Technologies to Enhance Self-Regulated Learning in Online and Computer-Mediated Learning Environments

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To be described as a self-regulated learner, the learner must activate "self-generated thoughts, feelings, and actions that are planned and cyclically adapted to the attainment of personal goals" (Zimmerman, 2000 p. 14). Self-regulated learners plan, set goals and engage in strategies to achieve those goals. Through evaluation and reflection, these strategies are monitored and modified to enhance one's progression towards goal achievement. The beneficial effects of self-regulated learning (SRL) have been found in academic achievement across all educational levels (e.g. Dignath & Büttner, 2008; Panadero, 2017) and different learning settings (e.g. Broadbent & Poon, 2015; Richardson, Abraham, & Bond, 2012).

In the digital age, more learning is occurring online and is increasingly mediated by educational communications and technologies, even in schools and on campus. Online learning is an educational instruction that occurs using technology, which

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may be engaged in entirely asynchronously or with components of synchronous learning, and with no located face-to-face class time (Broadbent, 2017). The notion of blended learning has been used to describe a mix of face-to-face instruction with mediating technologies; although technology is now so widely used, the term could describe most classroom instruction. In higher education, traditional face-to-face and blended education has several advantages in supporting self-regulated learning over online delivery. For example, the structured nature of study through timetabled classes, practicals, seminars and tutorials helps supports time management and organisational skills. Availability of interactions with teachers and peers supports peer-learning and help-seeking strategies and even effort regulation. And the opportunity for immediate external feedback (from peers and teachers) in real time promotes metacognitive reflection and can be used to guide students to modify strategies during learning.

Online learning, on the other hand, provides learners with flexibility and accessibility to study anywhere, at any time, without requiring one's physical presence at a campus location (Means, Toyama, Murphy, Bakia, & Jones, 2009). This flexibility affords online learners the ability to live great distances from a campus location and juggle their studies with other priorities such as work or family. These benefits are often obtained at a cost, as the online mode may also result in reduced opportunities for student-to-teacher and student-to-student interactions and communication. Further, as time is not typically structured around fixed instruction, online learners may need to provide their own structure around learning, determine for themselves when and how to engage with course content, manage their time efficiently and persist in study despite competing life demands (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017). Online learning environments demand an increased level of self-regulated learning, but often with less support from teachers and peers than more traditional and blended learning classrooms. Unsurprisingly, completion rates for online learners are nearly half that of students in more traditional environments (Edwards & McMillan, 2015). Limited ability to self-regulate, a lack of self-regulatory skills and limited opportunities to develop either are possible reasons why the attrition rates are so high (You & Kang, 2014). Thus, finding ways for online students to develop SRL is critical when learning in online environments.

However, in many instances, educators move their instructional practices in and out of digital learning environments, without consideration of how the digital learning environments impact student's ability to self-regulate. It is likely that educators do not consider whether (1) students know how to self-regulate online, (2) students know how to adapt their self-regulation needs in online and face-to-face learning environments, (3) strategies applied in face-to-face learning contexts work equally as well in online environments, and (4) transferring traditional teaching design and material to the online learning environment will result in the same learning outcomes for students. Because of the importance of self-regulated learning to academic success and lifelong learning, educators need to be proactive in ensuring that digital learning environments, educational communications and educational technologies foster and enhance SRL (Azevedo, Taub, & Mudrick, 2018; Poitras & Lajoie, 2018).

This chapter explores how technologies may enhance SRL in online learning environments. The chapter first gives an overview of self-regulated learning theory and discusses how SRL may differ in online and face-to-face contexts. It then explores how educational and communication technologies can be used to help students develop SRL, either prior to or outside of course instruction or as technology embedded within online learning environments and used during learning. Ready-made online tools such as blogs, podcasts, social media (Twitter, Instagram, Facebook, etc.) and wikis are considered, as is the potential of learning analytics to enhance SRL. Lastly, the chapter examines some of the challenges of the field of SRL and the use of educational technologies.

What Is Self-Regulated Learning?

The field of SRL is currently one of the most prominent areas of research in educational psychology, as it provides a powerful theoretical and practical framing for the cognitive, motivational, emotional and behavioural aspects of learning (Panadero, 2017). As already defined, students that are self-regulated activate a diverse range of learning strategies to achieve the goals they have established. While there are a number of different models and perspectives used to explain this process, and we will be taking a socio-cognitive perspective in this chapter, all contain four common assumptions regarding how students can self-regulate their learning.

Firstly, all models assume that self-regulated students can monitor and regulate their cognition, behaviour, motivation and emotion (Panadero, 2017). While the different SRL models may place a stronger emphasis on different areas (e.g. Winne and Hadwin (1998) on cognition, Boekaerts (2011) on emotion and motivation), all assume that the four areas can be regulated by the students and, therefore, used strategically for increasing learning. Secondly, student behaviour is goal directed, and the process of self-regulation includes modifying behaviour to achieve those goals. Importantly, students construct their goals and meaning from both the learning context and prior experiences. Thus, it is crucial to create a positive learning classroom climate to enhance learning goals (e.g. Alonso-Tapia & Fernandez, 2008). Thirdly, SRL is cyclical and composed of different phases and sub-processes, with five of the six leading models of SRL analysed including three phases: preparatory, performance and appraisal (Panadero, 2017). And lastly, self-regulatory behaviour mediates the relationship between a student's performance, contextual factors and individual characteristics. In other words, SRL is constructed from experience in the social environment, and students need to consider the context to self-regulate successfully (Zimmerman, 2013).

The most cited SRL model, and for that reason the one we present in this chapter, is the cyclical phases model developed by Barry Zimmerman (2000, 2013). This model includes three phases. The first one is called the forethought phase in which the student analyses the task, sets goals and plans accordingly. This phase is energised by several motivational variables such as motivation, interest and self-efficacy.

The second is called the performance phase when the student executes the task using a number of self-control and self-observation strategies to monitor his/her progress towards the established goals. The final one is the self-reflection phase in which the student judges his/her work and, depending on his/her attribution style, reacts to the result. This experience will affect the student subsequent task performance. For the remainder of this chapter, we use Zimmerman's theory of SRL to frame our discussions. Like most other SRL models, Zimmerman's model has been applied most often in more traditional face-to-face learning environments. Thus, it is important to explore whether SRL deployment works the same in digital environments as it does for traditional learning contexts. For that reason, in the next section, we will explore what the similarities are in both contexts in relation to SRL.

Self-Regulated Learning in Traditional Versus Digitally Mediated Environments

The transition from secondary to tertiary education is typically characterised by a reduction in structured class time per week, less direct contact with one's teachers and greater reliance upon SRL. It is therefore in the higher education environments that the need for SRL is perhaps most apparent (Sitzmann & Ely, 2011). Further, within the higher education context, it is well established that the strategies students employ to self-regulate their learning impact their academic performance (Broadbent, 2017; Broadbent & Poon, 2015; Richardson et al., 2012). For example, in their meta-analysis, Sitzmann and Ely (2011) found that SRL strategies accounted for 17% variance in learning in their sample with a large proportion of university students. However, it is also clear that students differ in the strategies they employ to self-regulate their learning, as well as the frequency with which they utilise these strategies (Broadbent & Fuller-Tyszkiewicz, 2018; Dörrenbächer & Perels, 2016). While these individual differences likely reflect the strategies learners have been taught previously and/or found to be helpful, strategy utilisation preferences may also reflect the constraints of one's learning environment. Either way, better understanding of how, when and where strategies are utilised may help us personalise SRL interventions, particularly in an online context.

A large meta-analysis by Richardson et al. (2012) compared the findings of 126 studies of SRL motivations and strategies used by students in higher education settings. They found that the strategies of effort regulation, time management, metacognition, elaboration, critical thinking, help-seeking and concentration significantly predicted student's grades; weighted mean correlations (r) ranged from 0.15 to 0.32, with the highest predictor observed being a motivational one: performance self-efficacy. If we just focus on the explored strategies, the highest predictors were effort regulation, time management, elaboration and metacognition. However, Richardson et al. meta-analysis included studies performed in face-to-face contexts, and a growing number of students are now undertaking higher education wholly, or at least partially, online. Educators could easily assume that students self-regulate the same in both the online and face-to-face learning environments and that strategies students apply in face-to-face learning contexts work equally as well in online environments. Few studies ($n = 12$) have been conducted focusing on the SRL strategy use of online-only learners and their relationship with academic success in the last decade (Broadbent & Poon, 2015).

The meta-analytic review by Broadbent and Poon (2015) looking at the relationship between online learners, SRL and academic achievement found that only four learning strategies were significantly associated with online learner's grades – metacognition, time management, effort regulation and critical thinking – and that these relationships were weaker than those found for learners in traditional environments (Richardson et al., 2012). While it is important to keep in mind that the number of selected publications of this online meta-analysis is discrete in comparison to the ones in Richardson et al. (2012), some conclusions can still be extracted. Broadbent and Poon (2015) concluded that although SRL strategy use in more traditional settings appear to generalise to online learning environments, the effects of SRL strategies may be "dampened in the online learning environment" and "we should not assume that online learning in itself fosters SRL strategies use or development" (p. 12). Further to this point, educators should also not assume that learners know how to transfer their SRL skill to an online environment or that transferring traditional teaching design and material to the online learning environment will result in the same learning outcomes for students. In fact, the higher attrition rate of online learners in comparison to those students who attend face-to-face classes suggests this not to be the case (Clay, Rowland, & Packard, 2009) and that any lack of ability to self-regulate is a significant contributor to the dropout rate in higher education (Cho & Shen, 2013). It should be acknowledged that both meta-analyses focused on self-reported student data, which means these findings do not address students' real-time needs when using learning technologies across setting, domains and contexts. While previous online learning research is limited in this manner, online learning environments do present the promising potential to foster students' abilities to regulate their learning, using digital technologies that could be used for direct instruction of SRL skills (Azevedo et al., 2018).

Technologies to Support and Foster SRL in Online Environments

Digital technology-based interventions used to support and foster SRL in online environments usually take two approaches. First, some educational technologies (e.g. online training or mobile-based apps) provide direct instruction on how to acquire and develop SRL. This direct instruction is usually prior or parallel to (and outside of) course instruction. Here the technology is used for the primary purpose of helping the students learn how to regulate their learning. Second, other digital technologies and communications (e.g. nStudy, MetaTutor) are embedded within online learning environments to support and promote SRL while students are completing learning tasks (e.g. learning about the blood system). Embedded technologies use scaffolds, prompts and feedback to improve SRL and occur alongside (and within) course-specific content (Azevedo et al., 2018). Despite the complexity of SRL, both types aim to develop and enhance SRL strategies such as goal setting, planning, metacognition and self-reflection. Importantly, both types of technologies have been situated within what has been termed "the third wave of SRL measurement" (Panadero, Klug, & Järvelä, 2016). According to these authors, the latest SRL advancement is to employ tools that measure and scaffold SRL at the same time. Next, we will present some examples of both types of SRL interventions.

Regarding SRL direct instruction technology, one example would be online SRL training sessions prior to the course itself (e.g. Bellhäuser, Lösch, Winter, & Schmitz, 2016; Dörrenbächer & Perels, 2016). This particular intervention focusses on improving aspects of SRL within all three of Zimmerman's phases (discussed earlier). Training sessions are usually weekly, over several weeks, and may be accompanied by learning diaries. While originally conducted in face-to-face settings (Schmitz & Weise, 2006), SRL training has been successfully transferred to online web-based platforms, resulting in improvements in both student's SRL declarative knowledge and subsequent SRL behaviour (e.g. Bellhäuser et al., 2016; Dörrenbächer & Perels, 2016). Methodologically, daily learning diaries show promising intervention results as they expose daily fluctuations of SRL strategy use and also track changes in SRL use after training sessions (Panadero et al., 2016). The effect of the diaries on learning happens via self-monitoring (Panadero et al., 2016; Schmitz & Weise, 2006) and can target all three phases of Zimmerman's process model. However, the use of online and app-based SRL diaries, like the web-based training, is only in their infancy. Bellhäuser et al. (2016) have conducted one of the few studies that used online versions of daily diaries for SRL. They found that SRL training was more effective than daily diary use alone. This finding suggests that while daily diaries can enhance SRL, gains are minimal if students are not taught how to implement SRL strategies effectively.

A potent challenge for the SRL direct instruction technologies is that they require students to dedicate extra time in addition to their course instruction. Besides completing course-related activities, students are required to either complete a separate module on SRL or complete extra tasks throughout the semester to make entries into their diaries. As mentioned previously, time management is one of the main SRL skills related to online achievement (Broadbent, 2017; Broadbent & Poon, 2015). Therefore, such additional study load should be considered in the course design when implementing these technologies as an additional workload for students.

Regarding the second type of interventions, digital technologies can be embedded within online learning environments to support and promote SRL while students are completing learning tasks. Examples with large empirical support are gStudy, now defunct, that was later developed into nStudy (Winne et al., 2006; Winne & Hadwin, 2013). Winne and Hadwin's (2013) nStudy provides a combination of cognitive tools within an online learning environment where students learn about a certain topic using a wide range of multimedia resources. The web-based application assists students to apply "well-established principles to assist learning" (p. 809) while at the same time collects trace data about the students' learning experiences (e.g. personal comments, summaries, underlined passages). It also allows input from peers and teachers to direct their future learning experiences. This collected trace data are then feedback to the learner, who can then learn and adapt their future behaviour. Importantly, conclusions extracted from trace data should be used with caution, as the data only represents a behavioural measure of a process that is largely cognitive. In the case of nStudy, for example, it does not adaptively scaffold the students' learning, and all assessments to determine metacognitive behaviour are post hoc (Azevedo et al., 2018). This means that the data obtained are largely dependent on researcher interpretations (Bernacki, 2018). Further, embedded technologies such the former gStudy and the current nStudy are perhaps currently only suited to well-defined tasks/problems, where there are defined steps to follow during problem-solving. On the other hand, ill-defined problems, those that must synthesise a range of inputs and where problem-solving does not progress in the same manner each time, are more difficult to capture. This is not to say that nStudy is not effective, only that it should be noted that true metacognition during learning is more difficult to detect than it might appear at first.

A second example of embedded SRL interventions is intelligent tutoring systems (ITS) . Intelligent tutoring systems combine (1) tutoring functions, such as providing prompts and assigning tasks, with (2) a multidimensional student model, which is continuously updated based on students' current psychological states, such as their learning strategies used, current level of knowledge and emotions, while (3) at the same time fostering SRL development for future learning situations (Goldberg & Spain, 2014; Ma, Adesope, Nesbit, & Liu, 2014). For example, MetaTutor (Azevedo, Johnson, Chauncey, & Burkett, 2010) aims to scaffold the self-regulatory process to enhance academic achievement within a science context. Notably, MetaTutor contains both training aspects before learning and adaptive scaffolding during learning by providing feedback on performance. Importantly, this feedback can be used to correct ineffective learning strategies and replace them with new, more effective ones. However, like all scaffolding systems, proper scaffolding remains a challenge for MetaTutor. For example, SRL should be faded and even removed once independence has been reached. However, knowing when and how to fade is difficult and not achieved yet with MetaTutor. Until ITS can fade scaffolding intelligently, one research question would be if learners are better off using simpler tools over which they must exercise some control.

Further, the content-dependent nature of many of these ITS do rely on proper learning design to be employed, which can result in costly and time-consuming efforts to apply them in real-life courses (see section "Current Challenges to Enhance Students' Self-Regulation in Online and Computer-Mediated Environments" for an expansion of this argument). Further, as discussed by Self (1998), perhaps the best ITS are those that will work collaboratively with the student, where the computer would also learn from the joint activities with the student and without a student model. While out of the scope of this chapter to pursue further, it leads us to some important questions. Are student models needed to be able to appropriately fade scaffolding for students? Is this different for content-dependent/non-dependent and for well-/ill-defined tasks? In our opinion, both answers are yes.

Thus, while ITS like MetaTutor have potential, they struggle to have a direct, broad impact on SRL as they are designed at the moment in natural learning situations and are accompanied by high implementation costs. For these reasons, there is still a lot more work to be done in this area before the positive learning results found in these specific learning environments can be translated easily to other online or, even more, face-to-face situations.

The Use of Non-SRL Tools for SRL Purposes

All direct instruction (e.g. nStudy) and embedded digital technologies (e.g. MetaTutor) mentioned so far have been purposely built to support SRL. These are usually costly endeavours, mainly for research purposes in educational psychology. An alternative approach is to use digital technologies and communications that are already available, either to the general public or to the education sector, to support and develop SRL (or build up on top of these tools). Examples of ready tools include blogs, podcasts, social media (Twitter, Instagram, Facebook, etc.) and wikis. When purposefully incorporated in course design, these tools are particularly adept at encouraging collaboration, help seeking and peer learning, as well as goal setting, task strategies and self-monitoring, but less able to support the process of self-evaluation and time management (Dabbagh & Kitsantas, 2012). It is also unclear which elements of multimedia instruction might influence – negatively or positively – students' capacity for SRL or how these and similar types of resources (such as interactive modules, images, videos, etc.) influence students' capacity for SRL. More research is needed to understand how these tools and resources can be designed within these environments in subtle (i.e. design features) or in less subtle (i.e. metacognitive prompts, overt feedback for SRL) ways to scaffold and/or support SRL.

A New and Promising Area for SRL Research: Learning Analytics

The rapidly developing field of learning analytics has the potential to contribute to the progress of technologies to support and foster SRL. Learning analytics is the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Long, Siemens, Conole, & Gašević, 2011). That is, students' digital traces across different platforms can contribute to a better understanding of their learning process. The use of traces allows SRL to be conceptualised as an event, which means that students' real-time actions are taken into consideration, rather than the interpretation of their actions (Winne & Perry, 2000). Through learning analytics, a large amount of data can be collected and understood via innovative ways of interpreting and evaluating these data (Lodge & Corrin, 2017). Interpreting what digital traces might indicate about self-regulation has been one of the challenges in SRL research (Roll, Baker, Aleven, & Koedinger, 2014). Moreover, at present, the data being collected are often not interpreted in a timely manner sufficient for use by the student or teacher to have direct and positive impacts on the students' SRL. In order for this to occur, there are three points researchers need to prioritise (Roll & Winne, 2015).

First, learning analytics should capture student data related to all phases of SRL (this challenge is discussed further in the section "Current Challenges to Enhance Students' Self-Regulation in Online and Computer-Mediated Environments"). The embedded SRL tools previously presented have been designed to include features that record data already connected to specific SRL phases. In nStudy (Winne & Hadwin, 2013), students add tags to parts of the text they highlighted while studying (e.g. can do, can't do). These tags contextualise the behaviours with the cognitions of the student, allowing researchers to identify how students are regulating their learning. However, the vast majority of naturalistic online learning environments do not include specific features that connect data to SRL. One way researchers have been dealing with this challenge is using features of the context, such as the course learning design, to provide meaning to the data (Lockyer, Heathcote, & Dawson, 2013). That is, the way a course is designed informs the quality of students' actions and strategies used to regulate their learning. In a recent study, Corrin, Barba, and Bakharia (2017) investigated students' help-seeking behaviour across four massive open online courses (MOOCs). Firstly, the authors identified student actions that could represent help-seeking behaviour according to features commonly present in MOOCs learning design, such as search queries in discussion forums and seeking for specific content within a video. They then examined the prevalence of these actions across the courses. Findings indicated that courses with specific learning designs, such as providing integration between discussion forums within content areas, had more students engaging in help-seeking behaviours than other courses. Initiatives like these are a first step towards creating alternatives to capture meaningful learning analytics related to SRL in open online environments.

Second, methods of data analysis need to have a capacity for identifying particular patterns related to SRL. Advances in learning analytics over the last years have focused on using data mining and machine learning techniques to unveil students' complex patterns on the use of learning strategies. One example is the use of sequential data mining (e.g. Zhou, Xu, Nesbit, & Winne, 2010). This technique focusses on analysing students' actions that provide evidence of their cognition operations, taking into consideration the states preceding such actions (Winne & Perry, 2000). Recently, Siadaty et al. (2016) developed and implemented a protocol on how to analyse students' SRL sequential data in online environments. They detailed the important steps of defining the traces that would represent SRL processes in the sequential analysis and how they conducted that analysis. These included instructions on what types of events could be identified as SRL in a particular context, such as goal planning and implementing strategy changes, and how to parse the dataset taking into account the sequence of these events. This study highlights one of the crucial aspects of developing methods to identify SRL patterns: the creation of SRL data representations that can be adapted and applied to different online contexts and technologies to identify SRL patterns. However, this is still a work in progress. Even though these methods provide guidelines on how to identify SRL, application in real-world educational settings is currently considered to be costly and time-consuming.

Third, effective interventions to foster and support SRL using learning analytics need to be created based on the SRL data collected and analysed. One example of a learning analytics intervention that has gained traction from both researchers and the industry is the use of dashboards. Dashboards provide learning analytics back to students through visualisations as a form of feedback. Dashboard developers expect that students will interpret these data in a meaningful way, helping them to regulate their learning. This, however, is not always the end result, as dashboards rely on students' ability to interpret and act upon the data (Corrin & de Barba, 2014). Further, it appears that unless any tutorial or guiding tool occasionally compels the learner to engage in SRL phases, the impact may be negligible. For the learning analytics field to explore interventions that go beyond providing students visualisation of their data, the field needs to advance in the previous two priorities – collect meaningful SRL data and use adequate methods to identify SRL processes – to then investigate the effectiveness of SRL interventions (see also Lodge, Panadero, Broadbent, & Barba, 2019). This way, timely and personalised interventions to support and foster SRL can be successfully developed and implemented using learning analytics.

Current Challenges to Enhance Students' Self-Regulation in Online and Computer-Mediated Environments

There are a number of challenges we face in developing students' self-regulated learning in online learning environments (see Table 1). These challenges should be seriously taken by future researchers to ensure we find answers. Next, we will discuss six challenges to developing self-regulation in online and computer-mediated environments. First, a challenge we have discussed throughout the chapter is our reliance on inferring SRL processes through behavioural data. We will not discuss it further here.

Second, inherent in the definition of SRL is learning, and claims about an SRL process or processes being advantageous in different learning environments or for different types of learners must include evidence of a relationship with learning

Table 1 Challenges we face in developing students' self-regulated learning in online learning environments

1	Inferring SRL (meta)cognitive processes through behavioural data
2	Unexplored effects of the SRL interventions on learning and performance
3	Capturing the whole SRL process with all its phases rather than segments
4	Domain-specific or non-specific interventions
5	Change agent decision
6	Capacity of the technology-based SRL interventions to enhance the students' independent development of SRL

outcomes. Surprisingly, some studies on online SRL do not include academic achievement (e.g. grade, GPA), with only ten studies meeting this requirement in 2005–2015 (Broadbent & Poon, 2015). For SRL research to move forward, we must ensure that we target learning outcomes, so we can better understand how the different phases and strategies improve learning.

The third challenge is how research could capture the whole SRL process. Most theories and models define SRL as a recursive process between different phases (Panadero, 2017). If our research pulls apart individual pieces for scrutiny, it may not provide an accurate picture of the role that the pieces play in the larger construct of SRL. Work by Taub et al. (2017) is promising, which highlights the importance of using multimodal multichannel SRL data to capture different aspects of SRL at the same time. In their study, they used eye tracking combined with log files and examined how these data interacted to predict performance. However, multimodal researchers have not yet found a sufficient way to capture all aspects of the SRL process, for example, student motivation (Azevedo et al., 2018). At present, many studies provide support for different aspects of SRL, either through various tools, through access to tutors or feedback, through prompts and through peers. However, it is still unclear which aspects/tools are essential to promote SRL, what can be adapted and which can be changed to suit specific contexts. Exploring ways to investigate SRL that encapsulates the complexity is an ongoing challenge for SRL researchers (Bardach, Peeters, Panadero, Klug, & Lombaerts, under review). As suggested by Panadero (2017), future research needs to combine conclusions from previous meta-analyses with SRL model validation studies. Panadero further argues that this would allow researchers to test even more specific SRL models' differential effects. Lastly, it is worth considering if perhaps fidelity to "principles" that can be readily converted to design parameters rather than strict methodology and prescriptive approaches is the key (see also Horvath & Lodge, 2017). This is one example of the broader issues related to the translation of laboratory-based, controlled research to real-life educational settings (see Horvath & Lodge, 2017).

Fourth, another challenge is whether SRL interventions should be domain specific or general. Content-specific SRL training fosters SRL in students through implementing training alongside or within coursework (e.g. training on SRL strategies for mathematics within a mathematics course). A number of studies have shown that effective SRL strategies do vary across academic subjects (Green et al., 2015), suggesting that content-specific approaches may be more appropriate in scaffolding SRL development. On the other hand, content non-specific SRL training involves providing a program targeting SRL skills not specifically tied to any other content. Content non-specific training programs have also been shown to be effective in encouraging SRL knowledge and skills in students in a number of higher education courses (Dörrenbächer & Perels, 2016; Schmitz & Weise, 2006). We find an empirical answer to this challenge by looking at Hattie and Timperley (2007) meta-analysis: "simple strategies (such as mnemonics, memory systems) could be taught outside the content, but that most strategies have to be taught within the content domain" (Hattie, 2012 p. 115 referring to his 2007 publication). What are the implications of this tension for the type of SRL interventions we have been discussing (e.g. nStudy)? Given that many of the technologies have been purpose built within very specific content interventions, they might have a more limited transferability capacity, as we will further elaborate in our sixth challenge. However, technology-based SRL interventions can also be designed with a non-content-specific approach, with the intent of teaching SRL skills in a general manner (e.g. Bardach et al., under review). The main thing here is that the authors of the particular intervention, whatever the approach might be, need to be aware of the limitations and potentials of their approach based on the content specificity matter.

Fifth, another challenge is who should be the change agent. Dignath and Büttner (2008) found that SRL treatments were more effective when researcher led rather than teacher led in primary and secondary schools; however, this may be a result of inadequate teacher training as suggested by the meta-analysis authors. Still, this is problematic for scalability and transferability of interventions, if a researcher needs to be leading the interventions. It is possible these barriers may be overcome through the use of online web-based platforms, although a meta-analysis by Benz (2010) shows that computers have been less successful at improving SRL development than humans. Feasibly, this finding is confounded by the differences in the type of SRL development targeted via each of these mediums. Human support usually occurs before learning and targets strategy instruction, whereas computer-mediated support is often given as process support during the learning experience. Computer-mediated support may be less successful because it focusses on the employment of learning strategies without accounting for the learners' prior knowledge and understanding of the skill. Further, computer-mediated technology, at present, cannot provide the same quality of adaptive learning as provided by a human tutor. That is not to say that we give up on this path of SRL development as the flexibility, reach and cost-effectiveness of technology-enhanced SRL development put these types of SRL development programs in a promising position in the future. Further, as learning analytics continue to develop, they will eventually provide scalability of training by leveraging big data to target students' own online behaviours, e.g. intelligent tutoring systems and systems with automated feedback and flexible pathways. At present, however, some human guidance is needed to achieve higher learning outcomes for students.

Lastly, sixth, this brings us to the biggest and often overlooked challenge in the use of technology for the development of students' self-regulated learning, that is, does interaction with the technology build independent SRL skills in learners? Or does the technology support SRL on the assumption that the technological scaffold will always be there during learning? If we assume the latter, the technology aids the learner with "distributed metacognition" that prompts and supports SRL during the student's interaction with the technology. Distributed metacognition is a process whereby metacognition is shared between the learner and the computer to expand the metacognitive resources of the learner to beyond what they would have achieved alone (Kirsh, 2005). While this may improve learning outcomes, there is little empirical research that has addressed whether it also enhances metacognitive knowledge and independent self-regulation outside the interaction with the technology. Much of the technology we have discussed, nStudy, MetaTutor, learning analytics, etc., attempt to support students' self-regulation with the aim of achieving positive learning outcomes and increased content knowledge. However, most overlook the importance of student agency in their own self-regulation, and few consider the development of metacognitive skilfulness outside of interaction with the technology. We believe for technology to truly progress in this area; the onus for self-regulation ultimately still needs to lie with the student.

Conclusion

As described in this chapter, there are many avenues that are being explored to enhance the development of SRL when learning online and with a computer. These technologies can be used by students to plan their own learning activities, monitor themselves, collaborate with peers and self-evaluate their own learning outcomes. Importantly, when learning technologies are deliberately used to support self-regulation, motivation and engagement in online learning contexts, students' academic performance will significantly improve (Kitsantas, Dabbagh, Hiller, & Mandell, 2015). The technologies discussed in this chapter aim to support learning and ultimately foster students to learn how to learn. They aim to support and help students to develop their skills to set goals, plan their strategies, improve self-assessment skills and promote help-seeking behaviour. While an amiable pursuit, we are still a long way from achieving this aim, with a number of challenges and mixed findings from a range of technologies used to enhance SRL.

With this in mind, educators should not assume that learning online occurs in the same way it does in traditional settings, and they need to choose the technologies that both suit their pedagogical purpose and are appropriate for the medium. For example, if the purpose is to foster student-to-student interaction to enhance metacognitive monitoring, this will be facilitated in a very different way in an online environment than it would be in a live classroom. It should also be noted that these technologies are limited at the moment because a significant portion of the information provided back to the educator in the online environment is behavioural data, though this is changing due to the higher potential and accuracy of multimodal data as mentioned above (Azevedo et al., 2018). These crude data are problematic given the high-level nature of SRL as a complex set of cognitive/metacognitive processes. Currently, this is the reality of SRL research; it is a complex phenomenon of the mind impossible to observe for the teachers, an issue that is compounded when the pedagogical purpose and mode of delivery are not explicitly factored in. Thus, researchers and educators alike need to be mindful of the inferences we can make about SRL and how to intervene on the basis of behavioural data alone.

To conclude, the biggest agent in learning regulation is the student themselves. So, while educators should take advantage of the opportunities that technology afford to improve student's SRL, it is important to remember that the onus for self-regulation ultimately needs to be on the student. Technologies can only ever open the door for students; they cannot do the self-regulation for them, even if we assume a strong distributed cognition position on the role of machines in all this.

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