Self-Regulated Learning and its implications for edtech design and implementation

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The purpose of this paper is to introduce constructs of self-regulated learning to edtech designers, and to inspire evidence-based applications of these constructs.

WHAT IS SELF-REGULATED LEARNING (SRL)?

Self-regulated learning (SRL) is a learner's active management and adaptation of their learning processes to meet their learning goals, and overcome challenges (Winne and Hadwin 1993; Winne and Perry 2000; Schunk 2013; Pintrich 2000a, 2000b; Zimmerman 2000). This consists of cognitive elements, metacognitive elements and affective elements (Azevedo et al 2015; Pintrich 2000b).

- **Cognitive elements** are the intentional implementation of learning processes, such as learning strategies (Pintrich 2000a, 2000b; Winne 2018).
- **Metacognitive elements** are the components which require the learner to consider the process of learning, such as task analysis, goal setting, choice of learning strategies, and monitoring and reflections on learning.
- **Affective elements** are emotion and mindset which impact on, and in turn are affected by SRL. For example, learner motivation impacts a learner's will to persist despite challenges (which is a hallmark of SRL), and similarly, working through challenges effectively can boost confidence and thus motivation.

There is a diverse body of research on the concept of SRL. While most researchers agree on **fundamental aspects of SRL**, for example, striving to achieve goals, active construction of knowledge and the impacts of context; significant **theoretical differences exist**. These include conceiving SRL as an event or an aptitude, the role of context in modelling and scaffolding SRL and the granularity of the underlying processes and mechanisms (Azevedo et al., 2010, 2015).

SRL is of relevance to the design and use of edtech as it influences cognitive learning outcomes, as well as representing valuable learning outcomes in its own right. There is an extensive body of research which connects SRL to academic attainment (Duncan et al., 2007; McClelland et al., 2000). In addition, SRL overlaps with many of the 21st century skills that teachers and employers are seeking, such as critical thinking and flexibility and, as learning increasingly shifts online giving learners greater control over their own learning, understanding SRL is becoming more and more important.

EMERGING RESEARCH

There are two areas of research which are of particular relevance, both of which are further described in the sections below.

Firstly, the research on dominant theoretical models of SRL helps to develop an operational definition of SRL that is most suited to educational technology enterprises. Dominant theoretical models of SRL include those of Zimmerman (2000), Pintrich (2000b), and Winne and Hadwin (1998). Each model lends itself to a particular operational definition that is more appropriate in certain learning settings.

Staying abreast of the emerging research on new techniques for measuring and scaffolding SRL is of direct concern for edtech enterprises. As new forms of online analysis become available, there is scope for new types of analysis of self-regulated learning. Whilst SRL has been the subject of extensive research in the past, a significant portion of this research has been in non-digital environments with online research becoming more common only in the past few decades (Larusson and White 2014).

Online research enables self-regulation to be mapped out as a dynamic series of events, which unfold over the course of the learning activity. This is a new perspective on self-regulation, which allows the interaction between the various components of SRL to be examined at a granular level. It contrasts with the traditional approach of measuring SRL as an aptitude i.e. a continuous variable which varies over relatively longer periods of time. Researchers have noted the potential for the application of new forms of learning analytics to SRL (e.g. Bannert, Reimann and Sonnenberg, 2014; Behrens and Dicerbo 2014; Pardo 2014; Sedrakyan, De Weerdt and Snoeck, 2016; Juhaňák, Zounek and Rohlíková, 2017). Research findings could potentially be used both to develop visualisations of SRL, or as the basis for tools which scaffold and measure SRL in online environments.

DOMINANT THEORETICAL MODELS AND IMPLICATIONS FOR OPERATIONAL DEFINITIONS OF SRL

The conceptualisation of SRL can be described by three dominant models; the Zimmerman model, Pintrich model, and Winne and Hadwin model. The distinguishing features of each of these models, and the implications for operational definitions of SRL are now described.

ZIMMERMAN MODEL OF SELF-REGULATED LEARNING

Zimmerman developed a social-cognitive model of SRL. This model has three distinguishing features; (1) it is triadic in nature, (2) it conceptualises SRL as a cyclical process, and (3) it acknowledges the key influences on SRL from physical and social resources in the environment.

The Zimmerman model is triadic in nature, it recognises three reciprocal self-regulatory influences, rather than simply considering self-regulation to be driven by personal processes (Bandura 1977b, 1986, Zimmerman, B. J. 1989). The three influences are personal, behavioural and environmental processes.

Personal self-regulation is when the learner is aware of, and exercises control over their motivations and mindset with the aim to improve their learning outcomes. **Behavioural self-regulation** is when the learner monitors and adapts their behaviour e.g. through their choice of learning strategies. **Environmental self-regulation** is when the learner monitors and adapts the environment to enhance their learning e.g. by reducing distractions, creating incentives or seeking appropriate levels of help. These forms of regulation all have reciprocal influences, for example, learner behaviour such as self-recording can reciprocally impact both personal processes such as self-efficacy, and the environment resources available to the learner (Zimmerman, 1989).

In addition to recognising the triadic form of SRL, Zimmerman also emphasises its cyclical nature. He perceives SRL as a complex process, which is impacted by personal, behavioural and environmental factors that evolves in line with these, rather than being a fixed attribute (Zimmerman 2000). The process of self-regulation is structured across three phases; forethought, performance control/volition, and self-reflection and reaction (see figure 1). Forethought refers to the processes that precede a learning task, and prepare for it. Performance or volitional control are processes that occur during the execution of the learning task and require learner attention and actions. Self- reflection involves processes that occur after task execution, and shape the learner's response to that experience. These self-reflections, in turn, influence forethought regarding subsequent attempts to engage with the task, completing a self-regulatory cycle (Zimmerman, 2000).

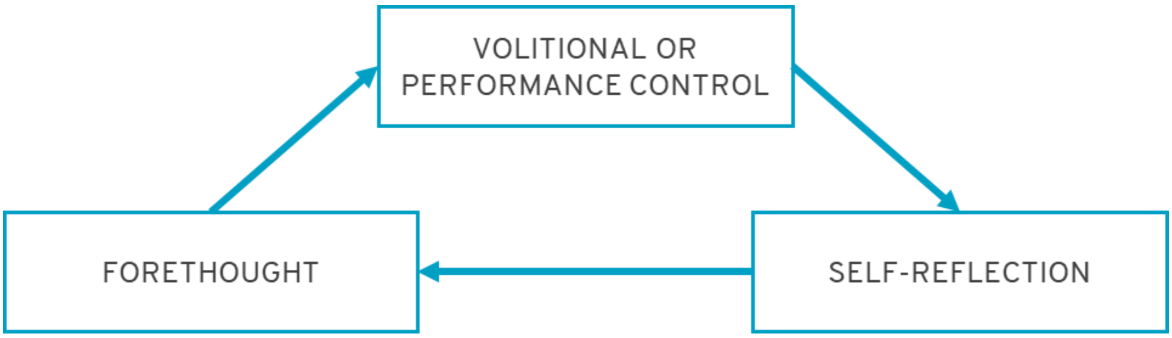

Figure 1 Zimmerman model of self-regulated learning

The third key element of the Zimmerman social cognitive model is the **strong influence of the social and physical environment on individual self-regulation** (Zimmerman 2000). The social and physical environment is seen as a resource for the individual to enhance forethought, performance control, and self-reflection. For example, modelling and certain types of instruction can be used to socially convey self-regulatory skills, such as motivational techniques (e.g. self-praise), or self-corrective methods (e.g. adaptive self-reactions). Conversely, social models can also inhibit the development of self-regulation, for example by modelling maladaptive forms of self-regulation such as defensive self-reactions (Zimmerman 2000).

The Zimmerman model conceptualises SRL as a dynamic, multi-layered and cyclical process, which is shaped by environmental and social factors. The model includes multiple variables, and a wealth of research that has been conducted on these variables. The multi-layered structure of the model lends itself to a range of operational definitions of SRL, with varying degrees of granularity. SRL can be conceptualised as an aptitude or as a series of events using this model.

THE PINTRICH MODEL OF SELF-REGULATED LEARNING

Pintrich developed a social cognitive model of SRL which has been used by multiple researchers in educational settings. It is distinguished by the emphasis it places on motivational processes, and goal orientation.

The social cognitive model developed by Pintrich is similar to the Zimmerman model, in that it is based on the concept of self-regulatory processes mediating the interaction between learners and their environments (Pintrich, 2000b; Pintrich & Zusho, 2002). The model consists of four phases of self-regulation and, for each phase, four possible areas for self-regulation (see Table 1).

Phases of Self-Regulation	Areas for Self-Regulation
Forethought, planning, activation	Cognition
Monitoring	Motivation
Control	Behaviour
Reaction, reflection	Context

Table 1: Conceptual framework of self-regulation

The model illustrates the possible range of self-regulatory activities, but does not necessitate them; the activities can occur in any order or number. It is also possible for learners to engage in SRL phases simultaneously. The framework thus acts as a heuristic to help researchers structure their thinking about self-regulation and operationalise research (Pintrich 2000b).

While the Pintrich model is similar to the Zimmerman model in terms of the elements of self-regulation, and the role of context, the model is distinct in the level of emphasis it places on motivational processes. Motivation is a distinct area for self-regulation, and in addition, it interacts with cognitive, behavioural and contextual factors to influence self-regulation across the model (Pintrich, Marx, and Boyle, 1993). This is in contrast to many other self-regulation models, which tend to emphasise cognitive or behavioural factors (Zimmerman & Schunk, 2001).

The Pintrich model of self-regulation has been used in multiple education settings, particularly classroom teaching, and acts as a strong foundation for exploring how social and environmental variables interact with personal factors to shape self-regulatory processes. For example, Ryan and Pintrich (1997) explored how personal factors such as level of social competence (rather than self-efficacy) influenced whether a learner was able to seek appropriate levels of help. In addition, Pintrich developed a measure based on his model of self-regulation to assess development of self-regulation, the Motivational Strategies Learning Questionnaire (MSLQ) (McKeachie, Pintrich, & Lin, 1985; Pintrich, 1989; Pintrich et al., 1987). This is a self-report instrument which is used by students to rate themselves on various cognitive and motivational items, and can be applied directly by researchers, or used to inform new tools and measures.

THE WINNE AND HADWIN MODEL OF SELF-REGULATED LEARNING

Winne and Hadwin structure their SRL model in a fluid manner which enables a detailed examination of the interaction between the various components of SRL, and the central role of monitoring and evaluation within SRL (Greene and Azevedo, 2007)). The model acknowledges that SRL occurs across phases but differs from other models by examining the set of information processes that occur within each phase, with the processes being driven and shaped by the components of SRL (Azevedo *et al.*, 2010; Winne and Hadwin 1998).

The various components of the model synthesise components of SRL referred to in existing literature (Greene and Azevedo, 2007; Azevedo *et al.*, 2010) and are referred to using the acronym COPES; Conditions, Operations, Products, Evaluation, Standards (Greene and Azevedo, 2007). The model is depicted below, followed by a description of the components of the model (Winne and Hadwin 1998).

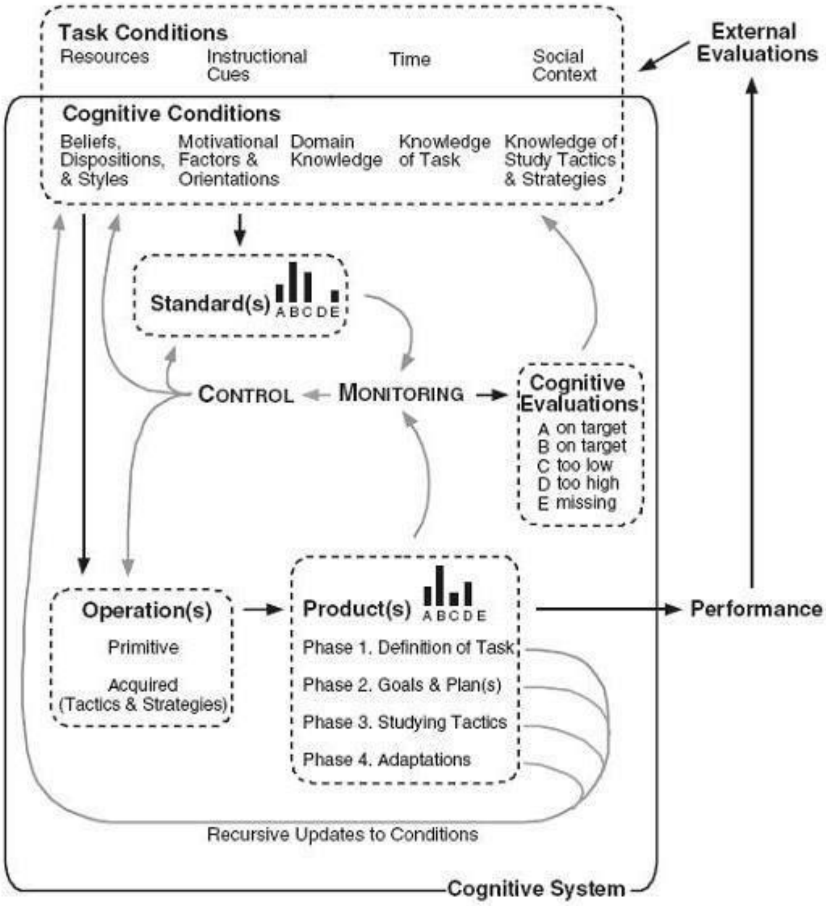

Figure 2 Winne and Hadwin model of Self-Regulated Learning

The ‘C’ in COPES refers to ‘conditions’. In a similar manner to Zimmerman’s and Pintrich’s models, Winne and Hadwin acknowledge the influence of the learner and task conditions on SRL. However, Winne and Hadwin’s model is unique in that it incorporates conditions within its structure and examines the information processes, which are shaped by an interaction of conditions with other components of the model (Azevedo *et al.*, 2010).

The ‘O’ in COPES refers to ‘operations’. In contrast to the models conceptualised by Zimmerman or Pintrich, the Winne and Hadwin model examines how the information generated from conditions is processed by the learner through primitive abilities (memory, verbal), as well as acquired abilities (e.g. reasoning), with the output being the product of the SRL phases. The processing can be done actively by the learner, or as a more subconscious process (Winne, 2018). By making the operations that a learner engages in explicit, the model accommodates the learner moving back and forth within a specific phase, as the context of the task evolves (Azevedo *et al.*, 2015). For example, the learner may start a task with a certain understanding of the aims of the task, based on which the learner formulates a task definition (product of phase 1 of SRL). As additional information is provided on the purpose of the task (i.e. the task conditions are updated), the learner may process this information and update their own definition of the task.

The ‘P’ in COPES refers to ‘products’, or the output from the phases of SRL. There are 4 phases; task definition, goal setting, task performance and reflection. These phases are similar to the phases in the Zimmerman and Pintrich model, with the key difference being the addition of the ‘task definition’ phase.

The ‘E’ in COPES refers to ‘evaluation’, and the ‘S’ refers to standards. The model proposes that the products of SRL phases are monitored and evaluated against internally held values, called standards. If there is no fit between the products and the standards, then the information is reprocessed, and/or learner conditions are adapted until there is a fit (Greene and Azevedo, 2007; Winne and Hadwin 1998). For example, a learner may be given a mathematics problem to do, which they initially judge as being very difficult to do. This assessment of task difficulty is one of the standards for the first phase of SRL, task definition. As the learner starts the task, the learner may be given additional information on task difficulty, from learning resources, peers, tutors etc. They process this information to make further assessments on task difficulty, and if the learner finds that the new information creates an assessment of task difficulty that does not match their initial assessment, then the learner may make adaptations to their own conditions (e.g. understanding of own ability, motivation, mindset), and reprocess information until there is a better fit.

The key difference between the Winne and Hadwin model, alongside the Zimmerman and Pintrich models, is the nature of the role that monitoring and evaluation play. While monitoring and evaluation are seen as key elements of SRL in all three models (Zimmerman, 2000; Greene and Azevedo, 2007; Pintrich 2000a, 2000b; Winne and Hadwin 1998), the Winne and Hadwin model is distinct in that it considers the impact of monitoring and evaluation at a component level, rather than as a phase of SRL (Azevedo *et al.*, 2010, 2015). This is a more granular approach, which enables an analysis of how changes on one component of SRL (e.g. task conditions) can lead to changes in other components (e.g. type of operations used by learner). Furthermore, the model is more fluid than other models. Whilst all models are weakly sequenced, the Winne and Hadwin model provides a framework for analysing how a learner can move back and forth within a phase of SRL, as well as between phases (Greene and Azevedo, 2007).

The Winne and Hadwin model has been noted as being suited to the analysis of online data (Azevedo *et al.*, 2010; Bannert, Reimann and Sonnenberg, 2014), as it synthesises all the various components of SRL from the literature into a heuristic framework that can be applied to educational settings rather than laboratory settings that have been specifically designed to explore SRL. By examining the information processes that occur within each phase, and how these are driven by the various components of SRL, the Winne and Hadwin model provides a rigorous framework for detecting SRL in a manner which reflects its fluidity. The model lends itself to operational definitions of SRL, which track SRL as a series of events, rather than as an aptitude.

MEASUREMENT OF SRL – OPPORTUNITIES AND CHALLENGES

The above theories of SRL share some common elements (e.g. active creation of knowledge, setting of goals), but also differ in fundamental ways. One of the ways in which theories of SRL vary is in whether they consider SRL to be an aptitude or an event (Azevedo *et al,* 2010, Winne and Perry 2000. SRL defined as an aptitude is an enduring personal trait, which is relatively consistent over context and time, while SRL as an event refers to behaviour which is fundamentally rooted in context, and dynamically unfolds over time. For example, in terms of the nature and frequency of processes that are used at different points in time, or through the adaptation of conditions. The conceptualisation of SRL as an aptitude or an event will determine the approach and techniques for measuring SRL (Azevedo *et al.*, 2010)

Measurement of SRL that is conceptualised as an aptitude aggregates over time or abstracts a quality of SRL based on multiple SRL events, relying on respondent memory and perceptions of these events (Winne and Perry 2000). Such measurement will typically use self-reporting tools such as questionnaires or structured interviews, or it may rely on teacher ratings (Azevedo *et al,* 2010, Winne and Perry 2000). Examples of tools are the *Motivated Strategies for Learning Questionnaire* (MSLQ), the *Learning and Study Strategies Inventory* (LASSI) (p. 2) and the *Self-Regulated Learning Interview Schedule* (SRLIS) (Pintrich et al., 1991, Weinstein, 1987, Zimmerman and Martinez-Pons 1986, 1988). While comprehensive, and well-tested tools have developed to measure SRL as an aptitude, there are significant challenges with this form of measurement. The main challenge with measuring SRL an aptitude is the reliance on learner self-reports which may be inaccurate (Beheshitha, 2015). For example, prior experience or lack of understanding of the task may distort learner perceptions (Bjork, Dunlosky, and Kornell 2013). In addition, students' aptitudes can change over the course of an activity, particularly in areas such as task performance which are particularly susceptible to being influenced by evolutions in teaching and the broader task context (Biggs, Kember, and Leung 2001). This is not captured by this conceptualisation of SRL or by surveys that aim to measure it.

There is increasing support for SRL to be conceptualised and measured as an event (Azevedo *et al.*, 2010). A significant body of research has accumulated in cognitive and learning sciences using more granular data such as online trace methodologies, such as eye tracking, concurrent think aloud protocols, keystroke analysis, and cognitive modelling, which demonstrates the fundamental role of context in SRL, and provides empirical support for viewing SRL as an event (Anderson & Lebiere, 1998; Azevedo *et al.*, 2010; Ericsson & Simon, 1993, 2006; Newell, 1990; Newell & Simon, 197). New methods for the measurement of SRL as an event are developing in online environments. This data is analysed through various forms of learning analytics. However, as the field of measurement of SRL has expanded, a number of challenges have been identified, including data availability, developing indicators of SRL events with reference to the data, and detection of cyclical SRL processes. Some of these challenges are described below.

Modelling SRL as an event poses challenges with regards to the nature of the data required. Typically, multiple streams of data, as described previously, will be required to make an accurate assessment of the learner behaviour. For example, when a learner is silent, video data can be used to understand whether they have disengaged or if they are doing deep thinking, or something else altogether (Winne and Perry 2000, Azevedo *et al.*, 2010, 2015). Think aloud audio data is most commonly used as the primary source of data, and it is supplemented with other sources of data. This can be a challenge in environments where only a single source of data is available. In addition to this, most research in this area has used audio data that is think aloud, and research using audio date from real world tutor-learner interactions is limited. There may be challenges in using this type of data, which merit exploring.

Apart from ensuring that there is sufficient data to model SRL, it can be challenging to develop a list of indicators, which can be used to code the SRL behaviour (Azevedo *et al.*, 2010). Indicators can be developed inductively (through comprehensive data review and analysis), and/or deductively (e.g. through literature review). The process of developing a comprehensive and accurate list of indicators is time consuming and labour intensive. While this is true for both offline and online environments, there is a greater volume of fine-grained data generated in online environments. This implies that a larger set of indicators will be collected at a smaller grain size, making the process of developing indicators and coding data even more intensive. Given these considerations of time and resource, many researchers choose to focus the scope of their research on one aspect of SRL, rather than model SRL in its entirety. For example, researchers may choose to focus on the cognitive and metacognitive regulatory processes involved rather than social regulatory processes (e.g. motivational, affective) (Azevedo *et al.*, 2010).

It can be challenging to accurately detect and interpret SRL processes. Azevedo (2010) suggests adding valence to micro level processes i.e. positive or negative values to SRL processes to allow feedback loops to be traced in greater detail. For example, a researcher would expect after metacognitive monitoring with a negative value for an adaptation to occur such as re-reading. If this adaptation is followed by monitoring with another negative value, and this is followed by re-reading again, could indicate a maladaptive cycle (which can act as a basis for intervention by the system or tutor)

In addition to the challenges with measurement set out above, there are a number of factors that researchers need to be mindful of when modelling SRL as an event, as articulated by Azevedo (2010). Firstly, conceptualisation of SRL as an event emphasises the inter-relationship of the various components of SRL. In order to model SRL successfully, researchers will need to be able to analyse how the various components interact, and consider what the presence/absence of certain processes implies about other processes. For example, if a learner does not use a learning strategy, a full measurement of SRL will require researcher to consider whether is driven by an element of the task condition e.g. nature of the task, or task environment (see Azevedo & Witherspoon, 2009; Winne, 2005; Winne & Nesbit, 2000), or learner condition e.g. lack of conditional knowledge of learning strategies, lack of ability to implement strategies, or limited experience in implementing strategies. Secondly, the dynamic nature of SRL means that the nature and frequency of SRL processes will fluctuate with time, and in line with changes to learner conditions. For example, increased domain expertise may lead to the learner relying less on learning strategies, such as note taking. Other strategies such as judgement of learning or feeling of knowing are applied at a consistent rate across learning activities (Azevedo et al 2008).

While there have been significant advances in the measurement of SRL as an event, there are still many areas which need further research and development. For example, while there have been advances in being able to detect the nature and frequency of learning processes, the technology is not yet available to assess the quality of the learner output. For example, systems may be able to detect when a learner monitors their work, but are not able to assess the accuracy of the monitoring. Various approaches are starting to be developed to advance the ability of technology to assess quality of output (see Azevedo *et al* 2010). These approaches include use of time thresholds, learner palettes, and eye tracking sensors.

CASE STUDIES ON THE SCAFFOLDING AND MEASUREMENT OF SRL

Learning analytics has been used to develop techniques for measuring and scaffolding SRL. In particular, there has been some interesting research done using process mining techniques.

Process Mining aims to discover, track, and refine processes by analysing data from event logs (Van der Aalst 2012). Traditionally, process mining has been applied most often in business process management, with the aim of improving processes and monitoring compliance, but there is increasing interest in the potential for its application in learning analytics and education in general (Bannert & Reimann & Sonnenberg, 2014). Process Mining is applicable when it is assumed that there is a process governing a particular sequence of events (Van der Aalst 2012); this is relevant for learning where learners and tutors can be assumed to engage in particular processes, depending on the specific nature of the task and underlying pedagogy. By reflecting the processual nature of learning, process mining enables process related issues to be highlighted and addressed. For example, bottlenecks within the process, which prevent learners from progressing their work, has been the focus of previous research (Van der Aalst 2012). Furthermore, by discovering and mapping out learner-resource, learner-learner and learner-tutor interactions, it is possible that process mining can also help to identify and understand what types of interactions are related to positive learning outcomes (Juhanak, Zounek & Rohlikova, 2019). Finally, process mining has the advantage of producing graphical depictions which are relatively easy for the end-user to interpret and understand (Juhanak, Zounek & Rohlikova 2019, Sedrakyan, De Weerdt & Snoeck 2016).

In their influential work in this research area, Bannert and colleagues (Bannert & Reimann & Sonnenberg, 2014) led a process mining study on the self-regulation of students working with hypermedia. The researchers coded think aloud verbal data from undergraduate students navigating a hypermedia site, using a theoretical framework specifically designed for hypermedia environments. The researchers selected two groups with high and low attainment scores for further analysis of their self-regulatory processes. Extreme groups were selected for analysis, as past research has demonstrated high variation in learning and regulating activities of students, meaning that an aggregation of learning processes from all students would not therefore be appropriate. A frequency analysis of coded events showed that less successful students relied on shallower learning strategies such as repeating, while more successful students showed a greater frequency of deeper processing, and more diversity in monitoring. Further, the application of Fuzzy miner process mining algorithm (from the open-source Pro-M toolkit) revealed the maladaptive patterns that less successful students engaged in, such as a loop between monitoring, and reading/repeating. specific online environment that it will be applied to. This study demonstrated the value of process mining as a form of learning analytics, in that it allows self-regulated learning to be examined as a process rather than simply examine it as a series of events. Similarly, (Sedrakyan, De Weerdt & Snoeck 2016) applied an adaptation of the Fuzzy miner process mining algorithm called Disco, when analysing the self-regulatory behaviours of computer science students engaging in complex problem-solving task (namely domain modelling). This study demonstrates the flexibility of process mining tools, which can be used to conduct analysis at multiple levels. For example, Disco was used to provide a bird's-eye level analysis for the entire group; between best performing and worst performing participants; and between early and late sessions. They also applied a fine-grained analysis at an event level, to further understand the differences between sequences of events

The above studies demonstrate the significance and power of process mining approach to detect patterns of self-regulated learning. Additional work needs to be done to ensure that these techniques are theoretically well-grounded, and understand how the output can be used to develop tools for measurement and scaffolding of SRL.

When designing products aimed at promoting SRL, ed tech entrepreneurs should consider whether what aspect of SRL they are seeking to develop, and the most effective way to promote this. For example, features can be added into products which promote self-evaluation, self-monitoring, goal setting or information seeking, amongst others. Entrepreneurs should determine which aspect of SRL is the primary focus, prior to evaluating the presence and quality of the relevant traces in their dataset. Entrepreneurs should also consider whether the design features should be learner facing, or alternatively support the scaffolding of SRL by a human. In the broader AI research community, there is increasing interest in the effectiveness of promoting learning outcomes through AI-human collaboration. This holds true for SRL, where research is being conducted into the effectiveness of AI which supports human tutors and evaluators as they seek to scaffold learner SRL.

In summary, SRL research is currently at an exciting stage for ed-tech entrepreneurs. SRL is being operationalised for online environments through the contextualisation of established theories, and identification of online traces for learning behaviours. Researchers are building on this by exploring the development of tools which track and scaffold SRL in real time, or soon after. These research developments create increasing opportunities for ed-tech entrepreneurs to design products which promote, or adapt to SRL learning outcomes.

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