effect of this intervention was that it helps users better understand the social context of their organization regarding their learning goals, and thus supports users in the planning phase of their SRL processes.

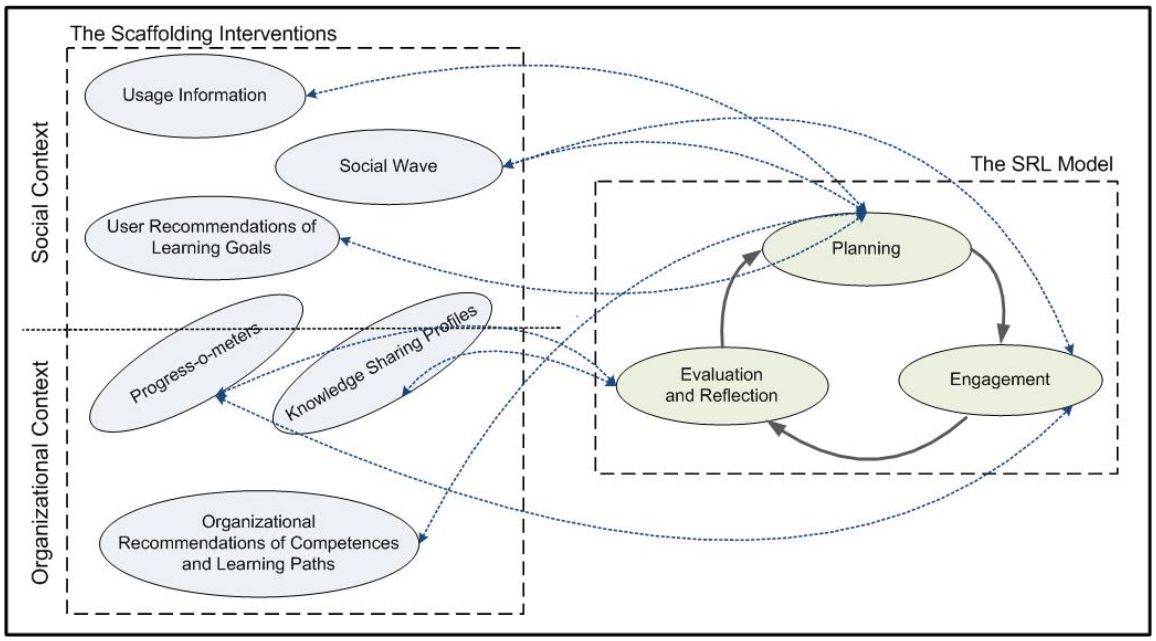

Figure 2. The theorized supporting effect of the scaffolding interventions on users' SRL processing within the context of the Learn-B environment.

3.1.7 Social Wave

The Social Wave intervention was designed to bring *waves* of the latest updates to knowledge workers about their learning goals, and the learning resources associated with each specific goal, plus updates from the learning activities of their colleagues whom they follow. The functionality of this intervention is similar to having a specific newsfeed for each specific learning goal or colleague about whom the user is interested in receiving updates. We hypothesized that Social Waves originating from users' learning resources or their followed colleagues support users in their planning and engagement processes.

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3.1.8 Progress-o-meters

We developed this intervention to help knowledge workers monitor their own learning progress within the context of their workplace. Being aware of one's progress in achieving learning goals, observing oneself within the social context of the organization, and comparing personal learning progress with colleagues provide users with the opportunity to gauge their learning strategies, apply the necessary changes if need be, and reflect on their learning process. The contextual hypothesis was that this intervention assists users with the engagement and evaluation/reflection phases.

3.1.9 User Recommendations of Learning Goals

This intervention enables users to recommend learning goals, along with all associated resources, to their colleagues. Allowing colleagues to recommend learning goals helps users with initiating their SRL cycles — i.e., the planning phase in particular — to perform task analysis and goal setting. Users can thus gain insight into how to define learning goals that target their learning needs, how such goals could be formulated, and how other members of the organization have approached these goals.

3.1.10 Organizational Recommendations of Competences and Learning Paths

This intervention informs users of the learning objectives and requirements of their organization, represented through a set of pre-defined and established competences, as well as recommended learning paths for achieving those competences. This helps learners harmonize their personal goals with organizational needs (Siadaty, Jovanović, Gašević, & Jeremić, 2010). Thus informing workers of the organizational competences of higher importance and relevance to them, their organizational positions, and level of expertise, along with paths for attaining each potential competence, helps them to identify their learning needs and therefore supports them in their planning.

3.1.11 Knowledge Sharing Profiles

Through knowledge sharing profiles, users can monitor the extent to which they share their learning experiences within their workplace in terms of owned learning resources, and compare their sharing activities with those of other users within the same group, project, or organization. This intervention informs users of the social context of the organization in terms of sharing and contributing to the collective, thus supporting users in the reflection phase. This intervention is meant to help users engage in the Reflection phase through increased self-awareness and social comparison.

3.2 The Measurement Process

Once the underlying SRL model is defined at both the macro and micro levels and the support provided by the scaffolding interventions is contextualized, researchers can capture user traces in a learning environment into log files and utilize them to measure the effect of the interventions on users' SRL processes/constructs of interest. We recognize three main steps within this measurement process (Figure 1.b). A complete reference for this process of identifying SRL and intervention events can be found in Siadaty et al. (2016a).

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3.2.1 Identifying SRL/Intervention events in the learning environment

Before collecting user traces into log files in a specific learning environment, those *events* that represent the enactment of the desired SRL (micro-level) processes must be identified. Perhaps the most straightforward way to trace users' learning activities is to log all their actions as they interact with different modules and components in the learning environment. However, one of the main challenges in analyzing log data for measurement purposes, especially in learning environments, is the complexity and excessiveness of the detail captured in raw logs. Log files can contain an abundance of low level events, such as mouse clicks on different components, which do not necessarily correspond to the learning variables and constructs of interest to a researcher (Zhou et al., 2010). To address these challenges, the scope of traced events should include only those that manifest the researchers' intended SRL context (defined via the second pre-requisite, see Section 0) and thus are of interest to their research questions and hypotheses.

Accordingly, in the first step of the measurement process, researchers need to define the sets of *SRL events* and *intervention events* that could occur. By *SRL events*, we mean those events that indicate that the user has enacted one of the micro-level SRL processes in accordance with the underlying SRL model, while *intervention events* represent the activation or usage of any of the scaffolding interventions. To identify these events, researchers should start by thoroughly examining the affordances of the learning environment or software in terms of the envisioned SRL processes and scaffolding interventions.

Descriptions of micro-level processes included in the underlying SRL model, which are elaborated on during the first pre-requisite to the measurement process (see Section 0), are used as a reference guide for identifying the related SRL events available in the intended learning environment. Looking up this reference guide, researchers should examine all the available software components and user interface elements per micro-level process, and decide whether and how any one of these components allows for enacting a particular process. For instance, we have defined the *Goal Setting* micro-level SRL process as *to explicitly set, define, or update learning goals.* Examining the Learn-B environment, we documented that users can define a new Learning Goal by "dragging and dropping an available competence to a new/existing learning goal" or update their learning goal by "removing a learning path from a competence." Sample events for each micro-level SRL process within the Learn-B environment can be seen in Table 2.

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Table 2. The micro-level processes included in the underlying SRL model and sample indicator events from the Learn-B environment (Siadaty, Jovanović, et al., 2012).

Micro-level SRL process	Sample SRL Events[1]
Task Analysis	Clicking on different competences under duties or projects related to the user Searching for a keyword
Goal Setting	Dragging and dropping an available competence to a new/existing learning goal Adding a new learning path to a new or existing competence
Making Personal Plans	Choosing an available learning path as the path for a certain competence Assigning a recommended learning path as the chosen path for a competence
Working on the Task	Request collaboration for a competence, learning path, or learning activity Marking a learning goal, competence, or learning activity as "completed"
Applying Strategy Changes	Adding a new activity to an existing learning path Updating the properties of a learning activity, e.g., its name, start date, expected duration, visibility, rating, keywords, and user progress
Evaluation	Rating a learning path, learning activity, or knowledge asset Adding new keywords to or updating existing keywords of a learning goal, competence, learning path, learning activity, or knowledge asset
Applying Strategy Changes	Adding a comment for a competence, learning path, or learning activity Recommending a learning goal to a colleague

To define the intervention events, researchers should follow an approach similar to the one above for SRL events. Here, the reference guide is the hypothesized effect of each intended intervention (as documented within the second pre-requisite; see Section 3.1 for more details). Referring to this guide, the researchers then scan the different forms and features of each scaffolding intervention, which are implemented and available in the intended software, and document the different ways that users can trigger a given scaffolding intervention. For instance, *Usage Information* is one of the interventions that we theorized would assist users with their planning practices. This intervention was implemented within the Learn-B environment via three different features: *Analytics*, *Social Stream*, and *Social Stand*, which were available for various resources such as competences, learning paths, and learning activities. Analytics, for example, provided users with statistical information such as the number of times that competences required for a specific duty were added the learning goals of other users. Thus, we documented that users can trigger this intervention by clicking the "Achievement tab (under Analytics)

[1] Within the scope of the research presented in Siadaty, Jovanović, et al. (2012), user learning goals are defined in terms of *competences.* Associated with each competence comes one or more *learning path(*s). Each learning path is comprised of one or more *learning activities*, and leads to the attainment of a specific competence at a specific level. Each *learning activity* is accompanied by a set of metadata specifying its content, process and planning information (e.g. title, description, average time required, and delivery mode), and a set of *knowledge asset*s. Knowledge assets can be in the form of learning contents such as documents, books, weblogs, videos, or presentations; or human resources such as a knowledgeable colleague who has already successfully completed this learning activity. Finally, a (*learning*) *resource* is the umbrella term used to refer to a competence, learning path, learning activity, or knowledge asset.

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of an available competence, learning path, or learning activity"; or, by clicking "the comments tab of a competence, learning path, learning activity, or knowledge asset" which represented the Social Stand dimension of this intervention. Table 3 provides sample events for the proposed interventions implemented within Learn-B, as discussed in Section 3.1.2. Appendix A: SRL and Intervention Events in the Learn-B Environment provides the full list of all SRL and intervention events collected in our research. Such events need not necessarily be unique; that is, an event could be representative of one or more micro-level SRL processes, or one or more scaffolding interventions. For instance, we had considered the event "Adding a new competence to an existing learning goal" as a traceable action for both micro-level SRL processes of *Applying Appropriate Strategy Changes* and *Goal Setting*, categorized respectively under the *Engagement* and *Planning* macro-level phases.

Table 3. The proposed scaffolding intervention and sample events from the Learn-B environment (Siadaty, Jovanović, et al., 2012).

Intervention Feature	Sample Intervention Events
Usage Information	Clicking on the Achievement tab (under Analytics) of an available Competence, Learning Path, or Learning Activity Clicking on the data tab of a Competence, Learning Path, Learning Activity, or Knowledge Asset
Social Wave	Clicking on the Social Wave tab of one's Learning Goal, Competence, Learning Path, Learning Activity, or Knowledge Asset Clicking on Duties, Roles, Tasks, or Projects folder
Progress-o-meters	Clicking on the Goal-o-meter tab (under Analytics) of one's Learning Goal Clicking on the Progress-o-meter tab (under Analytics) of a Learning Activity
User Recommendations of Learning Goals	Clicking on a single Learning Goal under the Recommended Learning Goals folder
Organizational Recommendations of Competences and Learning Paths	Clicking on Users who are acquiring/have already acquired an available competence Clicking on a Learning Path for an available competence Clicking on the data tab of an available Learning Path, Learning Activity, or Knowledge Asset
Knowledge Sharing Profiles	Clicking on one's Analytics tab (the Knowledge Sharing Profiles tab is the only tab, so will open automatically)

3.2.1 Translating Traces to SRL events

Once the desired SRL and intervention events are defined, a tracking tool can be developed to capture and record these events in log files. However, based on the affordances of a given learning environment, users' actual, traceable actions are most often at a lower granularity than the desired events that researchers aim to track and capture. That is, the learning environment captures user interface elements not directly related to the "semantics" of SRL micro-level processes and interventions. Often

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an entire sequence of traceable actions represents a single event. To fully capture all the occurrences of a desired event in a specific learning environment, therefore, researchers need to first identify the series of low level events (e.g., at the level of mouse clicks) that represent each of the desired SRL/intervention events (e.g., creating a new learning goal/task). The previous step of the protocol (see section 0) is meant to assist researchers in identifying these series. Accordingly, researchers can start by examining the primary paths — i.e., a sequence of actions within the learning environment — that lead to performing a specific event. Once the initial set of sequential actions is identified, researchers need to examine various use cases, such as alternate paths, for performing the desired SRL/intervention events to ensure that all possible actions leading to that event in the given learning environment are identified.
A tracking tool can then be developed to capture and store these identified user actions into log files. After all the log files are collected, researchers need to develop a *parsing* algorithm to *translate* the finer-grained user actions into chunks of coarser-grained desirable events. To this end, researchers can code a sequence of low-level, fine-grained actions into patterns that repeat across users' logged actions. Next, pattern matching mechanisms such as regular expressions (Mitkov, 2003, p. 784) can be utilized to develop an algorithm to mine users' log files and locate the matching patterns as defined by the researcher, translating them into the desired SRL/intervention events.

So far in this paper, we have focused on SRL events and described how they were defined, operationalized, and measured. In the following, we describe how this step of the measurement protocol was conducted in our research.

The raw learning logs generated by the system during users' interactions within the Learn-B environment often contained two or more events per mouse click. Each event was captured as a stand-alone record with a unique identifier; some were common across various user actions, and some were specific to one or more affordances of the software. For instance, when users clicked on different nodes representing various learning resources, two basic events were always fired: one selecting the node, which we called a *SelectNodeEvent*, and one opening a tab on the right-hand side of the tool where the user could see more detailed info about that resource, which we called an *OpenTabEvent*. On the other hand, creating a learning goal, a user-defined learning path, learning activity, or knowledge asset were all represented through the *Create* event. Thus, the attribute *eventType* (shown in Figure 3) was used to denote the *type* of each event as it was recorded by the system.

Moreover, to capture the *SRL* events in their authentic settings, it was important that users' actions be captured in their full context, containing all the events involved, as well as the detailed information related to each event. This additional information, for instance, included the *resourceType* (shown in Figure 3) on which the event was applied, the unique identifier to access that resource, and additional information such as the name of the node accessed and its hierarchical level in the tool. Accordingly, as users interacted with the different tools within the Learn-B environment, data were logged at the level of the abovementioned *eventTypes*, accompanied by additional information (if any), and written to records in the database tables set up in advance for this purpose.

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Figure 3 shows a snapshot of the trace data, collected by the system on the fly. For instance, when a user added a new keyword to a knowledge asset, the system recorded that a *TaggingEvent* was performed by this specific user, on this learning resource, followed by an *Edit* event. Both events were time-stamped to the full date and time of their occurrence. Further information included type of tag (e.g., keyword), text of the tag itself (e.g., "documentation"), the type and title of the learning resource being tagged (e.g., "Knowledge Asset" and "Basics of SW documentation — standards," respectively), as well as the URIs (Uniform Resource Identifier, which indicates where a resource is stored) of all the entities involved, i.e., the user, the knowledge asset, and the user-added tag. The blue box in Figure 3 represents this example.

userEvalUserNo	eventTime	eventId	eventType	propKey	propValue	resourceType	resourceURI
LA77	2012-0...	17684	SelectNodeEvent	nodeView	target	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17684	SelectNodeEvent	nodeid	1.1.3.1.2...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	tabName	Asset For...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	nodeTitle	Referenc...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	nodeRelName	ASSET	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	nodeView	target	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	serviceName	LPC	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	nodeid	1.1.3.1.2...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17686	TaggingEvent	keywords	website	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17687	Edit	keywords	website	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17687	Edit	visibility	Public	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17687	Edit	assetURL	/reference/	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17688	SelectNodeEvent	nodeTitle	The C Pro...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17688	SelectNodeEvent	nodeRelName	ASSET	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17688	SelectNodeEvent	nodeView	target	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17688	SelectNodeEvent	nodeid	1.1.3.1.5...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	tabName	Asset For...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	nodeTitle	The C Pro...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	nodeRelName	ASSET	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	nodeView	target	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	serviceName	LPC	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	nodeid	1.1.3.1.5...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...

Figure 3. A snapshot of the log files generated within the Learn-B environment.

To identify patterns indicating occurrence of the intended *SRL* events within the collected trace data, in the second step of the measurement process, we developed a *pattern* library. This library consisted of patterns of sequential event types corresponding to each of the previously defined SRL events. We systematically examined the Learn-B environment to identify these patterns, that is, sequences of lower-level events triggered, along with their specific details, and captured by the tracking tool when users performed each of the SRL events (see Table 2). This included running each of the micro-level SRL processes via their indicator events as defined in the previous step, and recording each triggered event. For instance, one of the identified SRL events for task analysis micro-level process was "exploring competences included in other colleagues' learning goals." Performing this single action triggered three low-level events in the environment:

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1) An *OpenTabEvent* could have been fired, depending on whether users clicked on the *Users* tab in the Learn-B interface or directly approached a specific competence
2) A *SelectNodeEvent* (clicking on the desired competence) would happen
3) An *OpenTabEvent* was fired to provide more information about that competence

Figure 4.a shows these three low-level events and the detailed information specific to each of them.

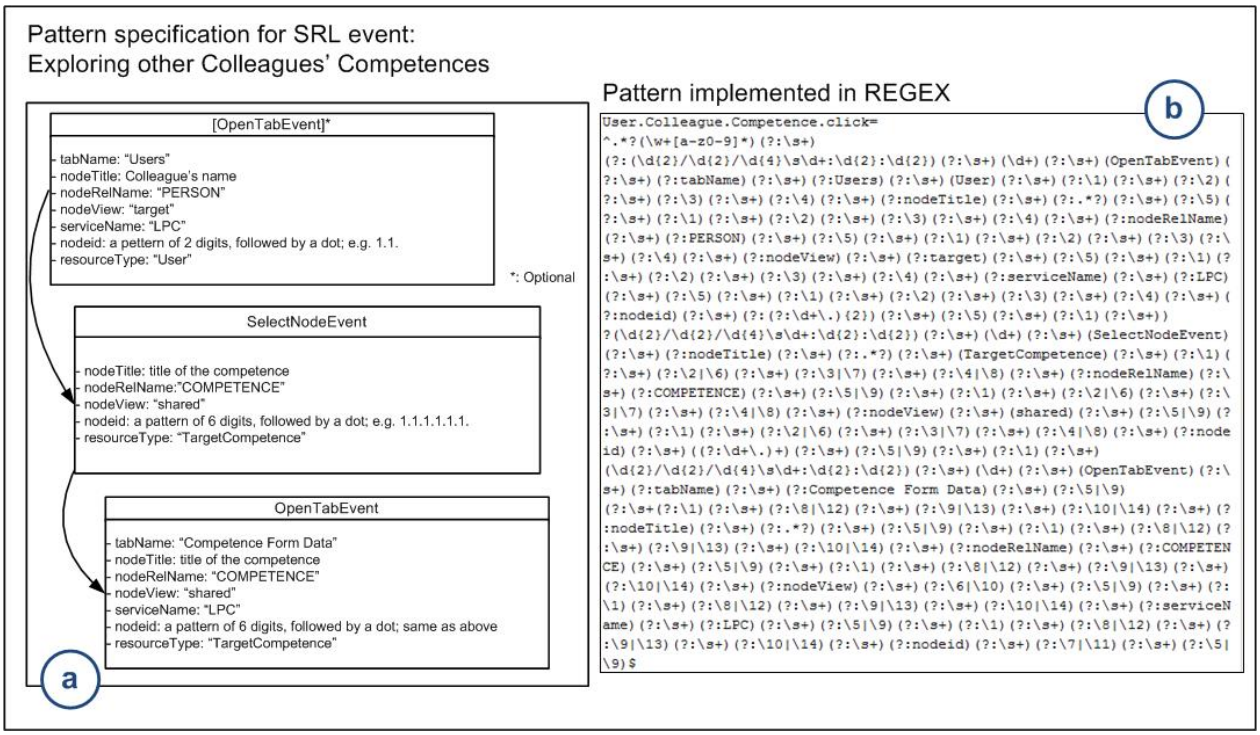

Figure 4.A sample pattern in the pattern library, denoting the SRL event "exploring competences included in other colleagues' learning goals": a) pattern specification, b) pattern implemented using regular expressions.

To implement the parsing process, we developed an analyzer module called *Log Parser*. This module received users' raw log files as input and matched them against the *patterns* defined in the *pattern library* — see Figure 1.b.II. The input was in the form of textual collections of trace records across various learning sessions, retrieved from the respective databases and aggregated into one concrete log file per user (a portion of such log files is shown in Figure 3). The patterns were defined in terms of regular expressions. Regular expressions, or "*regex*" in short, are basically strings of characters which denote a pattern and are often used to find a particular text, replace it with other text or validate a

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given input (Habibi, 2004). Figure 4b shows the regex implementation of the three-event pattern for the SRL event *exploring other colleagues' competences* as shown on the left of Figure 4.[2]

The pattern-matching algorithm in the Log Parser was implemented to first search for occurrences of all available patterns defined in the *pattern library* in users' log files, and then replace the matching event records with a single record indicator of the occurrence when a successful match was found. Thus, the output of the Log Parser was a new version of each user's log file in that extraneous events that did not have a matching pattern in the *pattern library* were removed from user's traces, and the output file contained only coarser-grained SRL (and Intervention) events aggregated from users' lower-level traceable actions. Figure 5 shows a portion of a user's raw log file as the input to the Log Parser (a), and the *event*-ized log file as the output of this module (b). As can be seen in this figure, the series of lower-level traces generated for the event record 15313, for example, are translated into the intervention event *User clicking on an Activity*. This represents the intervention feature "Organizational Recommendations of Competences and Learning Paths." The traces for event record 15315 are then translated into the SRL event *User clicking on a colleague's competences*, which represents the micro-level SRL process "Task Analysis."

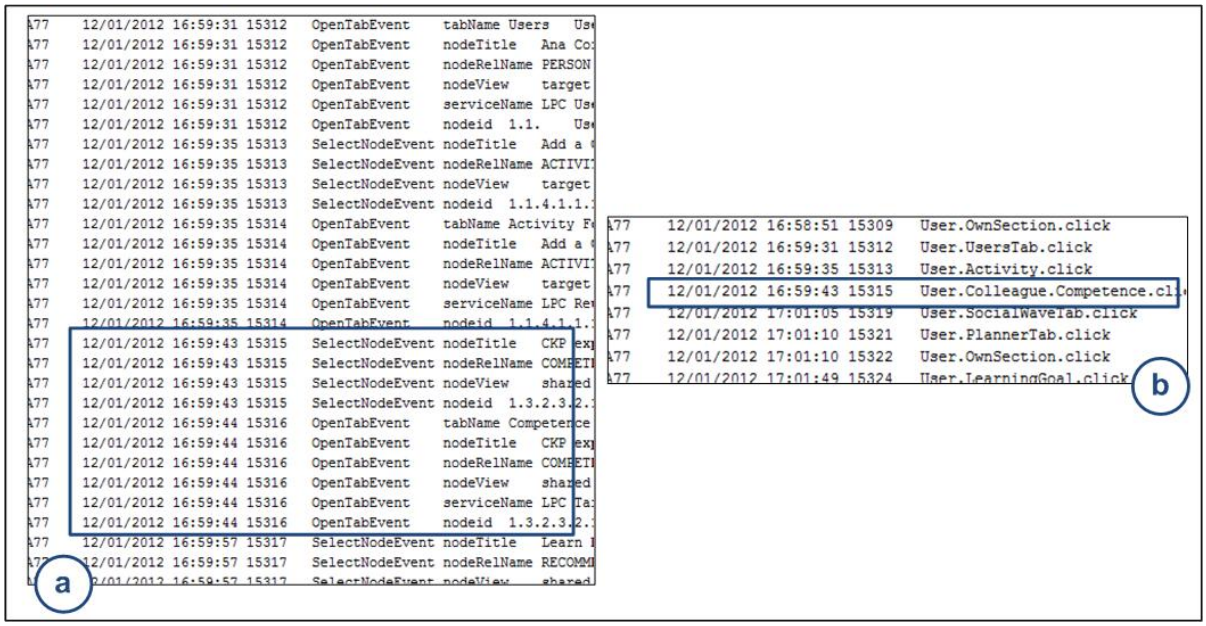

Figure 5. A sample user's a) raw log file, b) event-ized log file as the output of the Log Parser. The blue box shows the traceable records related to the SRL event in Figure 4.

[2] Tools for pretty printing of regular expressions are available, but their discussion is beyond the scope of this paper. Some relevant discussion can be found, for example, at http://stackoverflow.com/questions/5312301/is-there-some-good-visual-regular-expression-editor

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3.2.2 Creating Contingency records and Transition graphs

Translating users' raw traces into *event-ized* log files as described in the previous section (and depicted in Figure 1.b.II) allows for operationalizing the event-based conceptualization of SRL in terms of an event's *occurrence* (Azevedo et al., 2010; Winne, 2010b; Winne & Perry, 2000). An *occurrence* provides a window for the researcher to observe the evidence (or product) of user cognition operations. Hence, an occurrence is merely a tally of an observable state and does not convey any information about the context. As such, occurrences allow for performing frequency counts of users' engagement in SRL processes, but they fail to capture transitions between those processes. Such transitions can provide a fuller picture of the contextual, dynamic nature of self-regulated learning, especially in today's technology-enhanced learning environments (Winne, 2010a).

To include elements of context in the trace-based microanalysis measurement of SRL processes, we need to explore the *contingencies* between users' actions, and build the *transition graphs* of these contingencies in the third step of the measurement process. This allows for going beyond simple frequency counts of actions and occurrences and instead probing into the context of such occurrences, such as the states preceding a subsequent SRL event. Contingencies in general show what subsequent event was preceded by which prior event. Accordingly, they include some features of context in them and operationalize the event-based approach to measuring SRL at a higher level than *occurrences*. A *contingency* can be modelled in terms of a conditional *if-then* (condition-action) relationship (Winne & Perry, 2000; Winne, 2010b), where a set of *if-then* transitions can be used to represent the context of users' SRL processing as discussed earlier in Section 3.1. For example, when it is observed in the trace data of a given user that he/she "includes a specific competence in their learning goals" immediately after "knowing about other users' comments about that competence," the former event represents the *condition*, and the latter demonstrates the *action*. Here, the *condition* is a learning event indicating use of the respective scaffolding intervention, while the *action* is an SRL event indicative of the goal-setting micro-level process. For example, if out of 20 competences included in a user's learning goals, 12 were included immediately after viewing other users' comments, we can describe a conditional probability that this user metacognitively considers collective intelligence important when creating his/her learning goals (Pr[others comments|included competence] = 12/20 or 0.6).

In addition to the contingencies between learners' enactment of SRL events (and other relevant events, such as scaffolding Intervention events), researchers can build transition graphs of users' learning actions and examine the predominant transition patterns. Transition graphs illustrate users' navigation between various events, e.g., using some scaffolding Interventions and performing SRL processes. Moreover, they can reveal a variety of quantitative measures adapted from graph theory, which could be used in describing features of SRL processes. Centrality metrics, such as *degree*, *betweenness*, *closeness,* and *eigenvector* centrality, can be used to denote the relative importance of a node within a graph (Borgatti, Mehra, Brass, & Labianca, 2009; Landherr, Friedl, & Heidemann, 2010; Yan & Ding, 2009). For example, centrality metrics enable us to look at the more influential processes across users' learning sessions, or explore useful patterns such as strategies more practiced by users with a common

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background, organizational position, or project team. A detailed discussion of the use of graph statistics for analysis of different aspects of SRL is provided by Hadwin et al. (2007).

To mine the existing contingencies and build the transition graphs in the third step of the measurement process, researchers need to perform another level of pattern matching on users' *event-ized* log files. The objective of this step is to translate all indicator events, i.e., those included in the *pattern library*, to their respective SRL (and Intervention) events. Hence, the *pattern* library could be extended with additional sets of higher level, more general patterns that show which *patterns* manifest engagement in, or usage of which SRL or Intervention event. For example, Figure 6.a lists the textual description of the set of SRL events that show the *Working on The Task* micro-level SRL process, as described in Appendix A. Figure 6b shows how this micro-level SRL pattern can also be defined in terms of a regular expression containing the set of its representative SRL events, added to the extended *pattern library*. The blue box in this figure shows one of these SRL events generated from a user's low-level mouse clicks into their *event-ized* log file, as shown in Figure 5.

Events indicator of the SRL Micro-level Process: Task Analysis

Micro-Level SRL Process	SRL Events in Learn-B
Task Analysis	Clicking on Duties, Roles, Tasks or Projects folders
	Clicking on a single Duty under the Duties folder
	Clicking on a single Role under the Roles folder
	Clicking on single Task under the Tasks folder
	Clicking on single Project under the Projects folder
	Clicking on different Competences related to a Duty, Role, Task or Project
	Selecting Competences from other Colleagues' learning goals
	Searching for a keyword

a

Pattern implemented in REGEX

```
SRL.Planning.TaskAnalysis=
^.*?(\w+[a-z0-9]*)(?:\s+)(\d{2}/\d{2}/\d{4}\s\d+:\d{2}:\d{2})(?:\s+)(\d+)(?:\s+)
(Available.DutiesFolder.click|
Available.DutiesFolder.Duty.click|
Available.Competence.click|
Available.Competence.DataTab.click|
User.Colleague.Competence.click|User.Keyword.Search)$
```

b

Figure 6. A pattern in the extended pattern library that denotes all of the SRL events indicative of the "Working on the Task" micro-level SRL process: a) list of the indicative SRL events as described in Appendix A; b) the pattern implemented in REGEX.

It is important to note that depending on the underlying SRL model, each intervention or SRL *event* could be an occurrence indicator for one or more of the researcher's intended micro-level SRL processes. In the third step of the measurement process, hence, when translating the *SRL/intervention* events to higher-level micro-level SRL processes, each occurrence of an event should be translated into

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as many micro-level processes as it is defined to be representing (see Section 0). For example, in our research within the Learn-B environment, the SRL event "adding a new learning object (e.g., uploading a document or a bookmark to a web page) to an existing learning activity" was defined as an SRL event indicative of three different micro-level SRL processes: 1) *Goal Setting*, 2) *Making Personal Plans* (both related to the *planning* process), and 3) *Working on the Task* — related to the *engagement* process (see Appendix A). Accordingly, each instance of the event pattern "User.Activity.AddNewAsset" in a user's log file was translated into all three SRL events (see Figure 7).

Contingency records, built from user data, demonstrate the sequential stream of a user's actions as the users interact with different entities in a learning environment. In the last step of the measurement process, a graph analysis tool can be used to build the transition graphs out of users' contingency records. Once the transition graphs are generated, graph analysis techniques can be applied to elucidate graph statistics and study users' SRL processes and use of scaffolding interventions within a given learning environment.

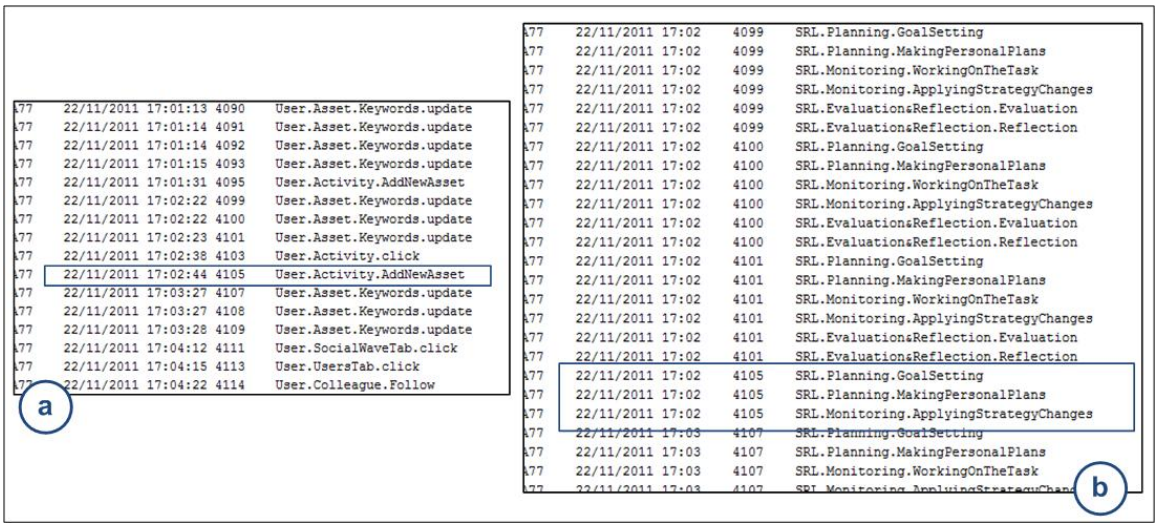

Figure 7: A sample user's a) event-ized log file, b) event-ized log file translated into contingency records. The blue boxes show how one event pattern could be indicative of, and thus translated into, two or more SRL/Intervention events.

In our research within the Learn-B environment, we used the Gephi open source software (Bastian, Heymann, & Jacomy, 2009) to build the transition graphs from users' contingency records, and analyze the generated graphs in order to paint a fuller picture of how the proposed scaffolding interventions and/or engaged in SRL processes were used. The Gephi tool supports multiple file formats for importing the graph file, including CSV, GDF, and GEXF. We used the CSV file format to store users' trace data in terms of nodes and edges in a graph, a format that could then be imported into the Gephi tool to generate the transition graphs. Here, a transition graph shows conditional contingencies, where nodes represent user actions — i.e., performing SRL or Intervention events within the Learn-B environment — and each directional link between nodes represents a transition between two events.

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Figure 8 shows a sample transition graph generated from a user's trace data. For a less cluttered visual representation, only the links of interest to our research question,[3] i.e., those directed from an Intervention event to other nodes (either SRL or Intervention nodes), are shown in this graph. The bigger the size of a node, the more influential in users' learning events, and the thicker a link, the more frequent that contingency has appeared in a user's parsed trace data. To investigate our research question, we calculated the graph theoretic centrality measures (Bastian et al., 2009) for each proposed scaffolding intervention within the graph of user learning actions. Centrality denotes the relative importance of a node within a graph and could be identified via degree, betweenness, closeness, or eigenvector centrality, the most commonly used centrality measures in various domains (Borgatti et al., 2009; Freeman, Roeder, & Mulholland, 1979; Landherr et al., 2010; Yan & Ding, 2009). These graph statistics can be used to reveal the relative importance of researchers' desired interventions within a network of user learning actions.

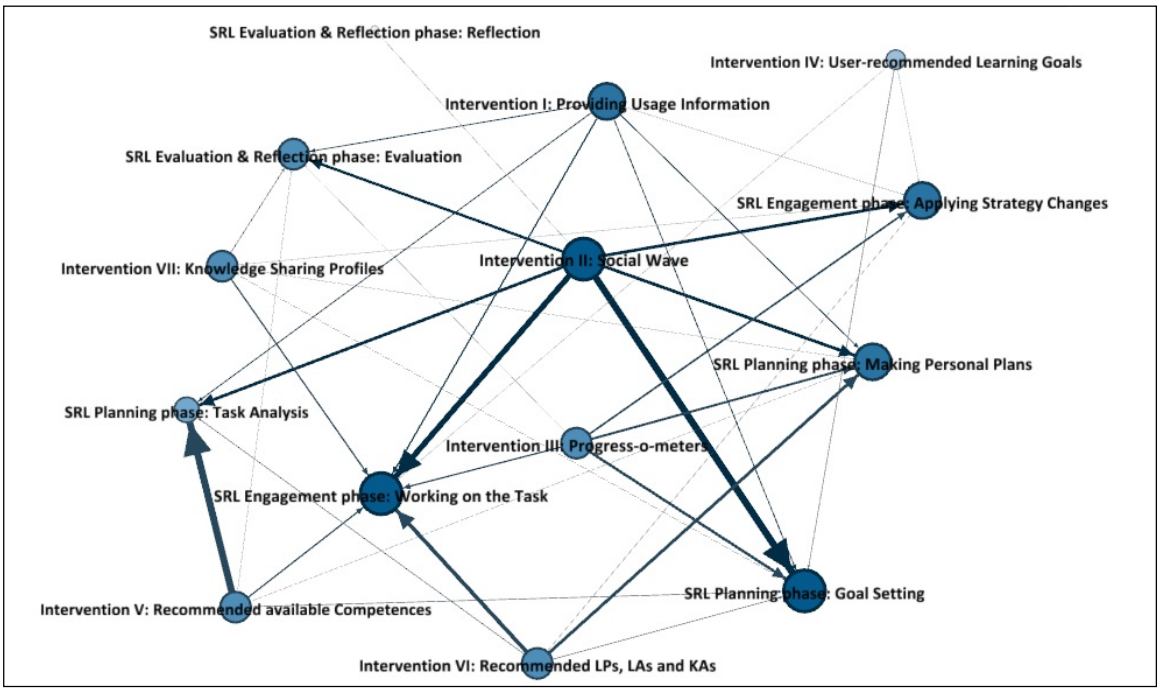

Figure 8: A sample transition graph from a user's log file translated into a time-stamped sequence of contingencies. Only the links starting at the Intervention nodes are shown in this graph. The size of a node indicates its influence in the graph; the thickness of a link shows how frequently that link occurred in user trace data.

[3] In one of our relevant research questions, we were particularly interested in investigating the most effective scaffolding interventions (developed within the Learn-B environment) in supporting users' SRL processes within the Learn-B environment.

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In the context of the Learn-B environment, we were interested to find out whether (and to what extent) usage of the proposed intervention could account for engagement in SRL processes within this environment. Accordingly, in the context of our research, centrality was considered to represent the importance of an intervention or SRL event within the network of user learning actions in the Learn-B environment. For instance, intervention events with higher degrees could indicate a variety of different usages in the learning process. Intervention nodes with higher closeness values indicate that users could easily perform their SRL practices or use the other interventions. High betweenness values specify those interventions used as a bridge to perform SRL practices or other interventions. Intervention events with higher eigenvalue centralities denote those used before/after other well-performed events. In addition to centrality metrics, graph statistics can be correlated with more variables collected from users' learning actions or via other instruments, such as self-reports, to study the effect of those cofounding variables (such as users' computer skills or motivational strategies) on users' SRL processes. For example, confounding variables such as general computer skills or familiarity with organizational responsibilities, collected via self-reports, could potentially affect the frequency of user engagement in certain SRL processes, which could be identified via the calculated centrality metrics.

In this paper, we do not report on the findings of the applications of this protocol in the context of the Learn-B environment, which instead are covered in Siadaty et al. (2016a, 2016b). We only summarize the main results here. As shown in Figure 8, through its central position and also confirmed through future multiple regression analyses, we have found that Social Wave intervention accounts for 68% of the variance in users' total frequency of performing all the SRL processes considered in our study (c.f. Table 1). This intervention was followed by another that offered system-generated recommendations about learning paths, learning activities, and knowledge assets to stimulate engagement in micro-level processes within the forethought or preparatory phase of SRL. Our analysis of covariate influence, such as users' computer skills or experience in their organizational positions, detected insignificant effects. Siadaty et al. (2016a, 2016b) indicate that both the social and the organizational contexts should be taken into account when tailoring SRL interventions to support the forethought and engagement phases.

4 IMPLICATIONS FOR RESEARCH AND PRACTICE

Although the elements of our research strategy and the proposed measurement protocol are not completely new, together they suggest, in our view, a new, unique, forward-looking approach for designing scaffolding interventions and measuring their support for SRL processes in technology-enhanced learning environments. Self-regulated learning has become an essential skill in today's knowledge-driven, rapidly changing society where individuals increasingly opt in to informal learning settings and hence need to self-manage their learning processes. However, as research on learning and metacognitive processes suggests, most learners are prone to assumptions and beliefs that can impair their effectiveness as self-managed learners (Bjork et al., 2013); in other words, they simply do not know how to learn (Margaryan, Milligan, & Littlejohn, 2009). Self-regulatory interventions can thus assist

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learners to define and manage their own learning processes. An important implication of this protocol is that it guides researchers to investigate the effectiveness of their desired SRL interventions grounded in an explicit theoretical framework and in the authentic context of their application. Our proposed protocol can be applied in any technology-enhanced learning environment where the authenticity of users' learning actions in their real context is important to researchers. Linking practice and research, the proposed protocol guides researchers to 1) formulate their hypotheses regarding the role of each designed intervention with regard to the underlying theoretical model and 2) avoid developing interventions isolated from real practice by designing, implementing, and aligning the integrity, effectiveness, and measurement of those SRL interventions with the nature of the actual learning environment.

Another direct implication of the proposed measurement protocol for both research and practice is that, through its prerequisites, it guides researchers to examine the provided support for SRL processes in their entirety, including those related to all SRL phases as defined in the underlying SRL model. Having reviewed the existing literature (e.g., Dettori & Persico, 2008; Greene & Azevedo, 2009; Puustinen & Pulkkinen, 2001; Sitzmann & Ely, 2011), we have articulated a set of more generic processes within the three phases of our underlying SRL model as *macro-level* processes, and defined the specific activities within each of these phases as *micro-level* SRL processes. These micro- and macro-level processes can be (re-)used as a guide by other researchers to build their very own underlying SRL model. Accordingly, examining the effect of the provided support at the level of the defined micro-processes enables researchers to provide a more accurate picture of the role of their intended interventions within the larger construct of SRL.

Because SRL processes are dynamic and contextual, the proposed protocol pursues an event-based conceptualization of those processes and aims to measure them as a sequence of events (traces) in the real context where they happen. Pioneered by Winne and associates, tracing methodology has started to find its way as another method for examining self-regulated learning processes in formal, educational settings (Hadwin et al., 2007; Winne & Jamieson-Noel, 2002; Zhou & Winne, 2012). Compared to questionnaires, trace data are not bonded to a certain point in time, and holistically operationalize "*what users do as they do it*" (Winne, 2010a, 2010b). In our view, the trace-based methodology, the core of the proposed measurement protocol, together with the microanalytical measurement method, provide a distinctive lens through which researchers can accurately measure and analyze how learners' SRL processes are supported by the intended interventions. Comparable with the potential objective of microanalytical protocols in formal education (Cleary, Callan, & Zimmerman, 2012), this combination of trace-based methodology and microanalytical measurement can guide researchers in intervention planning and development for various technology-enhanced learning environments.

Some practical implications are also brought forth by the proposed protocol. First, application of the proposed measurement protocol requires researchers to design and develop their intended scaffolding interventions in terms of software and log users' learning actions indicative of their use of SRL processes/scaffolding interventions. This would require the research team to have access to

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programmers to implement the intended interventions for them, as well as to build particular "hooks" into the intended learning environments to collect and trace users' generated SRL/intervention events (see Section 0). Second, the application of the protocol can be additionally costly, as implementation of the parsing algorithms for the SRL/intervention patterns requires resources for development, and given the contextual nature of SRL and the potential use of different software tools in different learning environments, such parsing libraries may not be easily transferable from one environment to another. It should be noted that the above implications, however, do not originate from our proposed measurement protocol; rather they are inherent to a need for effectively supporting the collection and analysis of trace data generated through software systems that aim to scaffold SRL processes for users.

5 FUTURE DIRECTIONS

The proposed trace-based, microanalytic measurement protocol is built upon the *event*-based conceptualization of SRL used to capture knowledge workers' SRL processes accurately on the fly and in their authentic context. As discussed earlier, any applied SRL measurement methodology should be in accordance with the underlying conceptualization (Greene & Azevedo, 2010). In future research, this methodology can be complemented with other forms of data that conceptualize SRL as an *aptitude* (Winne & Perry, 2000; Winne, 2010b). Although traces can provide researches with detailed, valuable information on users' learning activities "in action," they are subject to some limitations and biases, and thus, not inherently the best or only method for gathering data (Winne et al., 2010a, 2010b). *Aptitudes,* most commonly measured via self-reports, are also essential to researching SRL, as they represent what users have "in mind" when they engage in SRL processes. Together, traces and self-reports can be used to paint a much fuller and more detailed picture of users' actual engagement in SRL processes. Although self-reported measures can be used as an intrinsic part of learning environments to measure some other motivational constructs — for example, goal orientation in academic settings (Zhou & Winne, 2012) or perceived usefulness of the scaffolding — in our research within the Learn-B environment, measurements of some important SRL-based "aptitudes" can be done as by-products of such self-reports. In our future research, we aim to investigate the effective combinations and accordingly elucidate the best research practices in combining our proposed measurement protocol with other methods and instruments, such as self-reports or think-alouds, which could connect our proposed protocol with the work suggested by Bannert, Reimann, & Sonnenberg (2014).

Additionally, we recommend that future research investigate the extent to which different tools, aimed to provide scaffolding support, can support SRL processes. SRL is contextual; each software or tool delivers different cognitive affordances, according to which different traces of users' SRL activities could be expected and captured. These issues point to a need to design and evaluate how more mature, different types of tools can support different macro- and micro-level SRL processes. Methodologically, other modelling methods can be used instead of or in combination with graph theory (e.g., cluster analysis, hidden Markov models, sequence, and process mining algorithms). Questions to probe include 1) what common strategies learners follow when engaging in specific SRL micro-level processes, 2) what

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is the probability of changing one learning strategy for another under the influence of specific SRL technological scaffolding interventions, and 3) what types of processes are mutually exclusive with different process-mining algorithms.

6 ACKNOWLEDGEMENTS

The authors are thankful to Professor Philip H. Winne of Simon Fraser University for his guidance throughout the development of the measurement protocol and his comments of draft versions of this paper.

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APPENDIX A: SRL AND INTERVENTION EVENTS IN THE LEARN-B ENVIRONMENT

SRL Events	
Macro-Level SRL Process: Planning	
Micro-Level SRL Process	**SRL Events in Learn-B**
Task/Analysis	Clicking on Duties, Roles, Tasks or Projects folders
	Clicking on a single Duty under the Duties folder
	Clicking on a single Role under the Roles folder
	Clicking on single Task under the Tasks folder
	Clicking on single Project under the Projects folder
	Clicking on different Competences related to a Duty, Role, Task or Project
	Exploring competences included in other colleagues' learning goals
	Searching for a keyword
Goal Setting	Creating a new goal
	Dragging and dropping an available competence to a new or an existing learning goal
	Adding a new Competence to a new or an existing learning goal
	Adding a new Learning Path to a new or an existing competence
	Adding a new Learning Activity to a new or an existing learning path
	Adding a new Knowledge Asset to a new or an existing learning activity
	Removing a Competence from a learning goal
	Deleting a Learning Path from a competence
	Removing a Learning Activity from a learning path
	Removing a Knowledge Asset from an learning activity
	Setting the properties of a Learning Goal e.g. its name, deadline, visibility, priority, keywords and user's progress
	Setting the properties of a Competence, e.g. its name, deadline, visibility, current user's level, desired level, keywords and user's progress
	Setting the properties of a Learning Path, e.g. its name, expected duration,

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	visibility, rating, keywords and user's progress
	Setting the properties of a Learning Activity, e.g. its name, start date, expected duration, visibility, rating, keywords and user's progress
	Setting the properties of a Knowledge Asset, e.g. its name, URL, expected duration, visibility, rating, keywords and user's progress
	Sharing a Learning Goal with a recommended colleague
	Requesting collaboration for a Competence, Learning Activity or a Knowledge Asset
Making Personal Plans	Requesting collaboration for a Competence, Learning Activity or a Knowledge Asset
	Assigning a recommended Learning Path as the chosen path for a competence
	Requesting collaboration for a Competence, Learning Activity or a Knowledge Asset
	Adding a new Learning Path to a new or an existing competence
	Adding a new Learning Activity to a new or an existing learning path
	Adding a new Knowledge Asset to a new or an existing learning activity
	Removing a Competence from a learning goal
	Removing a sub-Competence from an upper competence
	Removing a Learning Path from a competence
	Removing a Learning Activity from a learning path
	Removing a Knowledge Asset from an learning activity
	Setting the properties of a Learning Path, e.g. its name, expected duration, visibility, rating, keywords and user's progress
	Setting the properties of a Learning Activity, e.g. its name, start date, expected duration, visibility, rating, keywords and user's progress
	Setting the properties of a Knowledge Asset, e.g. its name, URL, expected duration, visibility, rating, keywords and user's progress
Macro-Level SRL Process: Engagement	
Micro-Level SRL Process	**SRL Events in Learn-B**
Working on the Task	Assigning a recommended Learning Path as the chosen path for a competence
	Requesting collaboration for a Competence, Learning Activity or a Knowledge

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	Asset
	Marking a Competence as “favourite”
	Following a Competence
	Sharing a Learning Goal with a recommended colleague
	Recommending a Learning Goal to a colleague
	Searching for a keyword
	Marking a Learning Goal, Competence, or Learning Activity as “completed”
	Leaving a comment for a Competence, Learning Path, Learning Activity or Knowledge Asset
	Updating the properties of a Learning Goal e.g. its name, deadline, visibility, priority, keywords and user’s progress
	Updating the properties of a Competence, e.g. its name, deadline, visibility, current user’s level, desired level, keywords and user’s progress
	Updating the properties of a Learning Path, e.g. its name, expected duration, visibility, rating, keywords and user’s progress
	Updating the properties of a Learning Activity, e.g. its name, start date, expected duration, visibility, rating, keywords and user’s progress
	Updating the properties of a Knowledge Asset, e.g. its name, URL, expected duration, visibility, rating, keywords and user’s progress
	Following a colleague
	Creating a learning group for a Competence
Applying appropriate Strategy Changes	Adding a new Competence to an existing learning goal
	Adding a new sub-Competence to an existing competence
	Updating the properties of a Learning Goal e.g. its name, deadline, visibility, priority, keywords and user’s progress
	Updating the properties of a Competence, e.g. its name, deadline, visibility, current user’s level, desired level, keywords and user’s progress
	Updating the properties of a Learning Path, e.g. its name, expected duration, visibility, rating, keywords and user’s progress
	Updating the properties of a Learning Activity, e.g. its name, start date, expected duration, visibility, rating, keywords and user’s progress
	Updating the properties of a Knowledge Asset, e.g. its name, URL, expected duration, visibility, rating, keywords and user’s progress

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	Removing a Competence from a learning goal
	Removing a sub-Competence from an upper competence
	Following or unfollowing a competence
	Requesting collaboration for a Competence, Learning Activity or a Knowledge Asset
	Adding a new Learning Activity to an existing learning path
	Adding a new Knowledge Asset to an existing learning activity
	Removing a Learning Path from a competence
	Removing a Learning Activity from a learning path
	Removing a Knowledge Asset from an learning activity
Macro-Level SRL Process: Evaluation & Reflection	
Micro-Level SRL Process	**SRL Events in Learn-B**
Evaluation	Rating a Learning Path, Learning Activity or a Knowledge Asset
	Marking a Learning Goal, Competence, or Learning Activity as “completed”
	Leaving a comment for a Competence, Learning Path, Learning Activity or Knowledge Asset
	Adding new keywords to or updating existing keywords of a Learning Goal, competence, Learning Path, Learning Activity or Knowledge Asset
Reflection	Leaving a comment for a Competence, Learning Path, Learning Activity or Knowledge Asset
	Adding new keywords to or updating existing keywords of a Learning Goal, competence, Learning Path, Learning Activity or Knowledge Asset
	Updating the visibility property of Learning Goal, competence, Learning Path, Learning Activity or Knowledge Asset
	Sharing a Learning Goal with a recommended colleague
	Recommending a Learning Goal to a colleague
Intervention Events	
Intervention I: Providing Usage Information	
Intervention Feature	**Intervention Events in Learn-B**
Analytics	Clicking on the Achievement tab (under Analytics) of an available Competence, Learning Path or Learning Activity
	Clicking on Duties node (the summary tab will show in the right panel)

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Social Stream	Clicking on the Social Wave tab (under Analytics) of an available Competence, Learning Path, Learning Activity or Knowledge Asset
Social Stand	Clicking on the comments tab of a Competence, Learning Path , Learning Activity or Knowledge Asset
	Clicking on the data tab of a Competence, Learning Path, Learning Activity or Knowledge Asset
Intervention II: Social Wave	
Intervention Feature	**Intervention Events in Learn-B**
Generic Social Wave	Clicking on one's Social Wave tab
Learning Resources' Social Waves	Clicking on the Social Wave tab of one's Learning Goal, Competence, Learning Path, Learning Activity or Knowledge Asset
Bubble Social Waves	Clicking on the Social Wave Bubbles tab (under Analytics) of an available Competence, Learning Path, Learning Activity or Knowledge Asset
	Clicking on Duties, Roles, Tasks or Projects folder
	Clicking on a single Duty under the Duties folder
	Clicking on a single Role under the Roles folder
	Clicking on single Task under the Tasks folder
	Clicking on single Project under the Projects folder
Intervention III: Progress-o-meters	
	Clicking on the Goal-o-meter tab (under Analytics) of one's Learning Goal
	Clicking on the Competence-o-meter tab (under Analytics) of one's Competence
	Clicking on the Progress-o-meter tab (under Analytics) of a Learning Path
	Clicking on the Progress-o-meter tab (under Analytics) of a Learning Activity
Intervention IV: User-recommended Learning Goals	
	Clicking on a single Learning Goal under the Recommended Learning Goals folder
Intervention V: Recommended available Competences	
	Clicking on different Competences related to a Duty, Role, Task, or Project
	Clicking on Users who are acquiring/have already acquired an available competence
Intervention VI: Recommended available Learning Paths, Learning Activities, and Knowledge Assets	

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	Clicking on a Learning Path for an available competence
	Clicking on a Learning Activity within an available learning path
	Clicking on a Knowledge Asset related to an available learning activity
	Clicking on a recommended Learning Path
	Clicking on an abandoned Learning Path, i.e. a previously chosen recommended learning path
	Clicking on the data tab of an available Learning Path, Learning Activity, or Knowledge Asset
Intervention VII: Knowledge sharing Profiles	
	Clicking on one's Analytics tab (the Knowledge Sharing Profiles tab is the only tab, so will open automatically)

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