Dealing with Autonomy

Self-Regulated Learning in Open Online Education

Renée Jansen

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Dealing with Autonomy

Self-Regulated Learning in Open Online Education

Omgaan met Autonomie

Zelfregulerend Leren in Open Online Onderwijs

(met een samenvatting in het Nederlands)

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General Introduction

Over the past decades, learning materials are increasingly offered online (e.g., Allen & Seaman, 2016; Qayyum & Zawacki-Richter, 2018; Seaman, Allen, & Seaman, 2018; Shah, 2015), for instance in the form of open educational resources or massive open online courses (MOOCs). In general, open online education is freely accessible to all with an Internet connection. Open online education thereby provides opportunities for a variety of target groups. Adult learners may for instance broaden their (work-related) knowledge. This has led to great expectations of the effects of open online education, including supporting educational equality worldwide and supporting life-long learning (Fischer, 2014; Friedman, 2013; Pappano, 2012). However, expectations are lowered by the large numbers of learners that do not complete the courses in which they enroll. The drop-out rate of learners who start a course but never finish is estimated to be around 90% (Hew & Cheung, 2014). Several reasons for learner dropout have been identified, including a lack of incentive, insufficient prior knowledge, and conflicting priorities or commitments leading to procrastination and, consequently, dropout (Eriksson, Adawi, & Stöhr, 2017; Hew & Cheung, 2014; Zheng, Rosson, Shih, & Carroll, 2015).

The opportunities that MOOCs offer for life-long learning and educational equality are currently not fully met (Fischer, 2014). More research on open online education could help achieve these opportunities. Within the SOONER research project (The Structuration of Open Online Education in the Netherlands; NWO funding 405-15-705), such research is performed. Open online education is studied at three levels: macro (i.e., organizational embedding), meso (i.e., course level), and micro (i.e., learner level) to provide both quantitative and qualitative data on the opportunities and challenges of MOOCs. The current dissertation, which is part of the SOONER project, centers on learners' self-regulated learning (SRL) in open online education: the micro- or learner level is thus the focal point of this dissertation.

When learning in open online education, learners may decide on the topic they want to study, but also the timing, the location, and the pace of their learning. Learners are thereby offered great autonomy over their learning (Beishuizen & Steffens, 2011; Wang, Shannon, & Ross, 2013). Learners need to handle this autonomy in order to be successful in open online education. This means that learners must engage in more and different activities to regulate their learning online, before, during, and after learning (e.g., Azevedo, 2005; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Wang et al., 2013). Inaccurate SRL may result in early course dropout (Eriksson et al., 2017; Kim et al., 2017; Zheng et al., 2015). SRL is thus essential for successful learning in open online education.

Yet, while the importance of SRL for successful online learning has been repeatedly stated (e.g., Azevedo & Aleven, 2013; Beishuizen & Steffens, 2011; Garrison, 2003; Kizilcec & Halawa, 2015; Kizilcec et al., 2017; Wang et al., 2013; Waschull, 2001), little is known about how students' regulate their learning in online education. Furthermore, learners often struggle to adequately regulate their learning (e.g., Azevedo & Cromley, 2004; Bol & Garner, 2011; Dunlosky & Lipko, 2007; Peverly, Brobst, Graham, & Shaw, 2003). Knowledge on how SRL can be supported in open online education is also limited. Two causes for this gap in research can be identified. First, open online education is a relatively new form of education. There is currently little research on the challenges students encounter and how they can best be supported. Second, the measurement of SRL is challenging (e.g., McCardle & Hadwin, 2015; Winne, 2010). Therefore, the research in this dissertation is guided by the central question *"How to measure and support learners' SRL in open online education?"*

In this general introduction, conceptualizations of open online education and SRL are provided, including an overview of existing research. Next, difficulties in measuring SRL, specifically in open online education, are discussed. Finally, an overview is given of the chapters in this dissertation.

Open online education

Before delving into the concept of SRL, we first explain the differences between massive open online courses (MOOCs) and small private online courses (SPOCs), in relation to traditional, campus-based higher education, as the current dissertation contains studies in all three educational contexts.

Massive open online courses (MOOCs) are the most common form of open online education. MOOCs can generally be characterized as online courses, open to all with an Internet connection, without requirements for prior knowledge, and without costs involved to access the learning materials (UNESCO Institute for Information Technologies in Education, 2013). Often, a fee is payable solely to attain a certificate of completion. MOOCs are usually offered on designated digital platforms by distinguished universities worldwide. The easy access to MOOCs leads to large numbers of enrollments, hence the term *massive* open online courses.

The open nature of MOOCs offers MOOC learners greater autonomy to structure their learning process compared to learners in traditional education (e.g., Wang et al., 2013). In the absence of a curriculum, MOOC learners are free to decide what (parts of a) MOOC they study. The lack of scheduled lectures and meetings results in the freedom for MOOC learners to determine where they study and when they study, and, while there in some cases is a fixed start and/or end date to the MOOC, learners also have the freedom to decide on the pace of their studying. The differences in the characteristics of traditional higher education courses and MOOCs, and the consequences of these differences for learners' SRL, are further discussed in Chapter 3 in which a questionnaire to measure learners' SRL in open online education is developed.

SPOCs are somewhere in the middle of the continuum between traditional higher education and MOOCs (Fox, 2013; UNESCO Institute for Information Technologies in Education, 2013). Both SPOCs and MOOCs are complete courses, and SPOCs are similar to MOOCs in the way learning materials are offered: online video lectures, readings, quizzes, and assignments. However, in contrast to MOOCs, SPOCs are private; they are not open to all. There is a requirement for enrollment in a SPOC, one for instance has to be enrolled in the university offering the SPOC. Related to the private nature of SPOCs is the fixed start- and end-date SPOCs usually have. SPOCs commonly end with a traditional exam. SPOCs can thereby be part of a traditional curriculum. Finally, SPOCs are accessible to small groups of learners instead of the massive enrollment numbers MOOCs can have. Depending on the organization of the course, MOOCs and SPOCs may be more or less similar. In some cases, the learning environment of SPOC learners is identical to the learning environment of MOOC learners. The only difference in the learning of MOOC and SPOC learners is then the traditional exam SPOC learners take. SPOC learners may however also be separated from MOOC learners at the start of the course, for instance by having a separate course

forum for SPOC learners, or by providing instructor feedback on assignments made by SPOC learners but not on assignments made by MOOC learners. The formal accreditation offered to SPOC learners, which is not provided to MOOC learners, may lead to differences between SPOC and MOOC learners in terms of motivation and SRL. While quitting a MOOC has very limited consequences, quitting a SPOC has the consequence of not earning credits. SPOC learners are thus extrinsically motivated by the opportunity to earn credits. Therefore, SPOC learners are likely more motivated to complete an online course compared to MOOC learners. The increased motivation, in turn, may make SPOC learners more motivated to engage in SRL than MOOC learners (Pintrich & De Groot, 1990).

Self-regulated learning

The learner autonomy in open online education presses learners to self-regulate their learning, as they must manage their learning process to a great extent (e.g., Wang et al., 2013). However, defining SRL, and the activities it encompasses, is not straightforward, as many researchers have developed models of SRL (for reviews, see: Panadero, 2017; Puustinen & Pulkkinen, 2001). Fortunately, the central elements of these models are quite similar and differences mostly exist in terminology (Puustinen & Pulkkinen, 2001). In this dissertation, we define learners who engage in SRL as metacognitively, behaviorally, and motivationally involved in their own learning process, in line with Zimmerman's model of SRL (Zimmerman, 1986, 2002). Self-regulated learners monitor their learning, and control their learning activities, such as reading, self-testing, and note-taking. Learners engage in such learning activities at the object-level. At a meta-level, learners have a mental dynamic representation of their learning at the object-level. A continuous loop exists between the meta-level and the object-level (see Figure 1): learners monitor learning, which leads to knowledge of the learning process and progress at a meta-level, and control (i.e., regulate) learning activities at the object-level (Nelson & Narens, 1990). Self-regulated learners engage in SRL activities at the meta-level to adapt their learning activities at the object-level. These SRL activities are (mostly) covert activities, since they occur inside learners' heads, while the learning activities are (mostly) overt activities (Veenman, 2016). In this dissertation, we focus on SRL and thus on these (mostly) covert activities.

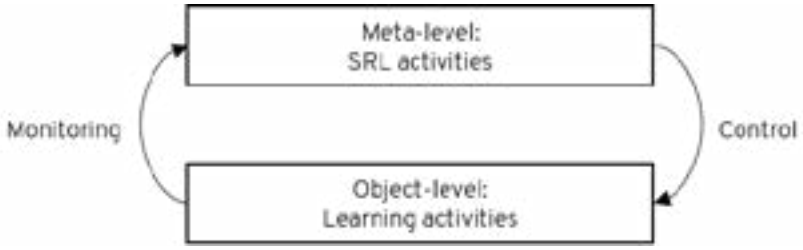

Figure 1 The relationship between monitoring and control (Nelson & Narens, 1990).

SRL proceeds through three phases: a preparatory phase, a performance phase, and an appraisal phase (Panadero, 2017; Pustinen & Pulkkinen, 2001). In each phase, self-regulated learners are actively involved in their learning process. In the preparatory phase,

which occurs before learning, learners plan their learning and set goals. In the performance phase, learners engage in cognitive learning activities to master the learning materials. Learners monitor their progress and adapt their learning activities accordingly. Furthermore, learners manage their time, pick a suitable study location, seek help when needed, and persist when they are less motivated to continue. Finally, in the appraisal phase, learners reflect on their progress and the strategies they used. Together, these activities are termed SRL activities and they allow learners to adapt their learning activities to the situation at hand. SRL activities can be clustered into metacognitive activities (planning, goal setting, monitoring, reflecting) and behavioral and motivational resource management activities (time management, environment structuring, help seeking, and persistence; Pintrich, 1999). The construct SRL is further described in Chapters 2 and 3.

Strong self-regulated learners are actively involved in all these SRL activities: they accurately monitor their learning and successfully adapt their learning activities to the context. The influence of SRL on learning activities is assumed to explain why it is consistently found that those with high scores on SRL measures also achieve better grades: the learning activities of learners with high SRL scores are better aligned with their needs, which in turn result in differences in achievement (Nelson & Narens, 1990; Winne & Hadwin, 1998; Zimmerman, 2002). To gain further insight into the relationship between SRL and learning activities in online education, we study this relationship in Chapter 4. Furthermore, the significant positive relationship between SRL and achievement, in combination with learners' difficulties to engage in SRL, makes it relevant to study what SRL interventions are effective in supporting learners' SRL activities, and if these interventions are also effective in supporting learners' achievement. Therefore, in Chapter 2, we review the relationships between SRL interventions, SRL activities, and achievement in higher education.

Next, we present an overview of previous research conducted on SRL in online education. We discuss the major strands of research conducted and indicate how the studies presented in this dissertation are connected to, and build on, this prior research.

Previous research on self-regulated learning in online education

Over the past years, the argumentation for an increased need for SRL in online education has been described extensively (e.g., Azevedo & Aleven, 2013; Beishuizen & Steffens, 2011; Garrison, 2003; Waschull, 2001). These theoretical descriptions of the need for SRL have been accompanied by a number of empirical studies measuring the relationship between SRL and success in online learning and how students regulate their learning in online education (e.g., Broadbent, 2017; Littlejohn, Hood, Milligan, & Mustain, 2016; Wang et al., 2013; Whipp & Chiarelli, 2004). Artino (2007) reviewed the results of eleven early empirical studies on SRL in distance education and concluded that learners with adequate SRL are more successful in learner-controlled environments than their more weakly self-regulating peers. The role of SRL for successful learning in online education was repeatedly found in later empirical studies. Wang et al. (2013) for example showed that SRL is related to course achievement and course satisfaction in online learning. In addition, Broadbent (2017) showed that students in online education make more use of SRL than learners in blended learning. Together these studies have firmly established the need for SRL in online education.

Research on the importance of SRL in open online education was mostly conducted with questionnaires. In open online education an additional source of data is available to study learner behavior: trace data. In trace data, all activities of a learner in the online learning environment (e.g., LMS, MOOC) are stored with a user ID and a timestamp. Trace data thereby contains a highly detailed account of all learner behavior within the online learning environment. We consider the majority of this behavior to be learning activities (e.g., playing a video, answering questions), but not all learner behavior is directly related to learning (e.g., logging in, clicking on a page). Trace data can be used for a variety of research aims, including studying the influence of learner characteristics on behavior, as well as studying the influence of learner behavior on achievement. Trace data may also contain information that can serve as a proxy of learners' SRL activities.

The availability of trace data has spurred SRL researchers to explore its possibilities, for instance by coupling SRL questionnaire data to trace data, or by using trace data as a proxy of SRL activities (e.g., Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007; Panadero, Klug, & Järvelä, 2016). In this dissertation, we utilize learners' trace data to study learner behavior and learners' underlying SRL activities. Trace data research can be either data-driven or theory-driven. In this dissertation, we use both approaches. Our research in Chapters 4 and 6 is data-driven, while our research presented in Chapter 5 is theory-driven. In the next sections, relevant research on the use of trace data to study SRL is presented and linked to the studies in this dissertation.

Data-driven use of trace data to study SRL

In data-driven studies, variables are not pre-defined. Data are 'mined' for instance to identify clusters of similar learners or to identify frequently occurring sequences of activities. These data-driven studies of trace data have shown that learners engage in MOOCs in highly variable ways. Kizilcec et al. (2013) used MOOC trace data to analyze learner engagement. The results showed that MOOC learners could be clustered into four distinct groups: completing (finishing all course materials), auditing (watching videos but not taking quizzes), disengaging (decreasing in engagement over time), and sampling (watching only a few videos). The results indicate that clear differences exist between the ways in which learners engage with a MOOC. In later data-driven studies, trace data was used to analyze learner activity sequences. Both Jovanović et al. (2017) and Maldonado-Mahauad et al. (2018) clustered learners based on their activity within an online learning environment. More specifically, they clustered learners based on the sequences in their learning activities. In both studies, first all paths learners had taken from the start of a learning session to the end of a learning session were analyzed and clustered. This clustering resulted in various paths learners could follow from the start to the end of a learning session. Next, in both studies, learners were clustered based on the frequency of these different paths in their learning. The study by Kizilcec et al. (2013) had already shown that learners engage with MOOCs differently over the duration of the course. These latter two studies showed that learners also engage differently with MOOCs during learning sessions. Together, the studies thereby show the diversity of learner activity measurable with trace data.

These differences in learner behavior may be related to differences in learners' SRL. Learners' behavior in the MOOC would then be a proxy for their SRL activities. Learners' behavior (at the object-level; see Figure 1) captured in trace data could then be used as an overt measure indicating learners' covert SRL activities (at the meta-level). Kizilcec et al. (2017) specifically explored the relationship between trace data and learners' SRL. The

authors first identified the most important activities in the MOOCs they studied, which were video lecture and assessment events. Learners in the MOOC then filled out an SRL questionnaire. Next, they correlated learners' SRL scores with the frequency of learners' transitions from each activity to another activity. Differences in SRL scores were related to differences in transition frequencies. For instance, learners with high SRL scores were more inclined to revisit already finished lectures and assessments than those with low SRL scores. The results however did not provide information about students' learning processes as only transitions were studied. Studying learning processes (i.e., taking longer sequences of activities into account) is important for improving our understanding of the relationship between SRL and learner behavior, since the context of learning activities is taken into account when studying learning processes. Therefore, we explore the relationship between learners' SRL and learning processes in Chapter 4. We thereby build on the research studies just presented as we attain to improve our understanding of how learners' SRL influences learner behavior in a MOOC.

Theory-driven use of trace data to study SRL

Supplementing the data-driven approaches to studying trace data are the theory-driven studies that incorporate the analysis of trace data to understand learner behavior and predict learner achievement. In these studies, variables that can be extracted from learners' trace data and that are interesting to better understand learner behavior or achievement are defined before the start of data analysis. In several studies, such trace data variables have been used as indicators of learners' SRL. Regular studying is such a variable that can be extracted from trace data, and which may signal good SRL. You (2016) therefore focused on the regularity of learners' studying in an online elective course. Beforehand, several variables were defined that were thought to be related to learner achievement. These variables could all be extracted from the trace data. The number of learning sessions, as well as regular studying and the (lack of) late submissions of assignments were all positively associated with learners' course scores. The importance of distributed learning for course achievement was later replicated by Theobald et al. (2018). SRL however encompasses more than (the lack of) procrastination, and Min and Jingyan (2017) therefore attempted to study all three phases of learners' SRL in trace data. The authors defined activities that indicated SRL in either the preparatory, performance, or appraisal phase. These activities were short sequences of activities stored in learners' trace data. Learners were then clustered into groups based on their SRL activity. Four clusters of learners were created: sequences of all SRL phases present in trace data, missing one phase, missing two phases, or no SRL sequences in trace data. Those whose trace data showed indicators of engagement in all three SRL phases had higher grades and greater course persistence compared to those whose trace data indicated engagement in only one or two SRL phases. The authors hereby demonstrated the value of using trace data for studying learners' SRL in online education. We continue the practice of using trace data as an indicator of learners' SRL in Chapter 5. In Chapter 5, we present an SRL intervention study in which we explored the effects of the intervention on learners' SRL activities. We build on the studies presented here to define the trace data variables indicative of SRL. We thereby extend the use of trace data for the measurement of SRL from correlational studies to interventions studies.

Improving learners' SRL

The importance of SRL for successful online learning has also inspired researchers to investigate how to improve learners' SRL in MOOCs (Davis, Triglianos, Hauff, & Houben,

2018; Kizilcec, Pérez-Sanagustín, & Maldonado, 2016; Yeomans & Reich, 2017). Research on SRL interventions in MOOCs is new, and only few published studies exist. Both Kizilcec et al. (2016) and Yeomans and Reich (2017) implemented their interventions in a pre-course survey. Kizilcec et al. (2016) presented half of the MOOC learners with study tips in the survey, while Yeomans and Reich (2017) provided half of the learners with planning prompts and asked them to describe any specific plans they had for the MOOC. Davis et al. (2018) implemented an SRL intervention in a MOOC, which was presented to all learners. Learners were asked to express their motivation to follow the course, as well as to indicate the number of videos they intended to watch, the number of quizzes they intended to make, and the amount of time they intended to spend in the course. Learners were presented with their motivation statement as well as their self-set goals during learning. The results of all three studies showed some promising results: both course completion and course engagement were greater for learners who engaged with the interventions. The results were overall however less positive than expected. The authors describe a number of causes for the lack of intervention effects, including insufficient integration of the intervention in the course and learners' weak compliance to the interventions. These intervention studies thereby leave room for improvement. Furthermore, existing intervention studies focus on the effects of the interventions on activity frequencies and course completion, leaving the effects of the intervention on SRL unstudied. Therefore, in Chapter 5, we present an SRL intervention study in three MOOCs, in which the intervention effects were explored on both SRL and course completion.

Measuring self-regulated learning

Next to answering theoretical questions related to SRL in open online education, we also focus on methodological issues in this dissertation. The challenges involved in measuring SRL have been described repeatedly, and are not new to the context of open online education (e.g., Greene & Azevedo, 2010; McCardle & Hadwin, 2015; Winne, 2010; Winne, Jamieson-Noel, & Muis, 2002; Winne & Perry, 2000; Zimmerman, 2015). Nevertheless, accurate measurement of learner behavior and learners' regulation of their behavior is necessary to successfully support learners' SRL. The issues involved in measuring SRL are therefore relevant in the current dissertation. Additionally, the availability of trace data when conducting research in open online education, brings new possibilities and new challenges to the measurement of SRL (Hadwin et al., 2007; Winne et al., 2002).

Over the past decades, several authors have classified the different methods that can be used to measure SRL and addressed the strengths and weaknesses of these methods (e.g., Roth, Ogrin, & Schmitz, 2016; Winne & Perry, 2000). We consider the following two often mentioned issues to be most important for accurate measurement of SRL: (1) measuring covert SRL activities, and (2) measuring SRL over time (e.g., Molenaar & Järvelä, 2014; Sonnenberg & Bannert, 2016; Veenman, 2007; Winne, 2010). When measuring learners' overt behavior, for example by observation, one can only identify learner behavior at the object-level. For instance, one can observe where a student learns (environment structuring), but whether this was a deliberate decision, and what reasons underlie that decision, cannot be observed (Winne, 2010). Successful regulation is adaptive to the context at hand, and strategies should be the result of deliberate decisions. Therefore, knowledge of the covert SRL activities causing learners' to regulate their behavior in the way they do,

is necessary for accurate measurement of SRL (Greene & Azevedo, 2010; Winne, 2010; Winne & Perry, 2000). A range of measurement methods is used to grasp the covert SRL activities of learners, including diary studies, questionnaires, interviews, and think aloud protocols (Roth et al., 2016; Schraw, 2010). In Chapter 3, we add to the inventory of instruments a questionnaire specifically suited to measure SRL in open online education.

The adaptive nature of successful SRL not only leads to the necessity to measure SRL in context, but also makes it relevant to measure learner behavior over time (Greene & Azevedo, 2010; McCardle & Hadwin, 2015; Winne & Perry, 2000). The temporality of SRL and learner behavior is captured in process measures of SRL (Azevedo et al., 2013; Winne, 2010). Learners' trace data are stored automatically and contain temporal information. The presence of temporal information allows for the calculation of process measures. Trace data are therefore a valuable and easily available data source that is increasingly used to study SRL. For instance, SRL indicators may be extracted from trace data (Cicchinelli et al., 2018; Maldonado-Mahauad et al., 2018; Min & Jingyan, 2017) and trace data may be used for triangulation with SRL measurements (Hadwin et al., 2007; Howard-Rose & Winne, 1993). In Chapter 4 we study the relationship between SRL measured with questionnaires on the one hand, and learner behavior processes as stored in trace data on the other hand.

While trace data provides valuable information on learners' behavior and their SRL, accurate interpretation of trace data is challenging (e.g., Maldonado-Mahauad et al., 2018; Schraw, 2010). Trace data only provides information on the what and when of learner behavior; information on the how and why of learner behavior is missing (Jovanović et al., 2017; Min & Jingyan, 2017; Phillips et al., 2011). Trace data must therefore be used cautiously; staying aware of what information is and is not stored in the trace data. In Chapter 5, we make use of trace data to measure the effects of an SRL intervention in open online education. In an attempt to obtain the most valid variables from the data, trace data variables were based on a combination of theoretical knowledge of SRL and empirical studies showing the importance of specific activities for achievement and course completion. In Chapter 6, we revisit the methodological limitations of using trace data to measure learners' SRL. We present a mixed methods approach, combining trace data with interview data, to help solve the issues involved in interpreting trace data.

Throughout this dissertation we attempt to handle the challenges involved in measuring SRL adequately. We pay attention to the advantages and disadvantages of different measurement methods in our MOOC context and expand knowledge on SRL measurement by combining research instruments (i.e., questionnaire data and trace data in Chapter 4, trace data and interview data in Chapter 6). Thereby we aim to not only expand theoretical knowledge on SRL in open online education, but also to expand methodological knowledge on the measurement of SRL in open online education.

Overview of this dissertation

In this dissertation, five studies are presented which jointly aim to answer the central research question *"How to measure and support learners' self-regulated learning in open online education?"* While Chapters 2, 4, and 5 focus on how to support learners' SRL in open online education, Chapters 3, 4, and 6 focus on how to measure SRL in open online education. A wide range of methodological approaches was utilized to best analyze the gathered data. Figure 2 provides an overview of the studies presented in this dissertation in terms of their focus, the educational context in which they were conducted, and the specific type of data that was collected.

In **Chapter 2**, the relations between SRL interventions, SRL activities, and achievement in higher education are studied in a literature review. Existing meta-analyses have shown positive relations between each of the concepts separately, but the concepts have not yet been studied in an integrated manner. Meta-analytic structural equation modeling (MASEM) is used to study to what extent the effects of SRL interventions on achievement are mediated by improvements in SRL activities. Furthermore, meta-analyses are conducted of the relations between SRL interventions and achievement, (2) SRL interventions and SRL activities, and (3) SRL activities and achievement. Moderator analyses of each relation provide further insight into the influence of study, measurement, and intervention characteristics on effect sizes.

In Chapters 3,4, and 5, the focus shifts from higher education in general to open online education. In **Chapter 3**, a questionnaire to measure SRL in open online education is developed. First, a detailed description is given of SRL activities to be measured by the questionnaire, and how these activities differ between traditional higher education and open online education. Next, a first version of the questionnaire is developed. Then, in a second study, a revised version of the questionnaire is developed. Thereby, in Chapter 3, the need for a measurement instrument suitable to measure learners' SRL in open online education is addressed.

Chapter 4 starts from the assumption that, since differences in SRL lead to differences in achievement, there must be differences in behavior between those who differ in their SRL. These differences in behavior, in turn, lead to differences in achievement. This study therefore focusses on how differences in SRL relate to differences in learner behavior. The original questionnaire developed in Chapter 3 is used to measure learners' SRL. Learners are then clustered based on their self-reported SRL. Process mining of MOOC learners' trace data is used to analyze the differences in learner behavior between the different clusters of learners.

In **Chapter 5**, the knowledge gathered on supporting learners' SRL in Chapter 2, is combined with the knowledge gathered on measuring learners' SRL in online education in Chapters 3 and 4, to study the effects of an SRL intervention in three MOOCs. The intervention was integrated in the MOOCs and presented to half of the MOOC participants. The aim of the study was to measure the effects of the SRL intervention on both learners' SRL, as measured with questionnaire and trace data, as well as on course completion.

Chapter 6 results from the observation that trace data provides us with information about the what and when of learner behavior, but not on the how and why of their behavior. To understand learners' SRL, and to be able to interpret trace data correctly, information on the latter two questions is necessary. In this chapter, a mixed methods approach to studying SRL in open online education, combining trace data and interview data, is presented. Data from a pilot study with SPOC learners is used to show the benefits of the suggested methodology.

In **Chapter 7**, the insights gathered from the five studies are described and discussed. The implications of the research conducted are presented and future research suggestions are offered. To conclude, a reflection is given on the future of MOOCs and SRL support research.

As Figure 2 outlines, the studies in this dissertation employ a variety of methodologies, including quantitative, qualitative, and mixed methods designs, to study the support and measurement of learners' SRL in open online education. The studies presented in this dissertation thereby further our knowledge on learners' SRL in open online education.

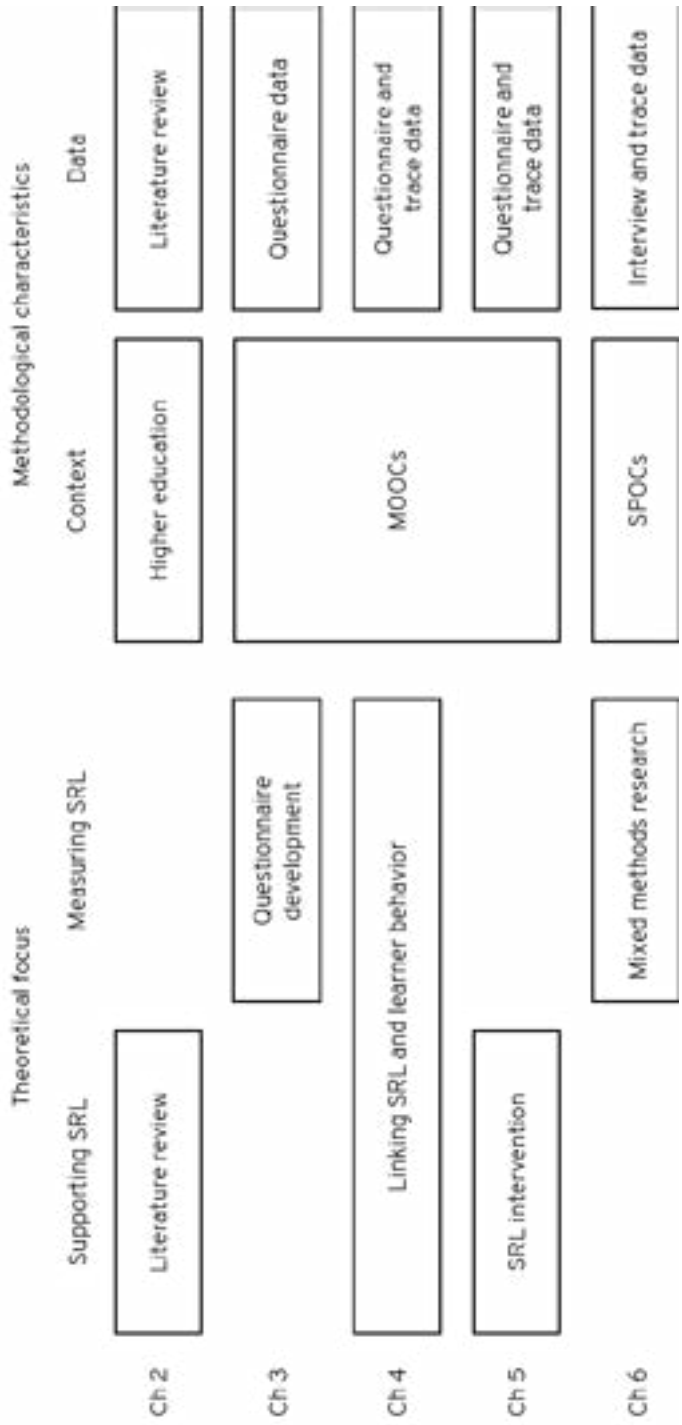

Figure 2 Schematic overview of the studies presented in this dissertation.

2

Self-Regulated Learning Partially Mediates the Effect of Self-Regulated Learning Interventions on Achievement in Higher Education: A Meta-Analysis

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This chapter is based on:

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RJ, AvL, JJ, and LK designed the study; RJ, AvL, and JJ constructed the coding scheme; RJ collected the data; RJ, AvL, JJ, SJ, and LK planned the data analysis; RJ and SJ analyzed the data; RJ drafted the manuscript; all authors contributed to critical revision of the manuscript; AvL, JJ, and LK supervised the study.

Abstract

It is often assumed that interventions aimed at supporting students' self-regulated learning (SRL) are effective for improving achievement because these interventions support SRL activity. In this study, meta-analytic structural equation modeling (MASEM) was used to test whether SRL activity indeed mediates the effect of SRL interventions on achievement in higher education. Contrary to popular belief, the results only provide evidence for partial mediation. Furthermore, three separate meta-analyses were performed to investigate the role of possible moderators of the relations between: (1) SRL interventions and achievement, (2) SRL interventions and SRL activity, and (3) SRL activity and achievement. Although SRL interventions were effective in improving SRL activity and achievement, most of the study, measurement, and intervention moderators did not explain significant variance of the investigated effect sizes. Other factors, such as task motivation and time on task, potentially influence the effectiveness of SRL interventions. Practical, theoretical and methodological implications are provided.

Introduction

Factors influencing academic achievement have always received great attention from scholars, and self-regulated learning (SRL) is no exception (Boer, Donker-Bergstra, Kostons, & Korpershoek, 2013). Higher education students who engage in SRL are actively involved in their learning process. As SRL activity has consistently been found to be related to student achievement, research into ways to support SRL is plentiful (e.g., Azevedo & Cromley, 2004; Azevedo, Cromley, & Seibert, 2004; Bannert, Hildebrand, & Mengelkamp, 2009; Broadbent & Poon, 2015; Nietfeld, Cao, & Osborne, 2006; Stark & Krause, 2009). In general, these SRL interventions that support students´ knowledge of SRL and their engagement in SRL activities, show positive results on achievement (e.g., Boer et al., 2013; de Bruijn-Smolders, Timmers, Gawke, Schoonman, & Born, 2016; Dignath & Büttner, 2008). It is assumed that SRL interventions are effective in improving achievement due to their effects on students' engagement in SRL activities: the SRL intervention improves students' use of SRL activities and this improvement leads to better performance. Proof that engagement in SRL activities mediates the effect of SRL interventions on achievement is nevertheless lacking. The first goal of this chapter is therefore to perform a mediation analysis with meta-analytic data, to test if engagement in SRL activities is a significant mediator of the effect of SRL interventions on achievement. Furthermore, it is not yet known what makes an SRL intervention effective for improving students' SRL activities or achievement. The second goal of this chapter is therefore to test which characteristics influence the effectiveness of SRL interventions. To do so, separate meta-analyses are conducted of (1) the effect of SRL interventions on achievement, (2) the effect of SRL interventions on SRL, and (3) the relation between engagement in SRL activities and achievement.

Self-regulated learning

SRL is central to students' learning process, as students that engage in SRL take control of their own learning process. Multiple models and frameworks of SRL exist (Pintrich, 2000, 2004; Winne & Hadwin, 1998; Zimmerman, 1990, 2002), but the main components of the models are similar (Pintrich, 2000; Puustinen & Pulkkinen, 2001). Students who self-regulate their own learning process are metacognitively, behaviorally, and motivationally active in their learning and they proceed through three phases: a preparatory phase, a performance phase, and an appraisal phase (Zimmerman, 1986, 2002). In the preparatory phase, students prepare for the learning task at hand, they plan their work, and set goals. In the performance phase, students engage in cognitive strategies to learn the material at hand, they monitor their learning, regulate their learning strategies, and they allocate their resources (e.g., time and help) in the most efficient manner. Lastly, in the appraisal phase, students reflect on their learning and determine which strategies were effective and what they could do differently the next time they study (Pintrich, 2000; Puustinen & Pulkkinen, 2001; Zimmerman, 2002).

In each phase, learners may engage in different activities to regulate their learning. Students' engagement in these different activities is captured under the umbrella term engagement in SRL activities. Students that are metacognitively involved in their learning strategically plan, monitor, and reflect on the cognitive strategies they use for learning. The SRL activities they engage in are goal setting and strategic planning before learning (preparatory phase), comprehension monitoring and strategy regulation during

learning (performance phase), and reflection after learning (appraisal phase; Puustinen & Pulkkinen, 2001; Zimmerman, 2002). Next to these metacognitive activities, SRL also entails behavioral regulation and motivational regulation (Zimmerman, 1986). Behavioral regulation includes the SRL activities time management, environmental structuring (i.e., studying in a suitable location), and help seeking. Motivation regulation includes persisting when motivation drops, which has also been termed effort regulation (Pintrich, 1999). Motivational regulation and behavioral regulation both mostly take place during learning (performance phase) and can together be classified as resource management activities, as these activities all focus on keeping resources (e.g, help, environment, attention) at an appropriate level (Pintrich, 1999).

SRL models differ in their explanation of the role of motivation (Panadero, 2017). Some consider motivation for learning part of SRL (e.g., Boekaerts, 1992; Zimmerman, 2002, 2008), while others consider persistence and regulating motivation part of SRL, but consider task motivation a precursor for successful SRL (e.g., Efklides, 2011; Ning & Downing, 2012; Pintrich, 1999, 2000; Schunk, 2005). In the latter models, it is reasoned that learners will not engage in successful SRL without sufficient motivation for the task at hand. We adhere to this latter definition, leaving motivation for learning (i.e., task value, goal orientation, and self-efficacy) outside of the scope of the current review.

The importance of SRL for student achievement

Students who self-regulate choose the most effective cognitive learning activity (e.g., rehearsal, elaboration, note-taking) depending on the current learning task and broader context (Boekaerts, 1992; Winne & Hadwin, 1998; Zimmerman, 2002). Students' SRL activities thereby influence their cognitive activities (Nelson & Narens, 1990), and students who actively self-regulate their learning thus engage in more effective cognitive strategies. Students' progress during learning is a result of their use of cognitive strategies (Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013). This progress is, in turn, used as input for further self-regulation through monitoring (Beishuizen & Steffens, 2011; Nelson & Narens, 1990). SRL and the use of cognitive strategies thus form a cyclical process during learning (Nelson & Narens, 1990; Veenman, 2016). The influence of SRL on the use of cognitive learning strategies likely explains why prior review studies consistently show that SRL is related to higher student achievement (Boer et al., 2013; de Bruijn-Smolders et al., 2016; Dignath, Buettner, & Langfeldt, 2008; Dignath & Büttner, 2008; Sitzmann & Ely, 2011). Cognitive strategies thus influence the effects of SRL on achievement. In the current review we however focus on the effects of SRL interventions, thereby placing engagement in cognitive learning activities outside of our scope.

Due to the importance of SRL for student achievement, numerous studies have been conducted on how academic achievement is affected by interventions that aim at supporting students' engagement in SRL activities (e.g., Azevedo & Cromley, 2004; Azevedo et al., 2004; Bannert et al., 2009; Broadbent & Poon, 2015; Nietfeld et al., 2006; Stark & Krause, 2009). These so-called *SRL interventions* take many forms. They are aimed at supporting students' engagement in SRL activities, either by supporting the quality of students' engagement in SRL activities, the quantity of students' engagement in SRL activities, or both. Examples of SRL interventions include informing students about effective SRL activities and their importance, or prompting students at the end of lecture activities to reflect on the course material, on the completed assignments, and on the strategies they used for learning.

The mediating role of SRL activities

Empirical studies exploring the effect of SRL interventions are usually focused on improvements in achievement. They are often based on the assumption that SRL interventions stimulate students' engagement in SRL activities (relation 2 in Figure 1), in turn leading to increased academic achievement (relation 3 in Figure 1). An indirect effect of the interventions on achievement is thus assumed. However, to the best of our knowledge, no studies have tested the mediating role of SRL activities, and only very few studies included all three relations between SRL interventions, SRL activities, and achievement (Garavalia & Gredler, 2002a; Greene, Hutchison, Costa, & Crompton, 2012; Schmidt & Ford, 2003) in their analyses. While some studies include both the effect of SRL interventions on SRL activities as well as the effect of SRL interventions on achievement, none of these studies tested the mediating role of SRL activities on the effect of SRL intervention on achievement. The majority of studies examined the direct relationship between SRL interventions and academic achievement (relation 1 in Figure 1; e.g., Azevedo et al., 2004; Bannert, Sonnenberg, Mengelkamp, & Pieger, 2015; Lusk, 2016).

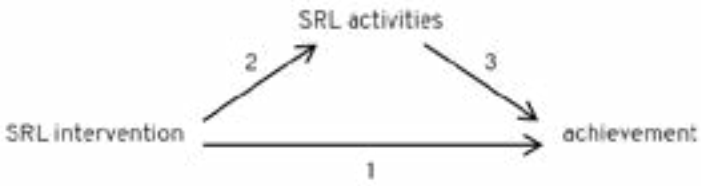

Figure 1 The effect of SRL interventions on achievement mediated by SRL activities.

Similarly, existing meta-analyses and systematic reviews focused only on parts of the framework presented in Figure 1, namely: the effect of SRL interventions on achievement (Boer et al., 2013; de Bruijn-Smolders et al., 2016; Devolder, Van Braak, & Tondeur, 2012; Dignath et al., 2008; Dignath & Büttner, 2008; Hattie, Biggs, & Purdie, 1996), the effect of SRL interventions on SRL activity (de Bruijn-Smolders et al., 2016; Dignath et al., 2008; Dignath & Büttner, 2008; Hattie et al., 1996), and the relationship between SRL activity and achievement (Broadbent & Poon, 2015; Dent & Koenka, 2016; Sitzmann & Ely, 2011). A meta-analysis that focuses on the mediating role of SRL in the effect of SRL interventions on achievement is missing. The first goal of this chapter is therefore to systematically review SRL as a mediator of the effect of SRL interventions on achievement, in the context of higher education. We will perform a meta-analytic mediation analysis to test the commonly made claim that SRL interventions are effective for improving student achievement by improving students' engagement in SRL activities.

Additionally, most existing reviews were conducted in primary and secondary education. Only a few reviews include data from students in higher education: Sitzmann and Ely (2011; higher education and employees), Broadbent and Poon (2015; online higher education), De Bruijn et al. (2016; higher education), and Hattie et al. (1996; primary, secondary, and higher education and employees). This lack of overview studies aimed at higher education is unfortunate because SRL is of great importance for student achievement in higher education. In higher education, learners are provided greater autonomy as there is limited external regulation of their learning process (Beishuizen & Steffens, 2011; Sitzmann & Ely, 2011). Learners for instance study mostly outside of the classroom at their own pace

and attendance is often not required. The increased independence of learners leads to a greater need for learners to take control of their own learning process in higher education compared to primary and secondary education making SRL more important (Beishuizen & Steffens, 2011; Wang, Shannon, & Ross, 2013). The lack of reviews focusing on SRL in higher education, combined with the importance of SRL in this context, leads us to focus on SRL in higher education in the current review.

What makes SRL interventions effective?

Due to the importance of SRL for student achievement, numerous interventions have been developed to support students' SRL activity. However, there are currently few guidelines available on how to develop effective SRL interventions in higher education. The second goal of this chapter is therefore to systematically review what characteristics of SRL interventions lead to improved achievement (relation 1 in Figure 1) and SRL activity (relation 2). Thus, while we group all intervention studies in the first part of the chapter, ignoring differences between studies to calculate the mediation by SRL activity, in the second part of the chapter we focus on the differences between studies by performing moderator analyses. Moderator analyses of the effect of SRL interventions could provide clues on how to design effective SRL interventions to support achievement and/or SRL activity. Such guidelines would be valuable for educational practice. In the second part of the chapter, we therefore perform meta-analyses of the three relations outlined in Figure 1. The relation between SRL activity and achievement (relation 3) is included in the current study to enable calculation of the mediation of the effect of SRL interventions on achievement by SRL activity; without inclusion of the relation between SRL activity and achievement this would not be possible. However, there already is an abundance of research consistently showing this relation to be significant and positive (Boer et al., 2013; de Bruijn-Smolders et al., 2016; Dignath et al., 2008; Dignath & Büttner, 2008; Sitzmann & Ely, 2011)

In the next section, we discuss existing knowledge about the effect of SRL interventions on engagement in SRL activities and on achievement. As there is ample research into SRL, SRL interventions, and achievement, we provide an overview of the current literature based on existing review studies. Even though the reviews discuss the three relations in isolation, and most reviews are conducted in primary and secondary education, they offer hypotheses of what might constitute an effective SRL intervention in higher education to improve both students' engagement in SRL activities and their achievement. Analyzing the existing knowledge on SRL interventions thereby provides indications for characteristics to include as moderators in the current study.

Potential moderators of the effectiveness of SRL interventions

Not all SRL interventions have been found to be equally effective in supporting students' engagement in SRL activities and students' achievement (Boer et al., 2013; Dignath et al., 2008; Dignath & Büttner, 2008). Characteristics that potentially influence the measured effectiveness of SRL interventions on SRL activity and achievement have been identified by analyzing the differences between empirical SRL intervention studies. Characteristics included in previous SRL review studies have furthermore been incorporated in the current review. These characteristics are used as moderators in the present study and are described below. We distinguish between five intervention characteristics and three measurement characteristics.

The first characteristic for which interventions show variety is whether *cognitive strategies are included*, so whether the intervention focuses solely on SRL, or also on cognitive strategies. Students must possess an adequate repertoire of cognitive strategies in order to be able to successfully self-regulate; without such a repertoire students cannot regulate their learning behavior as they have insufficient strategies to choose from (Hattie et al., 1996; Paris & Paris, 2001). It is likely that the need for instruction about cognitive strategies decreases when students reach higher levels of education, because by then, they have internalized more cognitive strategies. Students in higher education, therefore, may benefit more from interventions that aim at supporting their SRL activities, compared to strategies aimed at supporting their cognitive strategies. For instance, they would benefit more from support on how to plan their work (an SRL activity) than how to memorize facts (a cognitive strategy). As some studies include cognitive strategies in their SRL intervention (e.g., Dörrenbächer & Perels, 2016a; Wischgoll, 2016), while others do not (e.g., Greene et al., 2012; Nietfeld et al., 2006), the inclusion of cognitive strategies is incorporated as a moderator in the meta-analysis to test whether it influences the effectiveness of SRL interventions.

The second intervention characteristic is the *format of the intervention*. Students need to have knowledge about SRL and SRL activities in order to be able to successfully engage in SRL (Dignath & Büttner, 2008; Paris & Paris, 2001; Zimmerman, 2002). In primary education, Dignath and Büttner (2008) found that SRL interventions were most effective for improving students' achievement when they contained instruction on SRL as a concept and on possible SRL activities students could engage in. In secondary education, interventions with metacognitive instruction were less effective for improving students' achievement compared to interventions with metacognitive reflection (Dignath & Büttner, 2008). Thus, instead of instruction on metacognition and metacognitive activities, students benefitted most from interventions that stimulated them to reflect on their learning process and to engage in the metacognitive activities they already knew. Students in secondary education possess more knowledge on SRL activities than students in primary education and can, therefore, benefit from metacognitive reflection (Dignath & Büttner, 2008). For instance, while students in primary education benefit from instruction on what a planning is and how one should construct a planning, students in secondary education already know what a planning is but need to be stimulated to create a planning and monitor their progress. Students in higher education may have internalized even more knowledge on SRL and SRL activities. This would imply that SRL interventions for successfully improving students' achievement in higher education should focus on stimulating students to reflect on their cognitive strategy use and activate students' existing knowledge of SRL (Bannert & Reimann, 2012). This could for instance take the form of scaffolding, where students are for example prompted to self-explain their steps to mastery of the learning material until they no longer need to be prompted (Van Laer & Elen, 2017). Thus, whether the intervention provides instruction, application, or prompting of SRL will be included as a moderator to test potential differences in the effectiveness of interventions based on their format.

The third characteristic for which interventions show variety is the *timing of the intervention* in relation to the learning context. In some intervention studies, the intervention is placed before learning (e.g., Azevedo & Cromley, 2004). In other studies, the intervention is incorporated during the whole lab experiment or course (e.g., Delen, Liew, & Willson, 2014), or only in the second half (e.g., Nückles, Hübner, & Renkl, 2009). Incorporating the SRL support before the learning task allows learners to benefit from the support during

the whole task, which may lead to larger effects. On the other hand, incorporating the intervention at a later stage allows students to first get accustomed to the learning environment, which may reduce the possibility of overwhelming them with too much information. As there are thus differences in the timing of the intervention, and these differences may influence the effectiveness of the SRL interventions, timing is included as a moderator.

The fourth intervention characteristic that will be included as a moderator is whether the intervention is *tailored to the learning context*. As the effectiveness of SRL activities is partly context dependent, interventions should aim at helping students determine what the effective SRL activities are in the specific context at hand (Puustinen & Pulkkinen, 2001). Students can benefit from the synergy between domain-learning, cognitive strategy instruction, and SRL activities (Perels, Gürtler, & Schmitz, 2005). For this reason, domain-general prompts for SRL, asking students to reflect on their learning, have been found to be less effective for supporting students' SRL behavior than domain-specific prompts in which students, for instance, were asked how well they comprehended a specific concept within the domain (Devolder et al., 2012). To test whether this also holds in higher education, whether the intervention is tailored to the learning context (i.e., domain-specific) will be included as a moderator.

The fifth intervention characteristic is the *type of SRL activity supported* by the intervention. Broadbent and Poon (2015) and Sitzmann and Ely (2011) found diversity in the magnitude of the correlation between students' reported engagement in a range of SRL activities and student achievement in higher education. For instance, effort regulation in the form of persistence was found to be much more strongly related to achievement than help-seeking (Sitzmann & Ely, 2011). Some SRL activities are thus more strongly associated with achievement than others. This difference in the strength of the correlation between SRL activities and achievement may also explain why interventions aimed at some SRL activities are more beneficial for academic achievement than others (Boer et al., 2013). The question remains whether SRL interventions should focus on a subset of particular SRL activities (that are strongly related to achievement), or that interventions should focus on supporting students' SRL in general; and if the preferred focus is dependent on the goal of the SRL intervention (improving achievement, relation 1 in Figure 1, versus supporting SRL activity, relation 2). Therefore, the SRL activity the intervention is aimed at will be included as a moderator to explore whether SRL interventions that focus on different aspects of SRL have different effects. All metacognitive (e.g., planning, comprehension monitoring) and resource management (e.g., time management) activities introduced will be included. More information about the SRL activities included and how they are coded will be presented in the Method section.

The *type of SRL activity measured* is the first measurement characteristic that will be included as a moderator. It is included to see if the results of Broadbent and Poon (2015) and Sitzmann and Ely (2011), showing that some SRL activities are more strongly related to achievement than others, are replicated in the current meta-analyses.

The second measurement characteristic included as a moderator is the *instrument* used to measure SRL. The validity of instruments used to measure SRL is widely debated (e.g., Greene & Azevedo, 2010; Panadero, Klug, & Järvelä, 2016; Veenman, 2016; Veenman, Van Hout-Wolters, & Afflerbach, 2006; Winne, 2010). By incorporating the instrument used to measure students' engagement in SRL activities we assess whether differences in the

effects of SRL interventions on SRL activity, and differences in the relationship between SRL activity and achievement, are due to the instrument used to measure SRL.

Finally, the employed *achievement measure* is the third measurement characteristic included as a moderator. Different achievement measures are in use to test the effects of SRL interventions and the relation between SRL activity and achievement, including course grade (e.g., Cleary, Callan, Malatesta, & Adams, 2015; Van den Boom, Paas, & Van Merriënboer, 2007) and GPA (e.g., Masui & De Corte, 2005; McKenzie, Gow, & Schweitzer, 2004). By including the employed achievement measure as a moderator, we are able to test whether the achievement measure can explain variability between studies.

Present study

In the present study, we systematically review empirical research on the effectiveness of SRL interventions on students' engagement in SRL activities and on students' academic achievement. We first perform a meta-analysis on SRL activities as mediating the effect of SRL interventions on achievement. The research question we pose is *"To what extent is the effect of SRL interventions on students' achievement due to students' SRL activity?"* By calculating the mediating effect of SRL in the relationship between SRL interventions and academic achievement (relations 2 and 3 in Figure 1), we determine whether SRL interventions indeed lead to increased achievement through changes in students' SRL activity. We hereby aim to supply empirical evidence for this assumption.

Second, existing reviews (Boer et al., 2013; Dignath et al., 2008; Dignath & Büttner, 2008) have provided indicators of what constitutes an effective SRL intervention for supporting students' SRL activity and students' academic achievement in primary and secondary education. Unfortunately however, in line with the empirical research in the field of SRL, the reviews include only part of the framework presented in Figure 1. A comprehensive meta-analysis including all three relations at once is still missing. We will therefore perform meta-analyses of (1) the effectiveness of SRL interventions for improving student achievement, (2) the effectiveness of SRL interventions for supporting students' SRL activity, and (3) the relationship between SRL activity and achievement (Figure 1). The meta-analyses will be conducted for the context of higher education, as SRL becomes more important with an increase in autonomy, as is common in higher education (Beishuizen & Steffens, 2011). The research questions we thus pose are: *"Which factors significantly influence the effect of SRL interventions on achievement?"*, *"Which factors significantly influence the effect of SRL interventions on SRL activity?"*, and *"Which factors significantly influence the relationship between SRL activity and achievement?"*

Method

To answer the research questions, two types of analyses were conducted. First, a mediation analysis was conducted using *meta-analytic structural equation modeling* (MASEM; Jak, 2015) to test the extent to which the effect of SRL interventions on achievement is due to changes in students' engagement in SRL activities. Second, the overall effect of SRL interventions on academic achievement (relation 1), the overall effect of SRL interventions on SRL activity (relation 2) and the relation between SRL activity and achievement

(relation 3) were calculated, after which the variation within each of these relations was further explored. For each relation separately, factors that significantly explain variance in effect sizes were identified through moderator analyses. Thus, in addition to the mediation analysis using MASEM, three separate meta-analyses were conducted, each with complementing moderator analyses.

Literature search

To identify studies to include in the meta-analyses, a literature search was conducted on July 8th, 2016. The search queries included key words to narrow down the search to educational contexts and to exclude studies conducted in primary or secondary education. The search queries were kept broad on purpose to avoid missing relevant literature. This mainly concerned terms relating to SRL, as there are numerous terms in use in the educational literature describing SRL or SRL activities. There were no restrictions concerning date of publication; all hits registered in the databases until the search date were considered. Search terms for the relation between SRL intervention and SRL activity (relation 2 in Figure 1) were:

education/learn*/class* AND scholar*/student*/*grad*/pupil*/employee*/learner*/participant* AND SRL/SDL/self-reg*/self-dir*/self reg*/self dir*/metacogniti*/study skill*/study strateg* AND intervention*/experiment*/condition*/treatment*/compar*/train*/support*/improve*/scaffold*/effect* of AND NOT primary education/kindergarten/young child*/young-child* AND NOT gifted/disab*/disorder.

Searches were conducted in the PsycInfo, Scopus and Web of Science databases searching in title, abstract, and keywords. This search resulted in 4,236, 4,157, and 3,512 hits respectively. For the relation between SRL activity and achievement (relation 3 in Figure 1) the search terms were:

education/learn*/class* AND scholar*/student*/*grad*/pupil*/employee*/learner*/participant* AND SRL/SDL/self-reg*/self-dir*/self reg*/self dir*/metacogniti*/study skill*/study strateg* AND learning outcome*/achievement/*perform*/success*/grade AND NOT primary education/kindergarten/young child*/young-child* AND NOT gifted/disab*/disorder.

This search resulted in 5,041 (PsycInfo), 5,009 (Scopus), and 4,290 (Web of Science) hits. For the relation between SRL interventions and achievement (relation 1 in Figure 1) no separate literature search was conducted as this would have resulted in a subset of the articles already retrieved by the other two literature searches. For all three relations combined, there was a total of 26,245 hits. After removal of duplicates, 13,259 studies remained.

Titles and abstracts of the found studies were filtered based on a predefined list of inclusion and exclusion criteria, which can be found in Table 1. Some of these criteria were already included in the search terms to reduce the number of hits, for instance by excluding articles containing the words *gifted, disab** and *disorder* in the title, abstract or keywords. A total of 700 studies was retained after filtering based on titles and abstracts. Only the first identified reason for exclusion was recorded. The most often identified reason for exclusion was that the study did not focus on SRL as defined in the Introduction or that it did not

fit any of the three relations. Exemplary studies that were excluded for this reason focused on the effect of logical reasoning exercises on self-control (Bertrams & Schmeichel, 2014) or the validation of SRL-related questionnaires (Credé & Phillips, 2011). Other common reasons for exclusion were (a) other context than learning/education, (b) participants at school level below higher education (mostly studies from high school contexts), and (c) qualitative studies. For all remaining studies (journal articles, conference proceedings, and dissertations), we attempted to obtain a full text version. Full text versions were further screened based on the inclusion and exclusion criteria. Special attention was paid to the availability of statistical information necessary to calculate effect sizes.

Table 1 Overview of inclusion and exclusion criteria

Category	Inclusion	Exclusion
Language	Article written in English	Article not written in English
Population	Representative sample	- At risk students - Low/high performing students - Students with a disorder/disability
Setting	Self-regulation in an educational context (i.e., self-regulated learning)	Self-regulation in a different context (e.g., self-regulation of alcohol consumption)
Intervention	- Control group (simultaneous or non-simultaneous) - The intervention must be aimed at applying self-regulation in an educational context - Description of the intervention study must be included	- No control group - Intervention not directly aimed at improving SRL (e.g., meditation) - Description of the intervention is absent, making it impossible to infer the content of the intervention
SRL measurement	- Measure must solely incorporate (aspects of) SRL - Positive SRL behaviors	- Measures that combine SRL measurement with other measures (e.g., cognitive measures) - Negative SRL behaviors (e.g., avoidance of help seeking)
Achievement	Achievement measured with an individual task	Achievement measured with a collaborative task
Intervention studies	The intervention takes place before the achievement measure	The intervention takes place after the achievement measure
Correlational studies	The SRL measure precedes the achievement measure, or the SRL measure and the achievement measure relate to the same educational context	The achievement measure precedes the SRL measure and does not relate to the same educational context
Statistics	Quantitative studies	Qualitative studies

The final set of included studies contained 126 articles. The most common reasons for articles to be excluded were (a) that the article could not be obtained, mostly because it was a conference abstract for which no full version existed, (b) that there was no measure of SRL or achievement, and (c) that the intervention did not focus on improving SRL. For relation 1 (SRL intervention – achievement), 51 articles were included; for relation 2 (SRL intervention – SRL activities), 32 articles were included; and for relation 3 (SRL activities – achievement), 70 articles were included. Articles could include data on one or multiple relations.

Articles that included data on multiple relations were included in all meta-analyses for which they provided sufficient information. Thus, a study could potentially be included in all three meta-analyses if it provided information about the effect of an SRL intervention on achievement, about the effect of an SRL intervention on students' engagement in SRL activities, and about the relationship between students' SRL activity and their achievement. Each study could furthermore include multiple study samples and multiple effect sizes. For example, a study may measure multiple SRL activities, and correlate each of them separately to students' grades. If the study also included measures that we do not consider part of SRL (e.g., self-efficacy), effect sizes on these measures were excluded from the meta-analyses. If the SRL measure reported was a combination of aspects that we do and do not consider part of SRL, the effect size was excluded as it was not a measure that captured solely SRL. All studies included in one or multiple of the meta-analyses are marked with an asterisk (*) in the reference list. A visual overview of the literature selection process is presented in Figure 2.

Coding of included studies

All included studies were coded. When possible, the coded characteristics were based on existing knowledge of the effect of SRL interventions. The coding framework consisted of five segments and was developed in such a way that it was suitable for coding the different types of studies. The first and second segment were relevant for all studies and were labeled *educational context* and *sample characteristics*. For the educational context, we coded the type of study (lab or real course), the setting in which the study was conducted (online or offline), and the academic subject. For the sample characteristics, we coded participants' educational level, age, gender, and region.

The third segment focused on the *independent variable* of the study. For relations 1 (SRL intervention -> achievement) and 2 (SRL intervention -> SRL) the independent variable was the SRL intervention. For relation 3 (SRL -> achievement) it was SRL. For SRL interventions, we coded the length of the educational context, the length of the intervention (in weeks), the duration of the intervention (e.g,, actual training hours), the timing of the intervention relative to the learning task, the inclusion of cognitive strategy training, the format, the timing of the intervention relative to the learning task, whether the intervention was tailored to the task, and the type of SRL activity supported. We furthermore coded the type of control group, the manner in which students were allocated to groups, and group equality to determine study quality. For SRL measurements, we coded the instrument used to measure SRL, the reliability of the measure, and the type of SRL measured.

The fourth segment of the coding framework focused on the *dependent variable*. For relations 1 and 3 the dependent variable was achievement, while for relation 2 it concerned SRL. The coding of SRL as a dependent variable for relation 2 was identical to the coding of SRL as an independent variable for relation 3. For achievement we coded the achievement measure used. Finally, the fifth segment was labeled *timing of measures*, including the time between the SRL intervention and the measurement of achievement. Thereby all intervention and measurement characteristics presented in the Introduction (section 1.5) were included in the coding scheme. The complete coding framework is available as online supplementary material (bit.ly/dealingwithautonomy).

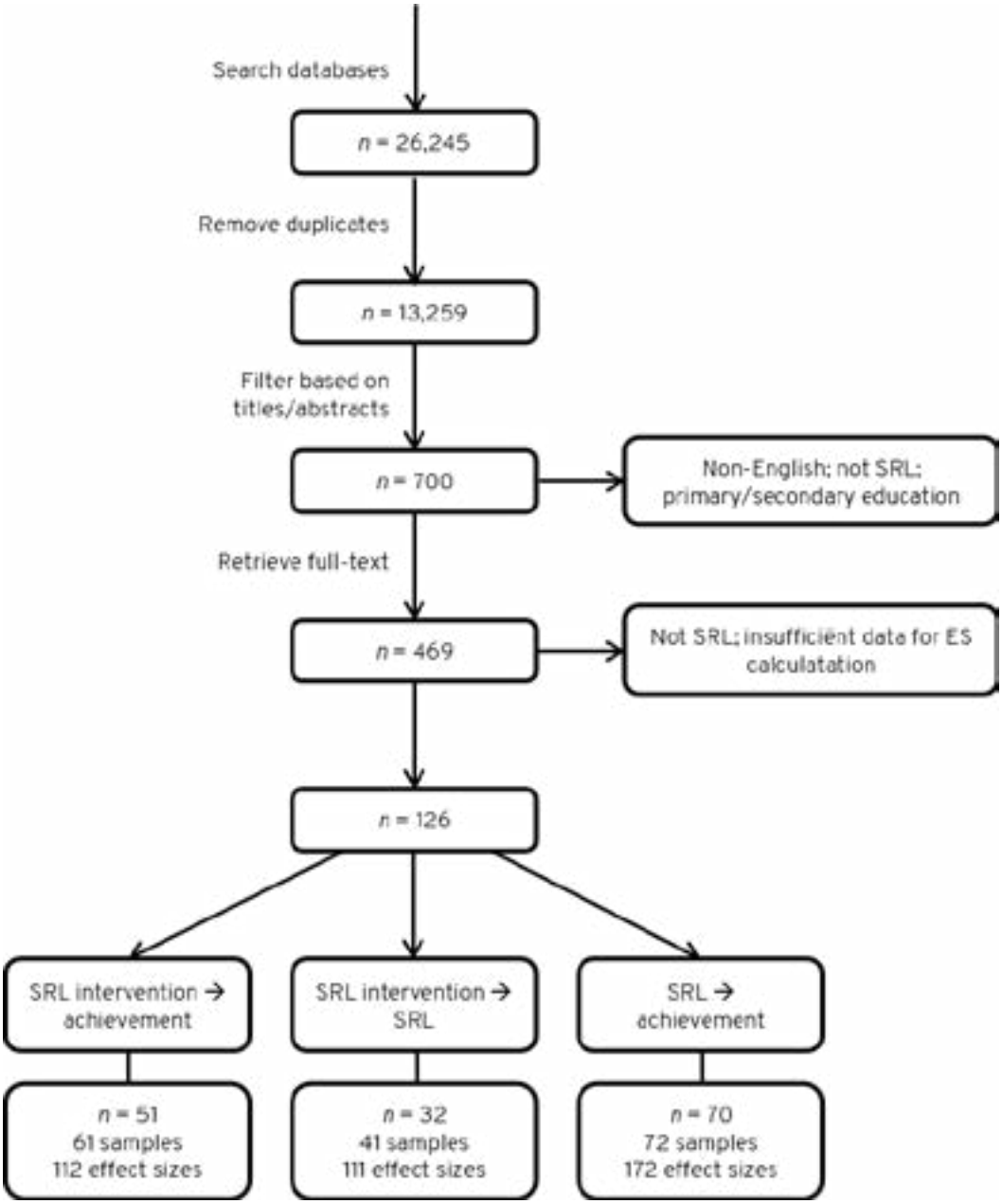

Figure 2 Overview of the literature selection process.

Reliability of the coding framework was assessed in two rounds. In the first round, two raters independently coded a random sample of 20 studies (10 studies by the first and second author, and 10 by the first and third author). For most of the variables in the coding scheme, not all options were equally likely, which means Cohen's kappa was not suitable as a measure of reliability (Feinstein & Cicchetti, 1990). Instead, percentage agreement was used as the reliability measure. The percentage agreement ranged between 50% and

100% for the entire coding scheme. Variables that were coded with insufficient reliability were discussed among the first three authors. As a result of this discussion, the coding options for two variables were adjusted to better suit the characteristics of the interventions as found in the sample set. A second round of coding was conducted with a new random sample of 21 studies (11 studies were coded by the first and second author, and 10 by the first and third author). The studies in this second sample set were all intervention studies (relation 1 and 2 in Figure 1). A sufficient agreement percentage ranging between 80% and 100% was found for the variables that addressed studies on the relationship between SRL and achievement (relation 3 in Figure 1) in round 1. It was therefore not necessary to include any more studies on this relationship in round 2. Interrater agreement for this second sample set ranged between 81% and 100%. The only exception was the type of SRL activity supported by the intervention with an interrater agreement of 71%. The discrepancies in coding had two main causes. First, in some primary studies, the descriptions of the intervention were unclear. Second, in some of the primary studies, the terminology used to label the intervention was different from the labeling with our coding scheme when considering the content of the intervention. These issues complicated accurate labeling of the type of SRL activity supported by the intervention. As this variable is crucial for the current meta-analyses, we decided that this variable would be coded by two authors for all studies. Disagreements on the coding of this variable were resolved by discussion. The interrater agreement for each variable is included in the coding framework available as online supplementary material (bit.ly/dealingwithautonomy).

Moderators

Based on the coding scheme, moderators were included in the conducted meta-analyses on the effect of SRL interventions on achievement (relation 1), the effect of SRL interventions on SRL activity (relation 2), and the relationship between SRL activity and achievement (relation 3). Three groups of moderators were included: study characteristics, measurement characteristics, and intervention characteristics. An overview of the included moderators can be found in Table 2.

Table 2 Included moderators

Category	Coded information
Study characteristics	Academic subject Educational setting (offline or online/web-based) Study design quality Context
Measurement characteristics	Measurement instrument SRL SRL activity measured Achievement measure
Intervention characteristics	SRL activity supported Inclusion of cognitive strategies Tailored Timing Format

Study characteristics

Academic subject of the study material was included as a moderator and was classified as social sciences, humanities, formal sciences, applied sciences, or a combination of these. The *educational setting* in which the study was conducted, either online or offline / web-based was included as the second moderator. The third moderator was the *quality of the study*. The quality of the studies was determined based on three coded aspects: whether the experimental and control group were simultaneous or non-simultaneous (i.e., same or different cohorts), how students were allocated to groups, and whether groups were equal on relevant covariates. Three quality levels were created. Studies of the highest quality had a simultaneous control and intervention group, students were randomly assigned to conditions, and groups were equal. Studies of the second level of quality had a simultaneous control group, but students were either allocated based on pre-existing groups or not-random at all. In all studies at level two, it was either assured by the authors of the primary study that groups were equal, or inequality was statistically controlled for by the authors of the primary study. The two studies with a non-simultaneous, non-random control group were also classified as quality level 2, as the authors of these studies assured that the control and intervention groups were equal. The third and lowest level of quality contained studies for which information about group equality was missing from the article. The fourth and final study characteristic included as a moderator was *study context*, which was either lab or real course. The educational grade level of students was not included as a moderator as there was too little diversity in this variable across studies.

Measurement characteristics

For studies in which SRL was measured (relation 2 and 3 in Figure 1) the *instrument* used to measure SRL and the *SRL activity or set of SRL activities measured* were included as moderators. SRL measurements were coded as either a questionnaire, a counted measure (a combination of think aloud and counting specific, observed behaviors), or self-assessment accuracy (the difference between a students' self-assessed score and the obtained score). The SRL activity that was measured was coded as one of fourteen values: measures focusing on a specific metacognitive aspect (6 values: planning, strategy regulation, goal setting, monitoring, reflection, and self-assessment), measures focusing on a specific resource management aspect (5 values: help seeking, environment structuring, time management, environment structuring and time management, and persistence), measures focusing on metacognition in general (1 value), measures focusing on resource management in general (1 value), and measures focusing on both metacognition and resource management (1 value). The type of SRL measured was coded based on our knowledge of the questionnaire included, example items included in the primary study, or the description of the measure in the primary study. As some values were coded only rarely, and to decrease the number of moderator dummies in the analyses, the measures were clustered into larger groups of SRL measures. These groups were: single aspect metacognitive measures, multiple aspect metacognitive measure, single aspect resource management measures, multiple aspect resource management measures and finally general measures incorporating both aspects of metacognition and resource management. For studies with achievement as the dependent variable, the employed *achievement measure* was included as a moderator. Achievement measures were classified as task performance, course performance, GPA, or performance on a transfer task.

Intervention characteristics

Five intervention characteristics were included as moderators for the meta-analysis of the effects of SRL interventions on achievement and the meta-analysis of the effects of SRL interventions on SRL. The *SRL activity or the set of SRL activities supported* by the intervention was included as a moderator. The SRL activities were clustered in the same manner as the measurement characteristic SRL activity measured. As there were no interventions that focused on a single aspect of resource management, or on resource management in general, three categories of SRL support remained: interventions aimed at a single metacognitive activity, interventions aimed at multiple metacognitive activities, and general SRL interventions aiming at both metacognitive and resource management activities. The second moderator was the *inclusion of cognitive strategies*, which indicated whether the intervention included cognitive strategy instruction. The third moderator indicated the *timing of the intervention* in relation to the learning context: before the learning phase, during the first half of learning, during the second half of learning, during the whole learning task, or both before and during learning. The fourth moderator was whether or not the intervention was *tailored to the learning context*. In tailored interventions, the SRL instruction or the SRL activity students had to engage in was coupled to the learning task, instead of a stand-alone instruction independent of the learning task. The final included moderator was the *instructional format* of the intervention. This moderator was recoded into three variables, each indicating whether a specific aspect was present in the intervention: instruction (yes/no), application (yes/no), and prompts (yes/no). It was planned to also include intervention intensity as a moderator by combining information on the length and duration of the intervention. This information was however reported in only very few articles and could therefore not be used as an indicator of study intensity.

Effect size extraction

After coding the studies, effect sizes were extracted. For the intervention studies (relation 1 and 2), Cohen's *d* was used as a measure of effect size. The preferred method to calculate Cohen's *d* was to use the means and standard deviations of posttest scores reported in the study, but if only other statistics, like means and standard deviations of the gain scores (difference between pre- and posttest) were reported, those were used instead [1].

The studies included for relation 3 (SRL activities -> achievement) were all correlational in nature. Pearson's *r* was used as a measure of effect size. In most cases, the correlation coefficient between a measure of SRL and achievement was reported and could be incorporated in the current meta-analysis. In a few cases, only the regression analyses or path coefficients from a structural equation model were reported. In these situations, the standardized betas or path coefficients were included [2].

After calculating all effect sizes, special attention was paid to the direction of the effect sizes concerning self-assessment accuracy (one of the measures of SRL). If the accuracy of self-assessment increases, the distance between the predicted score and the true

[1] For intervention -> achievement 12 of the 112 effect sizes could not be calculated based on the means and standard deviations of posttest scores. The way the effect size was calculated (posttest scores or another method) was found not to be a significant moderator (p = .466). For intervention -> SRL 10 of the 110 effect sizes could not be calculated based on the means and standard deviations of posttest scores. The way the effect size was calculated (posttest scores or another method) was found not to be a significant moderator (p = .653).
[2] For SRL -> achievement 17 of the 172 effect sizes could not be incorporated based on Pearson's *r*. The effect size used (Pearson's *r* or another correlational measure) was found not to be a significant moderator (p = .915).

score decreases. If students with higher accuracy obtain higher achievement scores, the effect size is negative. In these cases, the sign of the effect size was reversed. The relation between self-assessment and achievement was hereby coded in the same direction as all other relations: positive effect sizes indicated that a higher SRL value related to higher achievement.

Analyses

First, descriptive statistics concerning the number of extracted effect sizes were calculated. Next, the three sets of effect sizes (one for each relation) were separately checked for indicators of potential publication bias. Then, the potential mediating effect of SRL activity on the relationship between SRL interventions and achievement was evaluated with meta-analytic structural equation modelling (MASEM). With MASEM it is possible to combine the available information from separate studies and to test the mediation model presented in Figure 1, even though only three studies included statistical information on all three relations. MASEM combines the benefits of structural equation modeling (SEM) and meta-analysis (Jak, 2015). For the MASEM analysis, the random-effects Two Stage SEM approach was used (TSSEM; Cheung, 2014). TSSEM employs multivariate random-effects meta-analysis to pool correlation matrices at Stage 1. Then, at Stage 2, weighted least squares estimation with the inversed asymptotic covariance matrix of the Stage 1 estimates as the weight matrix is used to estimate the path model coefficients.

To conduct MASEM all effect sizes must be expressed in Pearson's *r*. The effect sizes for the effect of SRL interventions on achievement and SRL activities, which were expressed in Cohen's *d*, were converted using the formula $r = d / (\sqrt{d^2 + a})$ with correction factor $a = (n_1 + n_2)^2 / (n_1 n_2)$ (Borenstein, Hedges, Higgins, & Rothstein, 2009). It is not yet possible to conduct three-level MASEM for nested data. Therefore, if a study contained multiple effect sizes for the same relation, these had to be combined. This process is explained with the use of sample data presented in Table 3.

Table 3 Sample data for MASEM preprocessing

ID	Study	Relation	*n*	ES
1	1	1	80	0.6
2	1	1	80	0.5
3	1	2	70	0.5
4	1	2	60	0.5
5	1	3	90	0.4

First, the data was merged to make sure there was one effect size with one sample size per relation per study. In the sample data there are two effect sizes for relation 1 in study 1: ID 1 and 2. These studies have the same sample size, but a different effect size. These effect sizes must be merged. A weighted average of these effect sizes is taken based on *n*. The effect size for relation 1 in study 1 is therefore 0.55 with $n = 80$. The effect sizes for relation 2 in study 1 must also be merged (ID 4 and 5). The weighted effect size is 0.5. For each relation however, only one sample size can be included. Because for relation 2 in Table 3, these sample sizes differ, the average sample size is used. In this case this is 65. Second, the data had to be merged further to make sure there was one sample size per study with

up to three effect sizes (one effect size per relation). The sample size is the harmonic mean of the three sample sizes (80, 65, and 90). Leading to the following data for study 1: n = 76.93, ES relation 1 = 0.55, ES relation 2 = 0.5, and ES relation 3 = 0.4.

The mediation MASEM model allows us to evaluate the significance and size of the indirect effect of SRL interventions on achievement through SRL activity. If, in addition to a significant indirect effect, there is a direct effect of SRL interventions on achievement, it would indicate that the effect is *partially* mediated by SRL.

Although MASEM is the analytical technique to evaluate indirect effects between variables, the technique also has its shortcomings. Specifically, it is not (yet) possible to apply three-level models to account for nested effect sizes within studies in MASEM, or to evaluate the effect of continuous moderator variables. In our dataset, a large number of studies provided multiple effect sizes for the same relation. For example, a study may measure multiple aspects of SRL, and correlate each of them separately to students' grades. These so-called nested effect sizes within studies can be controlled for with multilevel analyses (Hox, 2010). Therefore, we also conducted univariate analyses using a meta-analytic method for handling complex meta-analytic data structures with robust variance estimation. Robust variance estimation accounts for the dependency of effect sizes within studies (Hedges, Tipton, & Johnson, 2010).

The univariate meta-analyses for the effect of SRL interventions on achievement and SRL (relation 1 and 2) were conducted with Cohen's d as a measure of effect size. The analyses for the relation between SRL and achievement (relation 3) were based on Pearson's r. As the variance in Pearson's r however depends too strongly on the correlation, the analyses were conducted in Fisher's Z (Borenstein et al., 2009). Pearson's r was converted into Fisher's Z with the following formula: $z = 0.5 * \ln((1 + r) / (1 - r))$. Then, the results were converted back to Pearson's r with the formula $r = (e^{2z} - 1) / (e^{2z} + 1)$. All results for the analyses concerning the relation between SRL and achievement are reported in Pearson's r to simplify interpretation, but were conducted in Fisher's Z.

As we did not expect a single true effect of SRL interventions on either SRL or achievement, nor a single true effect size of the relation between SRL and achievement, the MASEM analysis and all meta-analyses were conducted based on the random-effects model (Borenstein et al., 2009). Hereby we allowed the effects to vary from study to study, and thus accounted for heterogeneity of effect sizes.

The analyses on publication bias were conducted using CMA v3.3 (Borenstein, Hedges, Higgins, & Rothstein, 2014). The MASEM analysis was conducted using the metaSEM package (Cheung, 2015) for R (R Core Team, 2016) and parts of the example script created by Jak (2015). The univariate multilevel meta-analyses and moderator analyses were conducted using the Robumeta package (Fisher, Tipton, & Zhipeng, 2017) for R (R Core Team, 2016). This package implements the methods developed by Hedges, Tipton, and Johnsen (2010) for handling complex meta-analytic data structures with dependent effect sizes using robust variance estimation. The data files and syntax for both the MASEM analyses and the univariate moderator analyses are available as online supplementary materials (bit.ly/dealingwithautonomy).

Results

Descriptive statistics

A total of 395 effect sizes extracted from 142 studies published in 126 articles were included in the meta-analyses. The average sample size of the included effect sizes was *n* = 214 (range 13-8112). From the 126 articles, 112 originated from peer-reviewed journals, 9 were published in conference proceedings, and 5 were dissertations. In the majority of studies (117 out of 142 studies), participants were undergraduates. In other studies participants were in graduate education (5 studies), in vocational education (4 studies), in workplace learning (3 studies), or their educational level could not be determined (13 studies).

Some articles contained data from multiple studies, and some studies contained multiple effect sizes on the same relationship, or effect sizes on multiple relationships. For the effect of SRL interventions on achievement (relation 1), 112 effect sizes from 61 studies published in 51 articles were included. For the effect of SRL interventions on SRL activity (relation 2), 111 effect sizes were included extracted from 41 studies published in 32 articles. Finally, for the relationship between SRL and achievement (relation 3), 172 effect sizes were included from 72 studies published in 70 articles. An overview of all included studies can be found as online supplementary material. Overviews of the effect sizes included for relation 1, relation 2, and relation 3 are also available as online supplementary material (bit.ly/dealingwithautonomy).

Potential outliers were identified by creating boxplots. As all included effect sizes were calculated from published primary studies, there had to be a compelling reason to consider an effect size an outlier. One effect size was determined to be an outlier (Cohen's *d* = 5.7733) as it was more than two times the size of the second largest effect size (Cohen's *d* = 2.5192). In the experiment that yielded the largest effect size, students were requested to watch a lecture and afterwards to write about their learning process while watching the lecture. Students in the experimental group were prompted to write about their comprehension monitoring and strategy regulation. The researchers afterwards counted the number of times students wrote about these topics (Berthold, Nückles, & Renkl, 2007). The prompting led to an inflated count for the students in the experimental group. This effect size, for the relation between SRL interventions and SRL, was excluded from further analysis. Therefore, for the effect of SRL interventions on SRL not 111, but 110 effect sizes were included from 41 studies published in 32 articles.

Publication bias

Studies with larger samples and studies with significant results are more likely to be published than studies with smaller samples and studies with non-significant results (Borenstein et al., 2009). This results in publication bias, which may lead to bias in the sample set selected for inclusion in a meta-analysis. As there is no formal statistical test to determine the presence of publication bias and its effect, it is advised to combine several analyses (Banks, Kepes, & Banks, 2012; Borenstein et al., 2009). In the current study, the funnel plot with trim and fill, cumulative meta-analysis, Orwin's fail safe N (Orwin, 1983), adding the sample size as a moderator, and adding the source of the study (journal article, conference proceedings, or dissertation) were used to test for the potential presence of publication bias in the sample sets included in these meta-analyses (Banks et al., 2012;

Borenstein et al., 2009; Hox, 2010). The analyses were conducted for each of the three relations in Figure 1 separately. From the results of these five tests for publication bias, it can be concluded that there are no indications that publication bias has affected either of the three sets of included effect sizes. Source of publication was however found to be a significant moderator of the effect sizes for relation 1 (intervention -> achievement) and relation 2 (intervention -> SRL). Source of publication will therefore be included as a covariate in all moderator analyses conducted for these relations. A more detailed description of the publication bias analyses and their results is available as online supplementary material (bit.ly/dealingwithautonomy).

MASEM analysis

In Stage 1 of the MASEM analysis, a pooled correlation matrix between the three variables was estimated. All three pooled correlations were positive, and significantly larger than zero ($r_{\_int\_achievement} = .22$, $p < .05$; $r_{\_int\_SRL} = .22$, $p < .05$; $r_{\_SRL\_achievement} = .25$, $p < .05$), indicating medium sized correlations for all three relations (Cohen, 1988). These average correlation coefficients from the Stage 1 TSSEM analysis, together with the associated number of studies and total sample sizes are presented as online supplementary material (bit.ly/dealingwithautonomy). Next, we fitted the mediation model from Figure 1 to the pooled correlation matrix. The estimates of the indirect (relation 2 and 3 combined) and direct effects (relations 1, 2, and 3) can be found in Table 4. A significant indirect effect was found of SRL interventions on achievement. The indirect effect equals the product of the direct effect of SRL interventions on SRL ($\beta = .22$, $p < .05$) and the direct effect of SRL on achievement ($\beta = .22$, $p < .05$). The significant indirect effect indicates that part of the effect of SRL interventions on achievement is mediated by SRL activity, although the indirect effect is small ($\beta = .05$, $p < .05$). Furthermore, a significant direct effect of interventions on achievement was found ($\beta = .18$, $p < .05$). This existence of the significant direct effect while incorporating SRL activity as a mediator, indicates that the mediational effect through SRL is partial as opposed to full.

Table 4 Standardized regression coefficients of the stage 2 MASEM analysis

Relation	β	95% CI
SRL interventions -> achievement	0.18	[0.13; 0.22]
SRL interventions -> SRL	0.22	[0.16; 0.28]
SRL -> achievement	0.22	[0.16; 0.27]
SRL interventions -> SRL -> achievement	0.05	[0.03; 0.06]

Univariate multilevel meta-analyses

The results of the univariate multilevel meta-analyses are presented in Table 5 and indicate medium sized effects for all three relations; a medium sized effect of SRL interventions on achievement, a medium sized effect of SRL interventions on SRL and a medium sized relation between SRL and achievement.

Table 5 Results of random-effects univariate meta-analyses with Robumeta

Relation	k	# of ES	Intercept (std. error)	τ^2	I^2
SRL intervention -> achievement	61	112	*d* = 0.488 (.053)	0.126	68.95
SRL intervention -> SRL activity	41	110	*d* = 0.499 (.080)	0.206	78.61
SRL activity -> achievement	72	172	*z* = 0.284 (.031) *r* = 0.277	0.050	93.43

Note. τ^2 is the between-study variance component I^2 represents the proportion of variance in effect sizes at the study-level. *r* is the *z*-to-*r* backtransformed correlation coefficient.

Moderator analyses

While the overall effect sizes are found to be significant (Table 5), the effect sizes within each set of studies vary as indicated by the I^2 values, which are above 65% for all three relations (Higgins & Thompson, 2002). Moderator analyses were conducted to determine if aspects of the included studies can explain part of the variance in effect sizes. Three groups of moderators were coded: study characteristics, measurement characteristics, and intervention characteristics. Moderator analyses were conducted for each relation separately, and each group of moderators was tested separately for significance. By testing the moderators per group, we balance the risk of type I errors (that would be induced by testing all moderators individually) and type II errors (that would be induced by testing all moderators simultaneously).

Moderator analyses SRL interventions -> achievement

For the effect of SRL interventions on achievement, moderator analyses were conducted with all study and intervention characteristics. Furthermore, the employed achievement measure was included as a moderating measurement characteristic. The results of the moderator analyses are presented in the left columns of Tables 6-8. Study characteristics (left columns Table 6) did not moderate on the effect of SRL interventions on achievement. The only exception was academic subject, with higher effect sizes for studies conducted within the humanities domain compared to social sciences. Effect sizes were found to differ based on the achievement measure used in the experiment, as studies that used GPA as an indicator of academic achievement reported lower effect sizes compared to studies that used course performance as an indicator of academic achievement. As this result is however based on only 1 effect size with GPA as achievement measure, it should not be interpreted (left columns of Table 7). None of the intervention characteristics significantly moderated the effect sizes (left columns Table 8).

Moderator analyses SRL interventions -> SRL

For the effect of SRL interventions on SRL activity, moderator analyses were conducted with all study and intervention characteristics. From the measurement characteristics, the instrument used to measure SRL and the measured SRL activities, were included as potential moderators. The results of the moderator analyses are presented in the middle columns of Table 6 and 7 and the right columns of Table 8. None of the included study characteristics significantly moderated the effects of SRL interventions on SRL (middle columns of Table 6). The instrument used to measure SRL was a significant moderator, with larger effects of SRL interventions on SRL activity when SRL activity was counted

compared to when SRL activity was measured with a questionnaire. The measured SRL activity was also a significant moderator; the measurement of a single resource management aspect resulted in smaller effect sizes compared to the measurement of both resource management and metacognitive aspects of SRL (middle columns of Table 7). None of the intervention characteristics were significant moderators of the effects of SRL interventions on SRL (right columns of Table 8).

Moderator analyses SRL -> achievement

For the relationship between SRL and achievement, moderator analyses were conducted with all mentioned study and measurement characteristics. As these studies did not include an intervention, no moderator analyses were conducted with intervention characteristics. The results of the moderator analyses are presented in the right columns of Tables 6 and 7. None of the study characteristics significantly moderated the relationship between SRL and achievement (right columns Table 6). The instrument used to measure SRL was also not a significant moderator. The measured SRL activities were significant moderators. The relationship between SRL and achievement was stronger when both metacognitive and resource management activities were measured compared to when a single or multiple resource management aspects were measured (right columns Table 7).

Discussion

The aim of our meta-analysis of SRL in higher education was twofold. The first aim was to study the potential mediating role of SRL activity in the relationship between SRL interventions and academic achievement. The second aim was to perform meta-analyses of the effect of SRL interventions on achievement (relation 1 in Figure 1), the effect of SRL interventions on SRL activity (relation 2 in Figure 1), and of the relationship between SRL activity and achievement (relation 3 in Figure 1). For each of these meta-analyses, moderator analyses were conducted to determine which study, measurement, and intervention characteristics could significantly explain variability in the effect sizes reported. The results of the moderator analyses may help develop guidelines for the design of effective SRL interventions.

Mediation of SRL activity in the relationship between SRL interventions and academic achievement

SRL activity was expected to mediate the relationship between SRL interventions and achievement: the SRL interventions were assumed to lead to improvements in students' engagement in SRL, and thereby to improvements in students' achievement. The result of the MASEM analysis confirmed that SRL activity mediates the effect of SRL interventions on achievement. However, the results also show that this indirect effect of SRL interventions on achievement is small ($\beta = .05$), and that a significant direct effect of SRL interventions on achievement remains after including SRL activity as a mediator ($\beta = .18$). Contrary to common belief, SRL activity is thus only a *partial* mediator of the effect of SRL interventions on achievement. So, on the one hand, the results support the often-made assumption that improvement in student achievement after implementing an SRL intervention is due to improvements in students' SRL activities. On the other hand, the results

Table 6 Results of the moderator analyses with study characteristics

	Intervention -> achievement					Intervention -> SRL					SRL -> achievement				
Moderator	k	#ES	Est	*SE*	*p*	k	#ES	Est	*SE*	*p*	k	#ES	Est	*SE*	*p*
Intercept	61	112	0.425	.105	.001	41	110	0.650	.210	.011	72	172	0.306	.064	.000
Academic subject															
Social sciences (ref)	17	41				15	34				26	46			
Humanities	10	12	0.607	.251	.026	4	20	-0.111	.323	.750[+]	3	8	0.060	.076	.479[+]
Formal sciences	14	22	0.100	.100	.324	6	13	-0.129	.256	.625	11	27	0.138	.102	.192
Applied sciences	13	23	0.070	.115	.548	4	8	0.175	.391	.671	18	57	-0.160	.090	.079
Mixed	7	14	0.011	.163	.948	11	31	-0.266	.153	.113	12	30	-0.084	.090	.362
Setting															
Study offline (ref)	29	51				26	75				61	144			
Study online	32	61	-0.191	.130	.157	15	35	-0.254	.301	.420	11	28	0.065	.139	.645
Quality															
Quality level 1 (ref)	40	63				20	45								
Quality level 2	16	38	-0.039	.109	.727	12	49	-0.241	.207	.266					
Quality level 3	5	11	0.110	.209	.616	9	16	0.001	.192	.997					
Context															
Real course (ref)	35	61				29	86				64	151			
Lab	26	51	0.138	.126	.285	12	24	0.342	.345	.350	8	21	-0.077	.064	.261

Note. k = number of studies; #ES = number of effect sizes.
For intervention -> achievement and intervention -> SRL, source was a significant moderator. Therefore source is included as a covariate in the moderator analyses conducted for these relations.
For intervention -> SRL, there is 1 study with 4 effect sizes for which information on academic subject is missing. The analysis was also conducted without academic subject as a moderator. This did not alter the significance of the results.
For SRL -> achievement, there are 2 studies with in total 4 effect sizes for which information on academic subject is missing. The analysis was also conducted without academic subject as a moderator. This did not alter the significance of the results.
[+] $df < 4$; the result should not be interpreted.

Table 7 Results of the moderator analyses with measurement characteristics

	Intervention -> achievement				Intervention -> SRL				SRL -> achievement			
Moderator	**#ES**	**Est**	***SE***	***p***	**#ES**	**Est**	***SE***	***p***	**#ES**	**Est**	***SE***	***p***
Intercept	112	0.605	.109	.000	110	0.521	.055	.000	172	0.334	.081	.002
Instrument SRL												
Questionnaire (ref)									147			
Count					16	0.825	.289	.014	10	0.095	.142	.539[+]
Self-assessment accuracy					12	-0.056	.129	.672	15	0.224	.128	.094
SRL activity measured												
General (ref)									13			
Metacognitive multiple aspects					18	-0.169	.140	.247	35	-0.155	.090	.103
Metacognitive single aspect					59	-0.201	.130	.147	51	-0.083	.111	.459
Resource management multiple aspects					8	0.028	.214	.900	13	-0.213	.087	.028
Resource management single aspect					18	-0.285	.122	.039	60	-0.214	.089	.026
Achievement measure												
Course performance (ref)	54								107			
Task performance	46	-0.157	.117	.185					20	-0.013	.074	.867
GPA	1	-0.241	.109	.037					41	0.091	.058	.122
Transfer task	11	-0.206	.154	.224					3	-0.012	.045	.807[+]

Note. #ES = number of effect sizes.
For intervention -> achievement and intervention -> SRL, source was a significant moderator. Therefore source is included as a covariate in the moderator analyses conducted for these relations.
For SRL -> achievement, there is 1 study with 1 effect size for which information on the achievement measure used is missing. The analysis was also conducted without achievement measure as a moderator. This did not alter the significance of the results.
[+] *df* < 4; the result should not be interpreted.

Table 8 Results of the moderator analyses with intervention characteristics

	Intervention -> achievement					Intervention -> SRL				
Moderator	**k**	**#ES**	**Est**	***SE***	***p***	**k**	**#ES**	**Est**	***SE***	***p***
Intercept	61	112	.728	.131	.000	41	110	0.355	.258	.212
SRL activity supported										
General (ref)	19	30				16	40			
Metacognitive multiple aspects	25	52	-0.238	.170	.174	16	50	0.286	.246	.279
Metacognitive single aspect	17	30	-0.186	.150	.227	9	20	-0.017	.178	.924
Exclusively SRL										
Exclusively SRL (ref)	41	70				26	72			
Not exclusively SRL	20	42	0.169	.115	.156	15	38	-0.012	.233	.961
Timing										
During whole course (ref)	42	71								
Before the course	1	6	-0.298	.193	.309[+]	30	77			
First half of course	3	6	-0.165	.160	.390[+]	3	13	-0.107	.434	.822[+]
Second half of course	7	8	-0.013	.163	.937	2	6	0.890	.707	.327[+]
Before and during course	8	21	-0.215	.128	.115	6	14	-0.031	.328	.927
Tailored										
Tailored to context (ref)	60	110				34	98			
Not tailored to context	1	2	-0.467	.263	.156[+]	7	12	-0.005	.249	.984
Format										
Instruction	27	60	0.086	.103	.412	21	53	0.152	.264	.574
Application	43	85	-0.042	.092	.656	30	86	-0.018	.213	.935
Prompting	28	51	-0.123	.116	.302	17	37	-0.121	.285	.678

Note.
k = number of studies; #ES = number of effect sizes.
For intervention -> achievement and intervention -> SRL, source was a significant moderator. Therefore source is included as a covariate in the moderator analyses conducted for these relations.
[+] *df* < 4; the result should not be interpreted.

also indicate that there are other factors leading to improvements in student achievement resulting from an SRL intervention, besides improvements in SRL activity. We therefore conclude that SRL interventions likely have side effects on other factors than SRL activity, which in turn lead to improvements in achievement.

Explanations for SRL activity as *partial* mediator

Several other factors potentially influencing the effect of SRL interventions on achievement can be identified. A possible explanation for the partial mediation of the effect of SRL interventions on achievement by SRL activity are difficulties with SRL measurements. Several authors have argued that self-report measures of SRL, which are used in a large number of the studies included in this review, are not always valid and reliable (Azevedo & Cromley, 2004; Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007; Winne & Perry, 2000). SRL is a process, while questionnaires do not measure how students strategically adapt their study tactics over time. Furthermore, the validity of questionnaire measures of SRL is debated (Veenman, 2016; Winne, Jamieson-Noel, & Muis, 2002). If the employed SRL measurements were insensitive to changes in students' engagement in SRL activities over time, then improvements in SRL activity due to the SRL intervention would not be measured accurately. This insensitivity would lead to an underestimation of the mediating role of SRL activities. More precise measures of SRL that are better able to accurately capture small changes in students' SRL activities could allow for an even better estimation of the mediating role of SRL activities in the relationship between SRL interventions and achievement. We refer the interested reader to the work of Panadero et al. (2016), Veenman (2016; Veenman et al., 2006), and Winne (2010; Winne et al., 2002) for an in-depth discussion of the issues concerning SRL measurement.

Another potential explanation for the partial mediation is the possible side effect of SRL interventions that they may not only lead to changes in students' engagement in SRL activities, but also to increased time on task for students. Stimulating students to monitor or reflect on their learning can trigger students to engage in corrective action, thereby making them spend additional time on learning that they would not have spent without the intervention (Belski & Belski, 2014). If time on task differed between intervention and control groups, then this could explain differences in academic achievement. Unfortunately, student time on task is not measured (or reported) in any of the experimental SRL intervention studies included in our analyses.

SRL interventions may not only lead to increased time on task, but also to an increased use of more effective cognitive activities during learning, as students' increased self-regulation may have caused them to engage in more, or more effective, cognitive activities. As described by Nelson and Narens (1990), learners have a mental representation of their learning process at a meta-level. Based on the discrepancy between this meta-level representation and the goal level of learning, learners regulate their learning at the object-level. Learners, for example, engage in different cognitive learning activities. Learners then monitor their learning at the object-level as feedback for the meta-level (Nelson & Narens, 1990). The inclusion of cognitive strategy training did not significantly moderate the effects of SRL interventions on either SRL activity or on achievement. However, an improvement in self-regulation activities may have caused students to engage in more effective cognitive activities. For instance, repeated monitoring of the learning progress may have caused students to realize what cognitive activities do and do not benefit their

learning. The increased engagement in effective cognitive strategies would then likely lead to increased student achievement (Dunlosky et al., 2013). In the current review, we focused on the effects of SRL interventions on achievement, engagement in cognitive activities therefore lies beyond the scope of the current review. Cognitive activities may, however, have explained part of the direct effect of SRL interventions on achievement. The role of cognitive strategies in the effects of SRL interventions on achievement is therefore an interesting topic for a future review study.

Finally, task motivation (i.e., motivation before learning) is described as consisting of self-efficacy, task value, and goal orientation. Task motivation also lies beyond the scope of the current review, as we considered it a precursor of SRL (cf. Artino & Stephens, 2006; Efklides, 2011; Ning & Downing, 2012; Pintrich, 1999). However, as described in the Introduction, task motivation is considered part of SRL in some theoretical models (e.g., Boekaerts, 1992; Zimmerman, 2002, 2008). If we would have included task motivation in our definition of SRL, then task motivation measures such as self-efficacy and goal orientation, would have been included in the analyses. This would have broadened the construct "SRL activity" in Figure 1. Thereby, SRL activity would most likely have explained a greater portion of the effect of SRL interventions on achievement, thus strengthening the mediation effect. The strength of the mediation by task motivation of the effect of SRL intervention on achievement is a worthwhile research question to gain further insight in the interrelations between SRL interventions, SRL activity, task motivation, and achievement.

Meta-analyses of the relations between SRL interventions, SRL activity, and achievement

The second aim of this study was to systematically review the effect of SRL interventions on achievement, the effect of SRL interventions on SRL activity, and the relationship between SRL activity and achievement in higher education. We found medium effect sizes for all three relations. SRL interventions are thus effective for supporting students' achievement and students' engagement in SRL activities. The effect sizes are smaller than the effect sizes reported in previous meta-analyses of the effect of SRL interventions on achievement and on SRL activities in primary and secondary education (Boer et al., 2013; Dignath et al., 2008; Dignath & Büttner, 2008). Students in higher education may have internalized a larger repertoire of SRL strategies than pupils in primary and secondary education. Instructing students on SRL and supporting students' SRL activities with an intervention may thus be less effective in higher education as there is less room for improvement. At the same time, the need for engagement in SRL activities increases in higher education due to the increase in student autonomy. The increased autonomy would imply that the relation between engagement in SRL activities and achievement would be stronger in higher education than in primary and secondary education. When comparing the relation between engagement in SRL activities and achievement for higher education in our meta-analysis ($r = 0.28$), with the relation reported by Dent and Koenka (2016) for primary and secondary education ($r = 0.20$), it becomes clear that engagement in SRL activity and achievement are more strongly related in higher education than in primary and secondary education. The correlation we found is also in line with the previous meta-analysis in higher education that examined the relation between SRL or specific SRL activities and achievement (Sitzmann & Ely, 2011). Correlations in this meta-analysis were found to range between $r = 0.11$ and $r = 0.37$.

The effect sizes we found were not homogeneous, but heterogeneous; their magnitude varied between studies. Moderator analyses were conducted to test which study, measurement, or intervention characteristics could significantly explain (part of) the variance in effect sizes between studies (see Table 2).

Measurement characteristics tested as moderators

We first discuss the measurement characteristics that were included as moderators. The instrument used to measure SRL did not significantly influence the effect of SRL activity on achievement. Interventions did have significantly different effects on SRL activity depending on how SRL activity was measured; effects were stronger when SRL activity was measured with a counted measure, compared to when SRL activity was measured with a questionnaire. The differences in effect sizes between studies with different measurement instruments may have been the result of measurement (in)validity. Questionnaire measures of SRL are debated, since students' self-reports may be inaccurate and questionnaire measures are not able to capture learners' SRL over time (Hadwin et al., 2007; Veenman, 2016). Learners' self-reported SRL has been found to be weakly correlated to actual counts of strategy use (Hadwin et al., 2007; Veenman, 2005). While this explanation is plausible, yet another explanation focuses on the setting in which the studies were conducted. Counted measures were mostly used in studies in which participants were stimulated to think aloud (e.g., Moos & Bonde, 2016), and their verbalizations were coded for utterances of SRL. All studies with counted measures were conducted in a lab setting, while almost all studies with questionnaire measures (77 of 82 effect sizes) were conducted in real courses. Interventions conducted in lab settings usually have greater intensity than interventions implemented in regular education, especially when participants are required to think aloud, as the experimenter is then continuously present while the participant studies the presented material. The experimenter not only prompts the student to verbalize his/her thoughts during learning, but also – implicitly – makes sure that the student adheres to the intervention. The increased intensity of lab studies using counted measures, and the resulting intervention fidelity, may thus explain why counted measures have resulted in larger effect sizes compared to questionnaire measures. Further research is necessary to determine what causes the increased effect sizes of SRL interventions on SRL activity when SRL is measured with a questionnaire (i.e., an offline measure) compared to a counted measure (i.e., an online measure).

The effect of SRL interventions on SRL activity was found to be stronger for general SRL measurements that included both metacognitive and resource management activities, compared to measures that focused on a single aspect of resource management (e.g., time management). While the effects of SRL interventions on resource management are often measured, there are no SRL interventions that solely focus on resource management; interventions either focus on metacognition and resource management, or only on metacognition. It is therefore not surprising that the effects of the interventions are smaller on resource management than on SRL in general, as resource management is either not at all part of the intervention (metacognitive interventions) or only a part of the intervention (general interventions). The difference in effect sizes is thus likely due to the misalignment of SRL interventions and SRL measures concerning resource management.

Besides moderating the effect of SRL interventions on SRL activity, the measured SRL activity was also found to be a significant moderator of the relationship between

engagement in SRL activities and achievement. General measures of SRL (i.e., including both metacognition and resource management activities) were more strongly related to achievement than both single and multiple aspect measures of resource management aspects of SRL. Metacognitive measures did not differ significantly from general measures, but the coefficients indicate that the strength of their relationship to achievement was in between those for general and resource management measures. Scoring highly on general SRL measures indicates that the student engages in a range of SRL activities, both metacognitive and resource management activities, instead of only resource management activities. Likely, this greater diversity also indicates greater engagement with SRL, especially as resource management activities are used only during the performance phase of learning, while metacognitive activities are used also before learning (planning) and after learning (reflection). As a result, general SRL measures were more strongly associated with achievement than resource management measures of SRL.

The final measurement characteristic that was tested as a moderator was the achievement measure used in the included studies. Almost all of the included studies used task performance, course performance, or GPA as achievement measure. A greater similarity between the training task and the achievement measure might have resulted in a greater effect size (Burke & Hutchins, 2007). The overlap between training and test is usually greater for task performance measures compared to course performance or GPA. Therefore, effect sizes might have been larger with task performance compared to course performance or GPA. However, no significant differences were found in the effect sizes. In the current study, achievement measure thus did not influence the effect of SRL interventions on achievement, nor the relationship between SRL and achievement.

Intervention characteristics as moderators

We now turn to the intervention characteristics that were tested as moderators of the effect of SRL interventions on either engagement in SRL activities or on achievement. Contrary to expectations, none of the intervention characteristics were found to significantly moderate either the effect of SRL interventions on SRL activity, or the effect of SRL interventions on achievement.

All intervention formats (instruction, format, prompting) and possible timings of the intervention (before the course, first half or second half of course, before and during the course, and during the whole course) were found to be beneficial for both SRL activity as well as achievement; none had a negative effect. However, no significant differences between the intervention formats and timings of the interventions were found. The inclusion of cognitive strategies in the SRL intervention was also an insignificant moderator on both relations. This finding is in line with the assumption that cognitive strategy training is important for younger children, but not for students in higher education. In contrast to students in higher education, young children have not yet internalized a sufficient repertoire of cognitive strategies they can implement during learning (Dignath & Büttner, 2008). No significant differences were found between interventions tailored to the learning context and interventions that were not tailored to the learning context either. The group of studies with interventions tailored to the learning context was, however, much larger than the group of studies with interventions that were not tailored to the learning context. Therefore, we cannot determine whether there is no influence of SRL interventions being tailored to the learning context, or if the lack of a significant result is due to too few studies

with a non-tailored intervention design. The results of the analyses with the format of the intervention (i.e., instruction, application or prompting) as moderator, however, also do not provide clear indications that tailoring the intervention to the learning context is crucial for the effectiveness of the SRL intervention to support students' engagement in SRL activities and/or their achievement.

The final intervention characteristic we tested was the SRL activity or set of SRL activities supported by the SRL intervention. Based on the finding that general SRL measures were more strongly related to achievement than resource management measures, it was anticipated that general SRL interventions would be more beneficial for achievement than interventions that focus on either metacognition or resource management. Developing a broad set of SRL skills could be considered more important for achievement. However, no differences were found in SRL intervention effectiveness depending on the set of SRL activities supported.

Non-significance of moderators

From the large range of moderators tested, only a few were found to be significant. Multicollinearity between coded characteristics may explain the lack of significant results. Some study, measurement, and intervention characteristics occurred together frequently, such as prompting in lab studies and using questionnaires in real courses. To reduce the risk of not finding significant results due to multicollinearity (type II errors), we tested each group of characteristics separately. However, there also was some multicollinearity between characteristics within each group. For instance, prompting only occurred during studies and not before. Furthermore, the SRL measurement and the type of SRL measured are related. Almost all measures of multiple SRL aspects (i.e., general, metacognitive multiple aspects, and resource management multiple aspects) were measured with questionnaires, and not with self-assessment accuracy or counted (e.g., think aloud) measures. Self-assessment accuracy on the other hand is a measure of self-assessment which is always coded as a "single aspect metacognitive measure". All moderators of one group were tested at once, as testing all moderators separately would have greatly increased the number of analyses and thereby the risk of falsely finding significant results. However, the frequent co-occurrence of specific characteristics within groups may have reduced the relative predictive strength of each moderator.

In addition, three aspects of the included studies may have significantly influenced the relations tested. These aspects may therefore have been significant moderators. They were however not included as moderators in the analyses as they could not be coded. First, as already indicated in the discussion of the mediation results, time on task may have differed between conditions. If the intervention caused students to spend more time learning, then time on task may have moderated the effect of SRL interventions on achievement. Time on task could however not be coded as it was not reported in any of the included studies. Another potential moderator that could not be coded was the intensity of the intervention, while it could be assumed that interventions with a greater intensity likely have greater effects. For instance, a 30-minute instruction on SRL right before a 45-minute learning task (Azevedo & Cromley, 2004) likely has a much greater effect compared to having students work through 10 modules of materials and the intervention consisting of a self-reflection prompt ("Do I understand all of the key points of the training material?") after five of these modules (Sitzmann, Bell, Kraiger, & Kanar, 2009). It was

attempted to code intervention characteristics that indicate intervention intensity (e.g., weeks the intervention ran, duration of the intervention in hours). In most studies however, this information was not reported clearly enough to be coded. Therefore the intervention intensity could not be tested as a moderator. A third moderator that could not be included due to missing information was participants' and teachers' fidelity to the intervention (e.g., the extent to which teachers instructed SRL as intended by the researchers). Participants and teachers likely adhered to the interventions in different degrees, which could influence the effects of the SRL intervention on both SRL activity and achievement. We consider these three potential moderators important to take into account in future SRL studies, as described as suggestions for future research.

Finally, students' motivation may also have influenced the tested relations. Students' with greater task motivation (e.g., self-efficacy) engage in SRL activities more frequently (Artino, 2008; Pintrich, 1999). Task motivation may also influence the effectiveness of SRL interventions, with students who are more interested in the task, also being more interested in learning ways to improve their SRL and achievement. Interventions would then be more effective in improving engagement in SRL activities and achievement for students with greater task motivation. Task motivation may therefore moderate the effect of SRL interventions on SRL activities as well as the effect of SRL interventions on achievement. In the current review, task motivation was not included as it is considered a precursor of SRL (Artino & Stephens, 2006; Efklides, 2011; Ning & Downing, 2012; Pintrich, 1999). However, as already indicated in the discussion of the mediation effects, the influence of task motivation on the relations between SRL interventions, SRL activities, and achievement is a worthwhile direction for further review studies to explore.

Implications and future research

To summarize, we investigated the mediating role of SRL activity on the effect of SRL interventions on achievement, and we explored which moderators significantly explain the variability in effect sizes for (1) the effect of SRL interventions on achievement, (2) the effect of SRL interventions on SRL activity, and (3) the relation between SRL activity and achievement. In this section, we discuss practical, theoretical, and methodological implications of our findings and suggestions for future research.

The positive effect of SRL interventions on both SRL activity as well as on achievement, leads to the practical implication that SRL interventions are effective in supporting students. We therefore advice practitioners to implement SRL interventions in higher education to support learners' engagement in SRL activities as well as their achievement. The lack of significant moderators of the effects of SRL interventions makes it difficult to provide concrete design guidelines for such SRL interventions. However, the lack of significant moderators also implies that there may be no 'wrong' intervention designs; as no intervention type is less effective than others, practitioners have great freedom in their intervention design. Based on our results, we thus cannot offer practical guidelines on *how* to develop the intervention, but we *do* emphasize the importance of implementing an SRL intervention to support learners' engagement in SRL activities and their achievement.

The partial mediation of SRL interventions on achievement by SRL activity results in the theoretical implication that the improvements in student achievement as a result of SRL interventions are *mostly* due to other factors than students' SRL activity. More insight

should be gained on what these additional factors are or could be. We have described the influence time on task, cognitive activity, and task motivation may have on the effectiveness of SRL interventions. It might be worthwhile to review the relations between SRL interventions, SRL activities, achievement, time on task, cognitive activity, and task motivation to further explain the effect of SRL interventions on achievement.

The differential effects of SRL interventions on SRL and achievement lead to methodological implications. As the results of our mediation analysis indicate, it cannot be assumed that the effect of SRL interventions on achievement is (solely) due to students' engagement in SRL activities. Therefore, it is important to test and report the effects of SRL interventions on both SRL activity and achievement, and that the correlation between SRL activity and achievement is reported as well. Doing so allows for the calculation of the mediating effect of SRL activity in the relation between SRL interventions and achievement, which is important for our understanding of the relation between these constructs, as well as for the design of SRL interventions.

Finally, several moderators could not be tested due to information not being (clearly) reported in the studies included in this meta-analysis (i.e., time on task, intervention intensity, and intervention fidelity). These moderators may however significantly explain part of the variance in effect sizes. We therefore recommend researchers to report information on these aspects in future studies, making it possible to test and review their influence.

Conclusion

In this study, we have performed meta-analyses of three relations: (1) the effect of SRL interventions on achievement, (2) the effect of SRL interventions on engagement in SRL activities, and (3) the relationship between engagement in SRL activities and achievement. With advanced statistical methods, we tested whether improvements in achievement after implementing an SRL intervention are mediated by SRL activity. We found evidence that the effect of SRL interventions on achievement is only partially mediated by SRL activity. Most of the effectiveness of SRL interventions for improving student achievement is thus not due to improvements in SRL, but due to other factors, contrary to common assumption. Furthermore, we provided insight into the factors that moderate each of the three studied relations in higher education. We have thereby shown that SRL interventions may have different effects on students' achievement and students' engagement in SRL activities. By combining mediation analysis with three separate meta-analyses, this systematic review provides a thorough and complete synthesis of current SRL research in higher education, while opening new avenues for future exploration.

3

Development of a Questionnaire to Measure Self-Regulated Learning in Online Education

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This chapter is based on:

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RJ, AvL, JJ, and LK designed the studies; RJ and MK collected the data; RJ, AvL, JJ, and LK planned the data analyses, RJ and AvL analyzed the data; RJ drafted the manuscripts; all authors contributed to critical revision of the manuscripts; AvL, JJ, and LK supervised the studies.

Abstract

The number of students engaged in Massive Open Online Courses (MOOCs) is increasing rapidly. Due to the autonomy of students in this type of education, students in MOOCs are required to regulate their learning to a greater extent than students in traditional, face-to-face education. However, there is no questionnaire available suited for this online context that measures all aspects of self-regulated learning (SRL). In study 1, such a questionnaire is developed based on existing SRL questionnaires. This is the Self-regulated Online Learning Questionnaire (SOL-Q). Exploratory factor analysis (EFA) on a first dataset led to a set of scales differing from those theoretically defined beforehand. Confirmatory factor analysis (CFA) was conducted on a second dataset to compare the fit of the theoretical model and the exploratively obtained model. The exploratively obtained model provided better fit to the data than the theoretical model. In study 2, a revised version of the questionnaire (SOL-Q-R) is examined further. In the revised version, the large scale "metacognitive skills" in the SOL-Q is split into three smaller scales: metacognition before, during, and after learning. The revised version of the questionnaire thereby has better theoretical validity and usability. As the scales of the SOL-Q-R have good reliability and model fit is sufficient, the SOL-Q-R is considered even better suited to measure SRL in online education.

Introduction

While traditional, face-to-face education is still serving most students, online forms of education are growing rapidly (Allen & Seaman, 2014, 2016). Massive Open Online Courses (MOOCs) are an example of these new forms of education. In most cases, these courses are free of charge and open for all; there often is no need for prior knowledge. MOOCs offer many opportunities. For example, they allow access to education for those in locations where high quality education is not available (Owston, 1997; Walsh, 2009). MOOCs also provide opportunities for professional development (e.g. employees can enroll in courses relevant to their careers). The rise of online education is, however, not without its challenges. As MOOCs are often not only open in access, but also in location, time and pace of completion, they allow students to study when and where they prefer. There is thus an increase in the autonomy provided to students attending a MOOC compared to students attending a traditional course. This presses MOOC students to take control of their own learning process (Garrison, 2003) and to engage more and differently in strategies to regulate their study behavior (Dillon & Greene, 2003; Hartley & Bendixen, 2001; Littlejohn, Hood, Milligan, & Mustain, 2016). Students must actively plan their work, set goals, and monitor their comprehension and the time they spend on learning. These activities can together be defined as self-regulated learning (SRL).

Self-regulated learners are described as learners who are active participants in their learning process (Zimmerman, 1986). Self-regulated learners are not only metacognitively and behaviorally active during the process of learning (performance phase, see Table 1), but also before (preparatory phase) and after the learning task (appraisal phase; Puustinen & Pulkkinen, 2001). SRL is described to encompass activities to regulate one's cognitive processes. In some cases SRL is described to also encompass these cognitive processes – task strategies – themselves (Winne & Hadwin, 1998). An overview of the activities belonging to each of the three phases can be found in Table 1. This overview is adapted from a review of theoretical models of SRL conducted by Puustinen and Pulkkinen (2001). The overview presents the commonalities found between theoretical models of SRL. Where general terms (e.g. control) were used by Puustinen and Pulkkinen (2001), the overview was adapted to include the specific processes mentioned in the individual SRL models (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2002).

Table 1 Overview of SRL activities categorized into three phases

Preparatory phase	Performance phase	Appraisal phase
Task definition Goal setting Strategic planning	Environment structuring Time management Task strategies Help seeking Comprehension monitoring Motivation control Effort regulation	Strategy reflection

Before starting a task (Table 1, preparatory phase), self-regulated learners define the task at hand, set goals for themselves and construct a plan on how to conduct the task (Puustinen & Pulkkinen, 2001). In traditional education, task definition and goal setting are generally carried out by the lecturer, for example by setting course goals and informing students of the aim of the lecture. In MOOCs, however, learning goals may be set less

strictly. First of all, due to MOOCs' openness in time, students can decide for themselves when they want to study which parts of the course (Deal III, 2002). Second, in MOOCs there often is no clear boundary between taking a course and not taking a course; students have autonomy over which parts of the course they want to master (Mackness, Mak, & Williams, 2010). Third, course objectives are often not specific or clearly communicated in MOOCs (Margaryan, Bianco, & Littlejohn, 2015). This requires additional goal setting and planning of students enrolled in MOOCs compared to students in traditional education.

Self-regulated learners are also actively engaged during the learning task (Table 1, performance phase). Activities students are involved in include environment and time management, task strategies to master the task content, comprehension monitoring, and help seeking (Pintrich, 2000; Puustinen & Pulkkinen, 2001; Winne & Hadwin, 1998). Furthermore, self-regulated students also keep their motivation up to par (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2002). While students in traditional education also need to engage in these activities, they are more important in MOOCs as they encompass greater student autonomy (Garrison, 2003). The openness in time and place makes students solely responsible for their time and environment management (Williams & Hellman, 2004). In a MOOC furthermore, students often do not have regular contact with fellow students; work is in most cases done individually (Toven-Lindsey, Rhoads, & Lozano, 2015). Without collaboration, there is also a lack of peer support, making it harder for students to stay motivated (Bank, Slavings, & Biddle, 1990; Nicpon et al., 2006).

After finishing the task (Table 1, appraisal phase), self-regulating students reflect on their performance by comparing their achievements to the goals they set (Zimmerman, 2002). Based on this evaluation, students adapt their study strategies in the – sometimes very near – future (Pintrich, 2000; Winne & Hadwin, 1998). Overall, the increase in student autonomy in a MOOC is what makes MOOCs accessible to larger groups of students than traditional courses. However, this increased autonomy makes self-regulation a necessity in MOOCs (Chung, 2015; Dillon & Greene, 2003; Garrison, 2003; Hartley & Bendixen, 2001; Littlejohn et al., 2016; Williams & Hellman, 2004).

Measuring SRL

Previous studies have shown the importance of SRL for achievement in traditional education (Pintrich & de Groot, 1990; Winters, Greene, & Costich, 2008; Zimmerman & Martinez-Pons, 1986). As student autonomy is greater in MOOCs than in traditional courses (Garrison, 2003) it is likely that SRL is even more important for achievement in MOOCs. In order to study the importance of SRL and the relationship between SRL and achievement in MOOCs, an instrument is needed to measure students' SRL in MOOCs. Existing questionnaires, however, are not fit for this purpose as they have not been validated for use in online education (including MOOCs). Furthermore, they do not measure the full range of SRL activities. In this chapter, therefore, a self-regulated online learning questionnaire is developed (SOL-Q, study 1) and revised (SOL-Q-R, study 2) in the context of MOOCs.

Several questionnaires are available to measure (parts of) SRL. These include the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1991), the Online Self-regulated Learning Questionnaire (OSLQ; Barnard, Lan, To, Paton, & Lai, 2009), the Metacognitive Awareness Inventory (MAI; Schraw & Dennison, 1994), and the Learning Strategies questionnaire (LS; Warr & Downing, 2000). When

comparing the aspects of SRL measured by the different questionnaires, as is done in Table 2, it becomes clear that the only aspect of SRL present in all four questionnaires is task strategies. Furthermore, it becomes clear that while all questionnaires measure some aspects of SRL, none of these questionnaires measures *all* aspects of SRL presented in Table 1. The MSLQ, for instance, which is the most widely used questionnaire in SRL research (Duncan & McKeachie, 2005), covers a range of scales from the performance phase, but does not measure self-regulatory behavior in the preparatory and appraisal phases. The MAI is the only questionnaire that includes scales from all three phases. The MAI, however, does not include time and environment management which are critical aspects of SRL in MOOCs due to the openness in time and place. The absence of an instrument that provides a comprehensive measurement of SRL is a first indication that there is a need for the development of a new SRL questionnaire.

Table 2 Overview of questionnaire scales

		MSLQ	MAI	OSLQ	LS
Preparatory phase	Task definition		X		
	Goal setting		X	X	
	Strategic planning		X		
Performance phase	Environmental structuring	X		X	
	Time management	X		X	
	Task strategies	X	X	X	X
	Help-seeking	X		X	X
	Comprehension monitoring		X	X	X
	Motivation control				X
	Effort regulation	X			
Appraisal phase	Strategy reflection		X		

Another issue concerning the existing questionnaires is that their validity in online settings has not been established. Measures developed for traditional classrooms must be validated for use in online settings (Tallent-Runnels et al., 2006). The MSLQ, the MAI and the LS have been developed for measurement of SRL in traditional face-to-face education. A recent study has shown that the MSLQ could not be validated in an asynchronous online learning environment (Cho & Summers, 2012). Additionally, the validity of the MAI and the LS in online settings have not yet been tested. The OSLQ is the exception as it specifically has been designed for use in online learning. This questionnaire is nevertheless limited in the aspects of SRL that it measures, as can be seen in Table 2. As the validity to use the existing questionnaires in an online setting – with the exception of the OSLQ – has not been established, this provides a second indication that there is a need for the development of an SRL questionnaire suitable for online education, in this study for MOOCs.

In conclusion, it can be stated that while all four questionnaires measure *some* aspects of SRL, no questionnaire is by itself suited and validated to measure *all* aspects of SRL in MOOCs, a form of online education. There is, however, need for such a questionnaire as SRL appears to be even more important for success in MOOCs than in traditional education. In the present study, a questionnaire to measure self-regulation in MOOCs will therefore be developed and validated. In study 1, the questionnaire is developed and a first

version is tested. In study 2, a revised version of the questionnaire is created to improve the usability of the questionnaire.

Study 1

A questionnaire to measure SRL in online education is constructed using items from the above mentioned questionnaires (i.e. MSLQ, OSLQ, MAI, LS). After administering this questionnaire in a MOOC, exploratory factor analysis is conducted (study 1A). Next, confirmatory factor analysis is conducted on a second dataset collected in a different MOOC (study 1B). With the confirmatory factor analysis, model fit of the exploratory found factors is compared to model fit of the factors originally specified in the questionnaire.

Questionnaire development

The questionnaire to measure self-regulation in MOOCs was developed by combining items from the discussed questionnaires (MSLQ, OSLQ, MAI, and LS) into a single questionnaire that covered the whole range of SRL activities as stated in Table 1. The items in the questionnaires were categorized as belonging to one of the three phases and to one of the activities within these phases.

When items within a scale were highly similar between questionnaires, only one of the overlapping items was retained. For instance, overlap existed between the factor "time and study environment" in the MSLQ and the factors "environment structuring" and "time management" in the OSLQ. Only part of the items in these scales were therefore retained. Furthermore, the phrase "in this online course" was added to all items to define the focus of the questionnaire, thereby informing students to what context the questions related. For example, the item "I think about what I really need to learn before I begin a task" from the MAI was changed into "I think about what I really need to learn before I begin a task in this online course". In some items the phrase "in this class" was already present. In those cases, "in this class" was replaced with "in this online course".

This final questionnaire contained 53 items divided over eleven scales. These scales were *task definition*, *goal setting*, *strategic planning* (preparatory phase), *environmental structuring, time management, task strategies, help seeking, comprehension monitoring, motivation control, effort regulation* (performance phase), and *strategy reflection* (appraisal phase). An overview of these scales and the number of items contained in each scale can be found in Figure 1. The origin of the questionnaire items can be seen in Table 2. All items had to be answered on a 7-point Likert scale, ranging from "not at all true for me" (= 1) to "very true for me" (= 7). This is in line with the answering format of the MSLQ, the questionnaire from which most items were obtained. The MAI, the OSLQ, and the LS employ a 5-point answering scale.

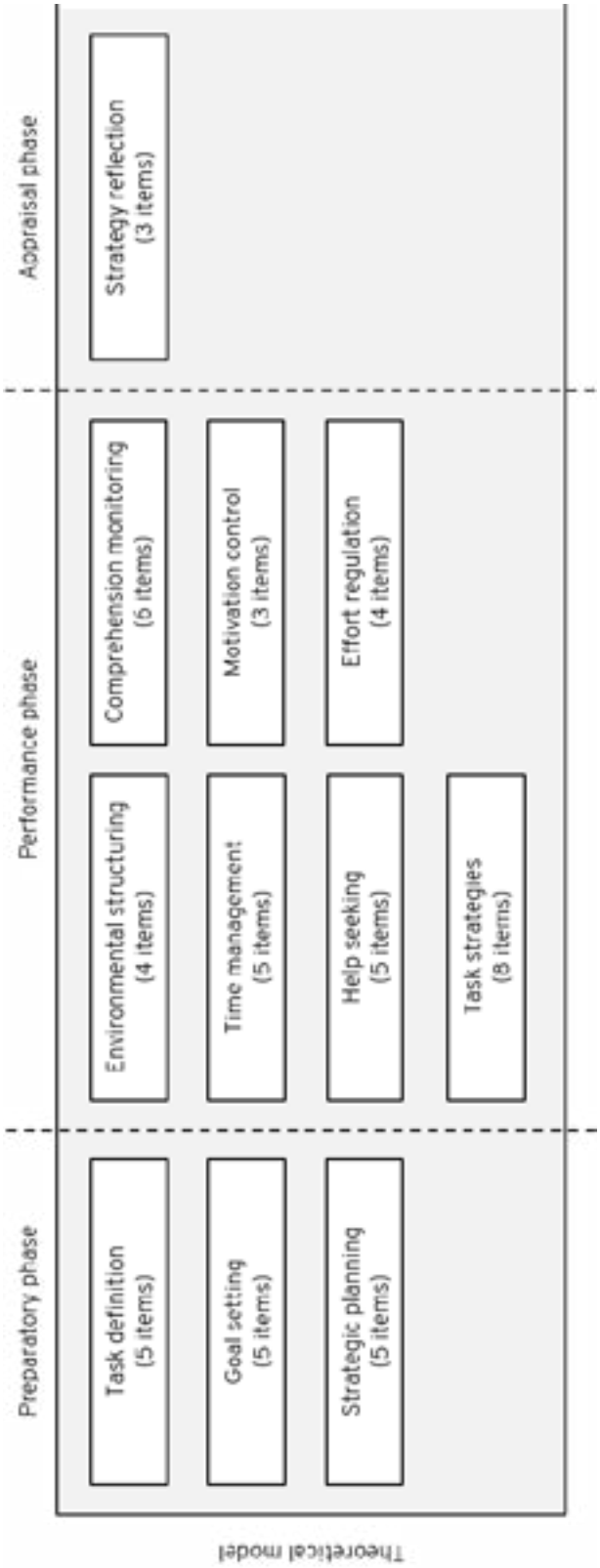

Figure 1 Overview of the scales in the theoretical model.

Study 1A: Exploratory Factor Analysis

Method

MOOC. The data for the exploratory factor analysis (EFA) was obtained from a MOOC on Marine Litter. This MOOC was offered by the United Nations Environment Programme (UNEP) and the Open University of the Netherlands (OUNL). The MOOC ran from October 2015 until December 2015 and lasted eight weeks. A total of 6452 students registered for the MOOC. Their participation in the MOOC was voluntary. Each week consisted of two blocks on related topics. Each block consisted of 30 minutes of video, 1 hour of studying background materials, and 30 minutes of tasks or assignments. Each week thus had a study load of 2 x 2 hours. The MOOC was open in terms of costs, program and time. The pace of the MOOC was however fixed, as the start and end date were set.

Participants. Complete questionnaire data was gathered from 162 students (M_{age} = 38.2, 49 males). The sample included 92 different nationalities. These students responded voluntarily to the invitation to fill out the questionnaire.

Procedure. Students in the MOOC on Marine Litter were sent an invitation by email to fill out the SRL questionnaire. This invitation was sent in week 6 of the course to make sure students could reflect on their actual self-regulation behaviors, and not on their planned behavior as would be the case when sending out the questionnaire at the start of the course. Before answering the questions, informed consent was obtained from all individual participants included in the study. All 53 items were then presented in random order. Filling out the questionnaire took 5 to 10 minutes. Students received no compensation for their participation. The procedures followed in this study, including those for the data collection and storage, were approved by the local ethics committee.

Analysis. EFA was conducted. The most commonly used methods to determine the number of factors to extract are the Kaiser criterion, which retains factors with an eigenvalue > 1, and the examination of the screen plot for discontinuities. However, these methods result in an inaccurate number of factors to retain, as the Kaiser criterion is known to overfactor and the examination of the scree plot is highly subjective (Zwick & Velicer, 1986). In their comparison of methods for factor retention, Zwick and Velicer (1986) found parallel analysis to be the most accurate procedure. With parallel analysis, random data matrices are created with the same sample size and the same number of variables as the gathered data. Factors are then extracted in each random data matrix and the found eigenvalues are averaged over all randomly created matrices. The final step is comparing the average eigenvalues with the eigenvalues found when extracting factors from the gathered data. The number of factors present in the gathered data is equal to the number of factors for which the eigenvalues from the gathered data are above the average eigenvalues from the random data (Hayton, Allen, & Scarpello, 2004). The underlying rationale in parallel analysis is that components underlying real data should have higher eigenvalues than components underlying random data (Schmitt, 2011). As parallel analysis is the most accurate measure to determine the number of factors to retain, parallel analysis was used as input for the number of factors to retain in the EFA.

Results

Data were removed from participants for whom the standard deviation of their answers was below 1 to filter the data for outliers. Data from 154 participants remained for analysis. Data from reverse phrased items was then recoded.

Parallel analysis. Parallel analysis (n = 2000) was conducted to determine the number of factors present in the data (O'Connor, 2000). Random data matrices were created by permutations of the raw data, as the data was not normally distributed. Five factors were found to be present.

Factor analysis. A factor analysis was conducted by using principal axis factoring with oblique rotation. The factor structure was specified to have five factors. The found distribution of items over the five factors was difficult to interpret. This was mostly due to items belonging to the scale task strategies that had scattered over all five factors. The eight items belonging to task strategies were therefore removed from the dataset.

A new parallel analysis (n = 2000) again indicated the existence of five factors in the gathered data, which now consisted of 45 items. Principal axis factoring with oblique rotation was repeated to determine the distribution of items across factors. The model found explained 46.58% of the variance in the data. The pattern matrix was inspected to identify items that did not fit in the factor structure. Two types of items were removed: first, items for which the highest factor loading was below 0.32 (Tabachnick & Fidell, 2001). Second, items with a factor loading above 0.32 on two or more factors for which the difference between the highest and the second highest factor loading was below 0.15. The resulting division of items over factors is in line with the results from the structure matrix. The pattern and structure matrices are available as online supplementary material (bit.ly/dealingwithautonomy). The resulting items were used to interpret and label the five factors. This was done by two researchers. The resulting factors were: *metacognitive skills, help-seeking, time management, persistence,* and *environmental structuring*. An overview of the factors, their reliability and the number of items in each factor can be found in Figure 2. The original scales (top) as well as the scales emerging from the EFA (bottom) are displayed in this figure according to the three phases of self-regulation. The arrows indicate how items 'moved' from the original scales into scales resulting from the EFA. Reliability of the scales obtained from the EFA ranged between α = .68 and α = .91.

Discussion

The EFA resulted in a factor model different from the model theoretically specified. In the theoretical model eleven scales were specified, while only five were found with EFA (see Figure 2). These five scales are labelled metacognitive skills, environmental structuring, time management, help seeking, and persistence. The models are similar when focusing on the scales environmental structuring, time management, and help seeking. The models differ in three important ways: the removal of task strategies, the large scale metacognitive skills, and the creation of the persistence scale to account for effort regulation and motivation control.

The scale task strategies was present in the theoretical model, but the items belonging to this scale were removed from the analysis to create the exploratory model. As mentioned in the results section, the items belonging to the task strategies scale scattered over all factors. This made it impossible to interpret the resulting factor structure. By removing

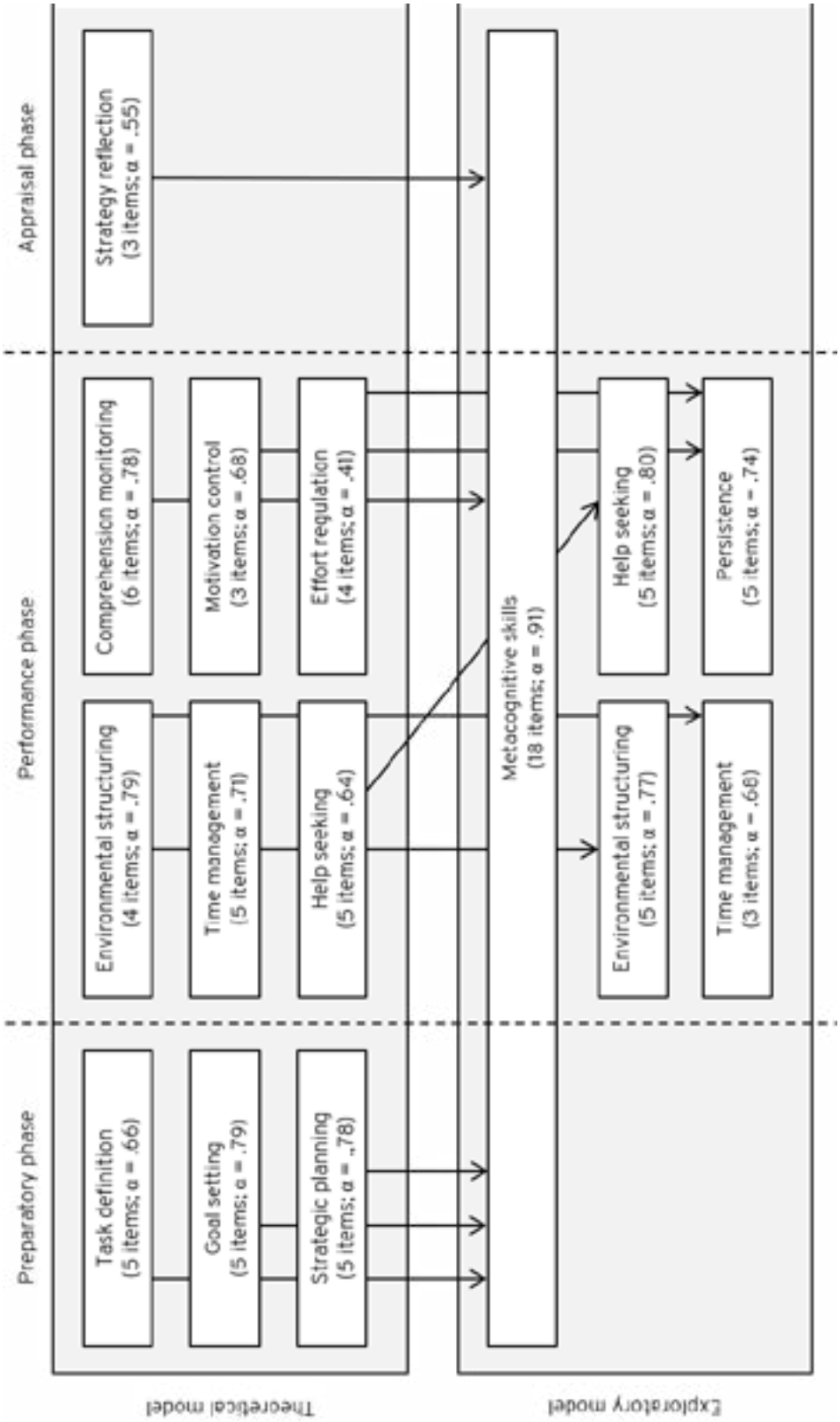

Figure 2 Overview of the scales in the theoretical model and in the exploratory model.

this scale, a different factor structure emerged; the other items were now also grouped differently. From a theoretical point of view, the removal of task strategies from the questionnaire to measure SRL suits the distinction between the execution of learning activities (task strategies) and the regulation of these learning activities (e.g. strategic planning; Nelson & Narens, 1990). This can be compared to the distinction often made between cognition and metacognition (Mayer, 1998; Van Leeuwen, 2015; Vermunt & Verloop, 1999).

Second, items belonging to five different scales in the theoretical model are combined into one large scale in the exploratory model: metacognitive skills. Not only did items belonging to the same phase of self-regulation (task definition, goal setting, and strategic planning) cluster; items from the two other phases (comprehension monitoring and strategy reflection) were also incorporated. Students indicated similar engagement in the different phases of metacognitive activities. There were no students who only engaged in for example task definition but not in comprehension monitoring. While theoretically different constructs, the results indicate that when students engage in metacognitive activities, they do so in all phases.

The third important difference between the theoretical and the exploratory model is the clustering of items belonging to motivation control and effort regulation into a single scale persistence. While motivation and effort are different constructs and the items came from different questionnaires, their merger into a single scale can be understood when inspecting the items. For instance, the item "When I begin to lose interest for this online course, I push myself even further" measures motivation control. The comparable item "Even when materials in this online course are dull and uninteresting, I manage to keep working until I finish" measures effort regulation. With similar items, it is likely that it was impossible to distinct between the scales, leading to their merger into the scale "persistence".

Thus, the EFA yielded a model that differed from the theoretical model in significant ways. In the next step, a confirmatory factor analysis will be performed on a different data sample to compare different models. The model fit of three factor models will be compared: (1) the theoretical model with the scale task strategies, (2) the theoretical model without the scale task strategies, and (3) the exploratory model.

Study 1B: Confirmatory Factor Analysis

Method

MOOC. The data for the confirmatory factor analysis (CFA) was gathered in the Dutch MOOC "The adolescent brain". This MOOC was offered by the Open University of the Netherlands on the Emma European MOOC platform. The MOOC ran from April 2016 until June 2016 and lasted seven weeks. Approximately 1000 students registered for the MOOC. Their participation in the MOOC was voluntary. The study load of each week was approximately 4 hours, excluding additional reading materials. Each week consisted of several video lectures, each linked to an assignment.

Participants. Complete data was gathered from 159 students. These students filled out the questionnaire as a voluntary assignment at the end of the third week of the course.

Due to technical difficulties, demographic data of these students was unfortunately lost. Demographics of the participants in the pre-course survey are likely to be similar (M_{age} = 44.1, 18.6% males). As the course was taught in Dutch, there was less diversity in nationalities than in the first dataset. Participants with 12 different nationalities participated in the pre-course survey.

Questionnaire. The questionnaire administered in this study was similar to the questionnaire described in the section Questionnaire Development. In this study, however, participants could choose between the original English version and a translated Dutch version. To create the Dutch version, two native Dutch speaking researchers (the first and second authors of this chapter) independently translated the questionnaire. Differences in their translations were resolved by discussion.

Procedure. Videos and assignments for each week were posted on the MOOC website. The last assignment for week 3 was the invitation to fill out the SRL questionnaire. Before answering the questions, informed consent was obtained from all individual participants included in the study. All 53 items were then presented in random order. Filling out the questionnaire took 5 to 10 minutes. Students received no compensation for their participation. The procedures followed in this second data study were also approved by the local ethics committee.

Analysis. CFA was conducted with SPSS AMOS. Three models were analyzed, the first being the theoretical model, including task strategies (53 items, 11 scales). The second model is the theoretical model without task strategies (45 items, 10 scales). The third model analyzed was the exploratory model (36 items, 5 scales). The three models were compared based on the χ^2, NC (normed chi-square), RMSEA (root mean square error of approximation), AIC (Akaike information criterion) and CFI (comparative fit index) scores (Hooper, Coughlan, & Mullen, 2008; Kline, 2005).

Results

Data were removed of participants for whom the standard deviation of their answers was below 1 to filter the data for outliers. Data from 153 participants remained for analysis. Data from reverse phrased items was then recoded.

An overview of the model fit statistics of the different models can be found in Table 3. The χ^2, NC and the RMSEA are absolute fit indices, whereas the AIC and the CFI are relative fit indices (Schreiber, Nora, Stage, Barlow, & King, 2006). The χ^2, NC, and the RMSEA are therefore not useful to compare the fit of the different models, but they provide an indication of the quality of the models tested. The χ^2 test indicates the difference between observed and expected covariance matrices; smaller values therefore indicating better model fit (Gatignon, 2010). The test should be non-significant for model acceptance, which it is not for any of the models tested in this study. Chi-square is, however, highly dependent on sample size (Kline, 2005). Therefore, normed chi-square (NC) is often considered instead of chi-square. For NC, chi-square is divided by the degrees of freedom. Smaller values are better and values of 2.0 to 3.0 are considered to indicate reasonable fit (Kline, 2005; Tabachnick & Fidell, 2001). All three models have NC values below 2.0, indicating acceptable fit. The RMSEA analyzes the difference between the population covariance matrix and the hypothesized model. Smaller values indicate better model fit; a value smaller than .08 is acceptable (Gatignon, 2010). The exploratory model thus shows acceptable fit, while

the theoretical models are bordering acceptable fit. The RMSEA, however, often falsely indicates poor model fit with small samples (Kenny, Kaniskan, & McCoach, 2015). Both absolute fit tests thus indicate that none of the models in itself provides a good fit to the data. Given this fact, the fit of the models may however still be compared between the three models.

Table 3 Model fit statistics CFA

Statistic	Theoretical model with task strategies	Theoretical model without task strategies	Exploratory model
χ^2	2530 (p = .000; df = 1270)	1782 (p = .000; df = 900)	1066 (p = .000; df = 584)
NC	1.99	1.98	1.83
RMSEA	.081 (.076 - .085)	.080 (.075 - .086)	.074 (.067 - .081)
CFI	.666	.705	.777
AIC	2852	2052	1230

The comparative fit indices CFI and AIC are used to determine which model fits the data best. The CFI compares the fit of the tested model to the fit of the independence model in which all latent variables are uncorrelated (Hooper et al., 2008). This statistic ranges between 0.0 and 1.0 and higher values indicate better model fit. A CFI value ≥ .95 indicates good fit; none of the models meets this criterion. We are however using the CFI to determine which model fits the data best, and the exploratory model performs better than both theoretical models. The AIC scores do not have a criterion value, but the smaller the value, the better (Schreiber et al., 2006). These scores also indicate that the exploratory model shows the best fit.

Table 4 Reliability of scales calculated from dataset 2

Theoretical model with/without task strategies		Exploratory model	
Scale	**α**	**Scale**	**α**
Task definition	.690	Metacognitive skills	.902
Goal setting	.790		
Strategic planning	.767		
Environmental structuring	.738	Environmental structuring	.674
Time management	.704	Time management	.705
Help seeking	.728	Help seeking	.830
Comprehension monitoring	.740		
Motivational control	.785	Persistence	.788
Effort regulation	.672		
(Task strategies)	.774		
Strategy reflection	.493		

The reliability of the scales (see Table 4) provides further information to compare the fit of the different models. Most scales show good to reasonable reliabilities; strategy reflection (.493) is the only exception. When combining this scale with the metacognitive scales from the preparatory and performance phase into one metacognitive skills scale (the exploratory model), reliability of the scale increases drastically (.902). Based on scale reliabilities, the exploratory model shows the best fit.

Discussion

In this study, a questionnaire to measure SRL in fully online courses was developed. This questionnaire was tested in the context of MOOCs by conducting an exploratory factor analysis (EFA) and a confirmatory factor analysis (CFA). The EFA resulted in a different factor model (the exploratory model) than the model that was theoretically specified beforehand (the theoretical model). The three major differences were the removal of the scale task strategies, the merger of effort regulation and motivation control into a single scale persistence, and the merger of the separate metacognitive scales into a single scale metacognitive skills. Based on the results of the CFA, it can be concluded that while none of the models provided absolute fit, the exploratory model clearly provided the best fit. The resulting questionnaire, the SOL-Q, thus consists of 5 scales: *metacognitive skills, time management, environmental structuring, persistence* and *help seeking*, and is presented in Appendix A.

When interpreting the results, a slight caution must be taken into account, which is the relatively small sample size and the high complexity of the models; with small samples one may have insufficient power to validate a complex model. The NC values are however all acceptable and the RMSEA values are acceptable for the exploratory model and bordering acceptance for the two theoretical models. The results thus provide enough evidence to draw two important conclusions.

First, evidence was found both in the EFA and in the CFA that task strategies are different from the other aspects of SRL. In the EFA, the items belonging to the scale task strategies scattered over all factors. This indicates that the items did not form a coherent scale. The results of the CFA further confirmed this finding. Both the absolute and the comparative fit statistics showed clearly better fit for the theoretical model without task strategies compared to the theoretical model with task strategies. Based on the present study, it is therefore not advisable to include task strategies as a separate scale in an SRL questionnaire because it could jeopardize the validity of the instrument. As indicated in the discussion of the EFA, the distinction between the execution of learning activities (task strategies) and the regulation of learning activities can be defended from a theoretical point of view as well, as it is in line with the distinction between cognition and metacognition (Mayer, 1998; Van Leeuwen, 2015; Vermunt & Verloop, 1999). It is therefore also not part of all theoretical models of SRL (Panadero, 2017; Pintrich, 2000; Zimmerman, 2002). The execution and the regulation of learning activities are, however, closely intertwined (Nelson & Narens, 1990). It is therefore advised to measure both when studying SRL, but with two different instruments.

From the EFA and CFA results, it further appears that learners did not differ in their engagement with the different metacognitive activities. For example, students who set goals, also monitor their comprehension and students who do not set goals, also do not monitor their comprehension. It is however still likely that students engage in different

metacognitive activities during the preparation, performance, and appraisal of learning tasks.

In the current study, items were divided over the three phases based on the type of activity they measured (e.g., task definition, comprehension monitoring). Some activities can clearly be assigned to one phase, planning for example happens before a learning session. However, some activities may be most important during one phase, but occur also in the other phases. For instance, students may think about the usefulness of their learning strategy during learning when they are not making (sufficient) progress and reflect on how they could improve their strategy for learning after a learning session. Both aspects of strategy regulation were present in the scale "strategy reflection". Dividing items based on their timing (before, during, or after learning) may allow for the measurement of the different SRL phases with separate scales, instead of combined in one large scale. This will be explored in Study 2.

Study 2

Although a satisfactory initial version of the SOL-Q was created, the scale "metacognitive skills" proved to be large and diverse. It consisted of items from a range of metacognitive self-regulation activities (e.g., goal setting, comprehension monitoring, strategy reflection) and covering all SRL phases (preparatory, performance, and appraisal phase). The clustering of metacognitive items into a single metacognitive scale is not unexpected. In the SRL model presented by Zimmerman (Zimmerman, 2008), significant correlations between the variables within an SRL phase are described, and Sitzmann and Ely (Sitzmann & Ely, 2011) indeed found strong correlations between SRL constructs. As described in Study 1, while learners may not be able to distinguish among all the metacognitive activities, learners may be able to distinguish among the SRL phases. Not only would a separation of metacognitive skills into three scales lead to an improvement of the face validity of the questionnaire, but it would also allow for more specific use of the questionnaire's (sub)scales, and for conclusions to be drawn about specific phases in the SRL process. We therefore propose to split the scale "metacognitive skills" into three separate subscales: activities before, during, and after a learning task. The aim of Study 2 is thus to create and test a revised version of the SOL-Q to improve its validity, reliability, and usability.

Method

SOL-Q revised (SOL-Q-R)

The scale metacognitive skills within the SOL-Q was expanded and revised to generate three subscales. The existing 18 items in the scale were divided over the three subscales (i.e., before, during and after learning) based on the meaning of the item and on words signaling the timing of the activity. For instance, the item "I am aware of what strategies I use when I study for this online course " was placed into the subscale "metacognitive activity during learning". Second, the subscales were complemented to make sure all relevant aspects of metacognition were sufficiently present in each subscale. While strategic planning is theoretically described as an activity during the preparatory phase, no items measuring strategic planning before learning were present in the questionnaire,

all focused on strategic planning during learning. Furthermore, there were only four appraisal items present. Therefore, an item measuring strategic planning was added to the scale "metacognitive activity before learning" ("At the start of a task I think about the study strategies I will use"), and two items measuring reflection on learning progress and learning strategies were added to the scale "metacognitive activity after learning" ("After studying for this online course I reflect on what I have learned" and "After learning for this online course, I think about the study strategies I used"). Specific attention was paid to words signaling timing when formulating the new items.

Furthermore, three small adaptations were made to improve the validity and reliability of the questionnaire. The first adaptation concerned the item "I know what the instructor expects me to learn in this online course", originating from the Metacognitive Awareness Inventory scale for task definition (Schraw & Dennison, 1994). Factor analyses during the development of the SOL-Q placed the item in the scale "environmental structuring". As the item does not measure environmental structuring and is therefore also not conceptually similar to the other items in the scale, the item was removed from the questionnaire leaving 4 items in the scale environmental structuring. Second, three negatively phrased items in the original design of the SOL-Q were removed after factor analyses, as they did not fit the factor structure. Polar opposite items (i.e., "I often feel so lazy or bored when I study for this online course, that I quit before I finish what I planned to do") are however known to result in lower internal-consistency reliabilities (Woods, 2006). These three items, two in the persistence scale and one in the help-seeking scale, were rephrased to be polar positive and added to the SOL-Q-R. Finally, the time management scale was slightly adapted to improve its reliability as it was the scale with low reliability in the SOL-Q, which was likely due to the small size of the scale (3 items). Therefore, two items were added to the scale. The first item was already part of the originally developed questionnaire but was removed as a result of the factor analyses. As the item conceptually fits in the scale, it was re-added ("I make good use of my study time for this online course"). The second item was formulated in line with the meaning of the scale ("I allocate studying time for this online course").

The answering format was not changed for the SOL-Q-R. All questions had to be answered on a 7-point Likert scale ranging from "not at all true for me" (= 1) to "very true for me" (= 7). The full SOL-Q-R can be found in Appendix B.

Participants and procedure

The SOL-Q-R was administered to two groups of MOOC participants. First, the questionnaire was implemented as a voluntary activity in a MOOC on Clinical Epidemology offered by Utrecht University, The Netherlands, on Coursera. This MOOC consisted of 7 modules: an introductory module, 4 content modules, a module with a peer-graded assignment, and a module with a final exam. While students were free to decide on their own pace of studying, one module per week was recommended. The questionnaire was added as a voluntary activity at the end of Module 2, to make sure students could reflect on their actual learning in the online course and would not answer based on what they planned or expected to do. Data was gathered in the first half of 2017. Complete data was gathered from 149 students. The responses of three students were considered outliers as they answered all questions identically (*SD* of their answers was 0). Responses of 146 students were used for analyses (M_{age} = 36.08, 48.6% male).

The questionnaire was also implemented as a voluntary activity in a MOOC on Environmental Sustainability offered by Wageningen University, The Netherlands, on edX. The MOOC consisted of seven modules: an introductory module and six content modules. In this MOOC, students were also free to study at their own pace, while one module per week was recommended. The questionnaire was added as a voluntary activity at the end of Module 2. Data was gathered in September and October of 2016. Complete data was gathered from 73 students. Three students were considered outliers (*SD* = 0). Responses of 70 students were used for analyses (M_{age} = 39.67 40.0% male).

Analyses

The reliability of the scales in the SOL-Q and the SOL-Q-R are compared. Furthermore, model fit was calculated using SPSS AMOS to test if the revised version had acceptable model fit. In line with the analyses conducted in Study 1, NC (normed Chi square) and RMSEA (root mean square error of approximation) were used as absolute fit statistics (Hooper et al., 2008; Kline, 2005).

Results

Reliability analyses were conducted to compare the internal-consistency reliabilities of the SOL-Q and the SOL-Q-R (Table 5). The results of the reliability analyses indicate higher reliabilities for the scales time management, environmental structuring, persistence, and help seeking in the SOL-Q-R. The reliability of the three metacognitive subscales are slightly lower than the reliability of the metacognitive skills scale. However, reliability is above .78 for all subscales, indicating good reliability.

Table 5 Internal-consistency reliabilities of the SOL-Q and SOL-Q-R scales

	Scales SOL-Q			Scales SOL-Q-R		
Scale	**Items**	**α in 1**	**α in 2**	**Items**	**α in 1**	**α in 2**
Metacognitive skills	18	.93	.91			
Activities before				7	.87	.84
Activities during				7	.82	.78
Activities after				6	.86	.86
Time management	3	.57	.72	5	.68	.72
Environmental structuring	5	.78	.74	4	.82	.77
Persistence	5	.78	.70	7	.82	.76
Help seeking	5	.87	.91	6	.88	.90

Note. Dataset 1 = MOOC Clinical Epidemiology and Dataset 2 = MOOC Environmental Sustainability.

An overview of the model fit statistics of the SOL-Q-R is presented in Table 6. For both MOOCs, Normed Chi square (NC) is below 2.0, indicating good fit of the SOL-Q-R in both datasets. Based on the RMSEA statistic, the revised version shows adequate fit only in the first dataset (value < 0.08), which also has the largest sample size. RMSEA is known to indicate poor model fit for small samples (Kenny et al., 2015), which may explain the RMSEA values above .08 for dataset 2.

Table 6 Internal-consistency reliabilities of the SOL-Q and SOL-Q-R scales

	MOOC 1	MOOC 2
NC	1.797	1.700
RMSEA	.074	.101

Note. Dataset 1 = MOOC Clinical Epidemiology and Dataset 2 = MOOC Environmental Sustainability.

Discussion

In Study 2, a revised version of the SOL-Q was presented and tested: the SOL-Q-R. In the revised version, the rather large scale metacognitive skills in the SOL-Q, is split into three scales measuring metacognitive activities before, during, and after learning separately. The revised version thereby has increased face validity, as the items within the scales were conceptually more similar. The revised version also has increased usability, as specific aspects of metacognition can be measured with the revised version. The theoretical and practical value of the questionnaire thus increases in the revised version. The results of the reliability analyses showed that the adaptations furthermore led to reliable scales overall (all α above .68), with increased reliability for most scales. Model fit statistics are somewhat ambiguous, but provide no argument against acceptance of the SOL-Q-R. We therefore conclude that the revised version of the SOL-Q, the SOL-Q-R, is an improved version of the SOL-Q in terms of validity, reliability and usability.

General discussion

In this chapter, a questionnaire to measure SRL in fully online courses was developed. In study 1, a first version of the questionnaire was developed and validated (SOL-Q, Appendix A). In study 2, a revised version of the questionnaire was presented (SOL-Q-R, Appendix B). The SOL-Q-R consists of seven scales: *metacognitive activities before learning, metacognitive activities during learning, metacognitive activities after learning, time management, environmental structuring, persistence*, and *help seeking*. In the revised version, metacognitive activities are no longer measured in one scale, but in three separate scales.

The development of this questionnaire allows researchers to not only measure learners' SRL in online education, but also to determine what aspects of learners' SRL are most in need of support, and to measure the effects of interventions in experimental research. Furthermore, as the developed questionnaire allows for the measurement of intervention effects on each of the seven included scales separately, it is possible to explore the transferability of metacognitive skills from one phase to the next. We consider this an important direction for future research.

Another direction for future research is to examine the transferability of the developed questionnaire to other contexts than MOOCs. The SOL-Q-R is developed for fully online courses with a focus on individual learning activities, and thus transferable to similar settings. Besides this type of education, the spectrum of online education also includes for example blended learning, in which online and face to face activities are combined (Staker & Horn, 2012). SRL in blended learning may involve more aspects than measured

with the SOL-Q. With the inclusion of additional scales, we hypothesize that the SOL-Q can be extended to measuring SRL in other types of online education as well.

Our goal for now has been to develop a questionnaire suitable for MOOCs. The present study not only provides an instrument which can be used and further refined in future research, but also indicates theoretical and practical implications concerning SRL. Theoretically, the role of task strategies and the temporal aspects of metacognitive activities were discussed. Practically, the results of this study provide indications for support of SRL in online education. As SRL is increasingly important in settings of open online education, valid measurement and adequate support of SRL are of vital importance. With the present study, steps have been made to contribute to these goals. The questionnaire that was developed, the SOL-Q-R, is considered a valuable tool for researchers to measure students' SRL in online education.

Appendix A: Self-regulated Online Learning Questionnaire (SOL-Q)

Metacognitive skills

1 I think about what I really need to learn before I begin a task in this online course.
2 I ask myself questions about what I am to study before I begin to learn for this online course.
3 I set short-term (daily or weekly) goals as well as long-term goals (monthly or for the whole online course).
4 I set goals to help me manage my studying time for this online course.
5 I set specific goals before I begin a task in this online course.
6 I think of alternative ways to solve a problem and choose the best one for this online course.
7 I try to use strategies in this online course that have worked in the past.
8 I have a specific purpose for each strategy I use in this online course.
9 I am aware of what strategies I use when I study for this online course.
10 Although we don't have to attend daily classes, I still try to distribute my studying time for this online course evenly across days.
11 I periodically review to help me understand important relationships in this online course.
12 I find myself pausing regularly to check my comprehension of this online course.
13 I ask myself questions about how well I am doing while learning something in this online course.
14 I think about what I have learned after I finish working on this online course.
15 I ask myself how well I accomplished my goals once I'm finished working on this online course.
16 I change strategies when I do not make progress while learning for this online course.
17 I find myself analyzing the usefulness of strategies while I study for this online course.
18 I ask myself if there were other ways to do things after I finish learning for this online course.

Time management

19 I find it hard to stick to a study schedule for this online course.
20 I make sure I keep up with the weekly readings and assignments for this online course.
21 I often find that I don't spend very much time on this online course because of other activities.

Environmental structuring

22 I choose the location where I study for this online course to avoid too much distraction.
23 I find a comfortable place to study for this online course.
24 I know where I can study most efficiently for this online course.
25 I have a regular place set aside for studying for this online course.
26 I know what the instructor expects me to learn in this online course.

Persistence

27 When I am feeling bored studying for this online course, I force myself to pay attention.
28 When my mind begins to wander during a learning session for this online course, I make a special effort to keep concentrating.
29 When I begin to lose interest for this online course, I push myself even further.
30 I work hard to do well in this online course even if I don't like what I have to do.
31 Even when materials in this online course are dull and uninteresting, I manage to keep working until I finish.

Help seeking

32 When I do not fully understand something, I ask other course members in this online course for ideas.
33 I share my problems with my classmates in this course online so we know what we are struggling with and how to solve our problems.
34 I am persistent in getting help from the instructor of this online course.
35 When I am not sure about some material in this online course, I check with other people.
36 I communicate with my classmates to find out how I am doing in this online course.

Items are answered on a 7-point Likert scale, raning from "not at all true for me" (= 1) to "very true for me" (= 7). All items are presented in randomized order.

Appendix B: Self-regulated Online Learning Questionnaire Revised (SOL-Q-R)

Metacognitive activities before learning

1 I think about what I really need to learn before I begin a task in this online course.
2 I ask myself questions about what I am to study before I begin to learn for this online course.
3 I set short-term (daily or weekly) goals as well as long-term goals (monthly or for the whole online course).
4 I set goals to help me manage my studying time for this online course.
5 I set specific goals before I begin a task in this online course.
6 I think of alternative ways to solve a problem and choose the best one in this online course.
7 At the start of a task I think about the study strategies I will use in this online course.

Metacognitive activities during learning

8 When I study for this online course I try to use strategies that have worked in the past.
9 I have a specific purpose for each strategy I use in this online course.
10 I am aware of what strategies I use when I study for this online course.
11 I change strategies when I do not make progress while learning for this online course.
12 I periodically review to help me understand important relationships in this online course.
13 I find myself pausing regularly to check my comprehension of this online course.
14 I ask myself questions about how well I am doing while learning something in this online course.

Metacognitive activities after learning

15 I think about what I have learned after I finish working on this online course.
16 I ask myself how well I accomplished my goals once I'm finished working on this online course.
17 After studying for this online course I reflect on what I have learned.
18 I find myself analyzing the usefulness of strategies after I studied for this online course.
19 I ask myself if there were other ways to do things after I finish learning for this online course.
20 After learning for this online course, I think about the study strategies I used.

Time management

21 I make good use of my study time for this online course.
22 I find it hard to stick to a study schedule for this online course.
23 I make sure I keep up with the weekly readings and assignments for this online course.
24 I often find that I don't spend very much time on this online course because of other activities.
25 I allocate studying time for this online course.

Environmental structuring

26 I choose the location where I study for this online course to avoid too much distraction.
27 I find a comfortable place to study for this online course.
28 I know where I can study most efficiently for this online course.
29 I have a regular place set aside for studying in this online course.

Persistence

30 When I am feeling bored studying for this online course, I force myself to pay attention.
31 When my mind begins to wander during a learning session for this online course, I make a special effort to keep concentrating.
32 When I begin to lose interest for this online course, I push myself even further.
33 I work hard to do well in this online course even if I don't like what I have to do.
34 Even when materials in this online course are dull and uninteresting, I manage to keep working until I finish.
35 Even when I feel lazy or bored when I study for this online course, I finish what I planned to do.
36 When work is difficult in this online course, I continue to keep working.

Help seeking

37 When I do not fully understand something, I ask other course members in this online course for ideas.
38 I share my problems with my classmates in this course online so we know what we are struggling with and how to solve our problems.
39 I am persistent in getting help from the instructor of this online course.
40 When I am not sure about some material in this online course, I check with other people.
41 I communicate with my classmates to find out how I am doing in this online course.
42 When I have trouble learning, I ask for help.

Items are answered on a 7-point Likert scale, ranging from "not at all true for me" (= 1) to "very true for me" (= 7). All items are presented in randomized order.

4

Exploring the Link Between Self-Regulated Learning and Learner Behavior in a MOOC

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This chapter is based on:

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RJ, AvL, JJ, and LK designed the study; RJ collected the data; RJ, AvL, JJ, and LK planned the data analysis; RJ analyzed the data; RJ drafted the manuscript; all authors contributed to critical revision of the manuscript; AvL, JJ, and LK supervised the study.

Abstract

Learners in Massive Open Online Courses (MOOCs) are presented with great autonomy over their learning process. Learners must engage in self-regulated learning (SRL) to handle this autonomy. It is assumed that learners' SRL, through monitoring and control, influences learners' behavior within the MOOC environment (e.g., watching videos). The exact relationship between SRL and learner behavior has however not been investigated. Insight in this relationship could improve our understanding of the influence of SRL on behavior, could help explain the variety in online learner behavior, and could be useful for the development of successful SRL support for learners. We therefore explored whether differences in SRL are related to differences in learner behavior in a MOOC. MOOC learners were grouped based on their self-reported SRL. Next, we used process mining to create process models of learners' activities. These process models were compared between groups of learners. Learners in all clusters closely followed the designed course structure. However, the process models also showed differences which could be linked to differences in the SRL scores between clusters. This study thereby shows that SRL may explain part of the variability in learner behavior. Implications for the design of SRL interventions include the necessity to integrate support for weak regulators in the course structure.

Introduction

Learners in a massive open online course (MOOC) experience much more autonomy over their learning process compared to learners in traditional campus-based education (Wang, Shannon, & Ross, 2013). Learners can study at any time, any place, and any pace they prefer, since course materials are available online over longer periods of time, and they can be studied by MOOC participants without guidance of a teacher. To handle the autonomy offered to them, students must engage in self-regulated learning (SRL) in MOOCs (Azevedo & Aleven, 2013; Beishuizen & Steffens, 2011; Garrison, 2003; Kizilcec & Halawa, 2015; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Wang et al., 2013; Waschull, 2001). To learn successfully in a MOOC, learners must take control of their own learning process. MOOC learners that are unable to adequately self-regulate their learning are likely to drop out (Hew & Cheung, 2014; Kizilcec & Halawa, 2015).

Self-regulated learners are actively involved in their learning, and they make conscious decisions about what, where, and how they study (Zimmerman, 2002). It involves activities such as planning, monitoring, time management, and help seeking. Nelson and Narens (1990) described SRL as a continuous cycle between monitoring and control (see Figure 1). Learners engage in learning activities to perform a task. These activities are overt; they can be observed by others. While working on the task, learners monitor their progress. As a result, learners form a metacognitive representation of their learning at a *meta-level*. Based on the progress monitored, and the gap between current and desired performance, learners control their overt learning activities at the *object-level*. Monitoring and control, which are covert activities, thereby help self-regulated learners to adapt their learning activities to the task at hand (Littlejohn, Hood, Milligan, & Mustain, 2016).

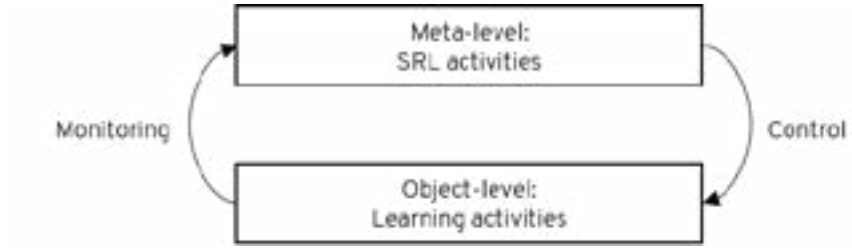

Figure 1 The relationship between monitoring and control (Nelson & Narens, 1990).

The automatic storage of all learners' activities in a MOOC learning environment into trace data enables researchers to study the relationship between covert SRL and overt learner behavior at a level of detail that is not feasible in traditional education. In trace data, all learner behavior is stored at a very fine granularity over the time span of the whole course. Empirical data of this kind cannot be collected in traditional education. In this study, we will make use of the opportunities trace data offer to study the relationship between SRL and learner behavior in a MOOC.

Investigating the relationship between SRL and learner behavior in a MOOC is however not only interesting for the empirical data that it provides. It also improves our understanding of the influence of SRL on online course behavior. Due to the autonomy provided to them,

MOOC learners can study in highly varying ways (Kizilcec, Piech, & Schneider, 2013). Research has shown that learners indeed make use of this opportunity and found great variety in the way learners study in online education: learners for instance differ in terms of the amount of material they complete, the (order of) activities they engage in, but also in the their forum activities, and in the timing of and time between their learning sessions (e.g., Goda et al., 2015; Jovanović, Gašević, Dawson, Pardo, & Mirriahi, 2017; Kizilcec et al, 2013; Kovanović, Gašević, Joksimović, Hatala, & Adesope, 2015; Maldonado-Mahauad, Pérez-Sanagustín, Kizilcec, Morales, & Munoz-Gama, 2018; Saint, Gašević, & Pardo, 2018). Theoretically however, little is known about the origin of the variety in learner behavior (Li & Baker, 2018). Differences between learners concerning, for example, prior knowledge and SRL, may be the cause of these differences in course behavior (Li & Baker, 2018). More research on how differences between learners influence learner behavior is necessary (Deng, Benckendorff, & Gannaway, 2019). The importance of SRL for successful learning in MOOCs leads us to focus on the relationship between SRL and learner behavior in this study.

Since insufficient SRL can lead to student dropout, multiple researchers have attempted to support learners' SRL by implementing an SRL intervention in a MOOC (Davis, Triglianos, Hauff, & Houben, 2018; Kizilcec, Pérez-Sanagustín, & Maldonado, 2016; Yeomans & Reich, 2017). Exploring the influence of SRL on learner behavior could help increase the impact of such SRL interventions. While compliance with the SRL support offered in these studies increased both learners' course activity as well as their course completion, these interventions suffered from low compliance by learners: many learners did not engage with the SRL support offered. It is known that weak learners often find it most challenging to identify their support needs (Clarebout & Elen, 2006; Clarebout, Horz, Schnotz, & Elen, 2010). It is therefore likely that learners who needed help most, did not engage with the SRL support. Increased knowledge of how learners' SRL influences how learners behave in the MOOC environment, especially of how weak self-regulating students behave, may help identify ways in which support could be implemented to increase learner compliance. Exploration of the impact of learners' SRL on their learning process in MOOCs may thereby help determine how SRL support should best be implemented.

SRL can thus be considered important for student learning in MOOCs, and there is considerable theoretical and practical value in investigating the relationship between SRL and learner behavior. This would provide data on the relationship between SRL and learner behavior, help explain the variability in online learner behavior and assist in the implementation of SRL support in MOOCs. Nevertheless, research on the influence of learners' SRL on learner behavior within MOOCs is limited. In the section below, we present existing research on the relationship between SRL and learner behavior in MOOCs and describe how the current study extends this knowledge.

Literature review

One of the first studies to link learners' activities, captured in trace data, with learners' SRL was conducted by Hadwin, Nesbit, Jamieson-Noel, Code, and Winne (2007). For eight learners, the association between specific self-reported SRL (measured by means of a questionnaire) and learners' trace data in a single study session was analyzed. Trace data provided additional, and in some cases conflicting, information to learners' self-reported SRL. While the authors mostly focused on single questionnaire items and absolute

frequencies of learners' activities, their results already showed that a better understanding of students' SRL could be gained by adding trace data to questionnaire data (Hadwin et al., 2007; Winne, 2010; Zimmerman, 2008). In a more recent study, Kizilcec et al. (2017) also investigated the relationship between learners' self-reported SRL and their learner behavior as measured with trace data. In contrast to the study conducted by Hadwin et al. (2007), Kizilcec et al. (2017) focused on scores on SRL scales, instead of on individual items, and on the frequency of transitions from one activity to the next, instead of on absolute frequencies of activities. For instance, they explored the relation between goal setting (an individual scale from the employed SRL questionnaire) and the action of revisiting a lecture after watching a lecture. Overall, they found that learners who reported more engagement in SRL activities were more likely to revisit materials they had already completed compared to learners who reported less engagement in SRL activities. The results thereby showed that SRL and learner behavior are related. This finding indicates that the relationship between SRL and learner behavior is not only found when analyzing questionnaire data per item (Hadwin et al., 2007), but also when analyzing questionnaire data at a higher level of aggregation, namely per scale (Kizilcec et al., 2017)

The approach taken by Kizilcec et al. (2017) however still provides limited insight in the influence of SRL on learner behavior. The six SRL scales present in the questionnaire (e.g., strategic planning, help seeking) were all individually correlated to the 36 behavioral transitions that were studied. Learners' scores on SRL components are, however, related (Sitzmann & Ely, 2011). Sitzmann and Ely (2011) for instance found metacognition to be correlated to time management and help seeking. It is therefore likely that the SRL scales were also correlated in the research conducted by Kizilcec et al. (2017). Multiple scales correlated to the same transition, namely revisiting assessments after passing an assessment. The correlation between SRL scales may explain why most of the scales were found to be significantly correlated to that same behavioral transition. In the current study, we take the correlation between aspects of SRL into account by studying SRL as a single construct by clustering learners.

Furthermore, by analyzing learning as a collection of individual transitions, the approach taken by Kizilcec et al. (2017) ignored the presence of a course structure that (partly) determined students' learning process (Bannert, Reimann, & Sonnenberg, 2014). The ordering of learners' activities is governed by this structure. In the present study, learners for instance transitioned from content videos to self-test questions when they followed the designed order of learning activities. The influence of the course structure is neglected when analyzing individual transitions but can be incorporated when analyzing learner processes (Bannert et al., 2014). Moreover, analysis of students' activities as a process instead of as individual transitions also presents a better representation of students' learning. As learning is cumulative, activities inherently build upon each other (Reimann, 2009). Larger sequences of learning than individual transitions should thus be taken into account to accurately model students' learning process. We therefore analyze learners' activities in the MOOC through process mining. Process mining allows for the analysis of large samples of ordered (i.e. time-stamped) activity data (Sonnenberg & Bannert, 2015, 2018). We thereby analyze all transitions at once, instead of focusing on each transition separately.

We know of only a single study in which online learning processes have been linked to SRL. Maldonado-Mahauad et al. (2018) focused on the activities learners engaged in between

starting a learning session and ending a learning session. Process mining was used to find all the different sequences of activities. Each session was then classified based on the overall occurring activity. Six types of learning sessions emerged, including only watching video lectures and attempting an assessment followed by watching the accompanying video lecture. For each type of learning session, the authors provided an explanation in terms of SRL that might underlie the learning activities performed in that session. For example, they suggested that the sequence of watching a video lecture followed by completing an assessment might signal the use of the SRL strategy self-evaluation. However, SRL was not measured in this study and the potential SRL explanations of the learning sessions are thus not based on data but on interpretation by the authors. In the current study we also focus on the relationship between SRL and the order of learning activities. In contrast to Maldonado-Mahauad et al. (2018) we combine learners' trace data with learners' SRL measured with a questionnaire.

The current study

In the current study, we explore the relationship between SRL and learner behavior in a MOOC. Due to the autonomy offered to learners in MOOCs, SRL is of considerable importance for successful MOOC learning (e.g., Kizilcec & Halawa, 2015). Insight into the relationship between SRL and learner behavior has both practical as well as theoretical relevance, as it helps determine how SRL support can best be implemented in MOOCs and improves our understanding of how SRL influences learner behavior. Learners' SRL will be measured with a questionnaire (Jansen, Van Leeuwen, Janssen, Kester, & Kalz, 2017). The trace data captured in the MOOC learning environment will be used to access learners' behavior (Hadwin et al., 2007; Kizilcec et al., 2017; Maldonado-Mahauad et al., 2018). The relationship between learners' SRL and their learner behavior will be analyzed by first clustering learners into groups with similar SRL and then analyzing the order of their learning activities with process mining (Bannert et al., 2014; Maldonado-Mahauad et al., 2018). We hereby extend existing research in two ways. We analyze SRL as a construct instead of as separate, independent scales, and we analyze behavior processes instead of individual transitions.

Method

Context

Data were collected in a MOOC on Environmental Sustainability offered by Wageningen University, The Netherlands, on the online learning platform edX. The MOOC ran from September 2016 to November 2016 and consisted of 7 modules. The first module was an introductory module, called module 0, and contained the course manual and introductory videos of the lecturers. Module 1-6 were all content modules. Each consisted of an introductory video, approximately 4 content videos each with one or two recap (i.e., self-test) questions, a summary video, a practice test, and a graded test. All questions in the course were multiple choice questions. Module 6 was the final module, which contained both a graded test and the final exam. The exam consisted of writing a peer-assessed essay. A course forum was connected to the course environment for the course instructors and designers and the course participants. Browsing and posting on the forum were

not required in the course, but the forum could be accessed at any time. The study pace advised by the course designers was one module per week, but learners were free to study at a faster or slower pace.

Participants

MOOC learners were presented a questionnaire which could be answered voluntarily and anonymously focused on their SRL. While there were more learners in this MOOC, we focus in this study on the learners who answered the questionnaire (n = 73). All participants who answered all questions identically were removed, as they were considered outliers due to the lack of deviation in their answers (n = 4). The remaining participants formed the sample of the present study (n = 69). Their mean age was 38.8, 40.6% were male.

Measurements

SRL

SRL was measured with the Self-regulated Online Learning Questionnaire (SOL-Q; Jansen et al., 2017). This questionnaire consisted of 36 items and measured learners' SRL using five different scales: metacognitive skills (17 items, α = .90), time management (3 items, α = .73), environmental structuring (5 items, α = .73), persistence (5 items, α = .69), and help seeking (5 items, α = .89). In the same order, example items of the five scales are "I ask myself questions about what I am to study before I begin to learn for this online course", "I find it hard to stick to a study schedule for this online course", "I know where I can study most efficiently for this online course", "When my mind begins to wander during a learning session for this online course, I make a special effort to keep concentrating", and "When I am not sure about some material in this online course, I check with other people".

All questions were answered on a 7-point Likert scale ranging from "not at all true for me" to "very true for me". The questionnaire was incorporated in the course environment as a voluntary assignment at the end of module 2. At that point, learners were able to reflect on their SRL during the MOOC. Learners were stimulated to answer the questions based on their experiences in the online course instead of based on their experience with learning in general by including the phrase "in this online course" in all questions.

Learner behavior

Learner behavior was defined as learners' engagement in thirteen learning activities. These learning activities (see Figure 2) were derived from the course structure because these activities formed the main components of the MOOC. The learning activities were: watching introductory videos, content videos, and summary videos (1-3), answering multiple-choice recap questions correctly/incorrectly, practice questions correct/incorrect, and graded questions correct/incorrect (4-9), handing in the essay assignment (10), assessing peers (11), and browsing and posting on the forum (12-13). The order of these activities as intended by the course designers is displayed in Figure 2. We filtered information on the thirteen activities analyzed from the trace data. In the trace data, all learner activities in the MOOC environment were automatically stored including a timestamp and a user ID.

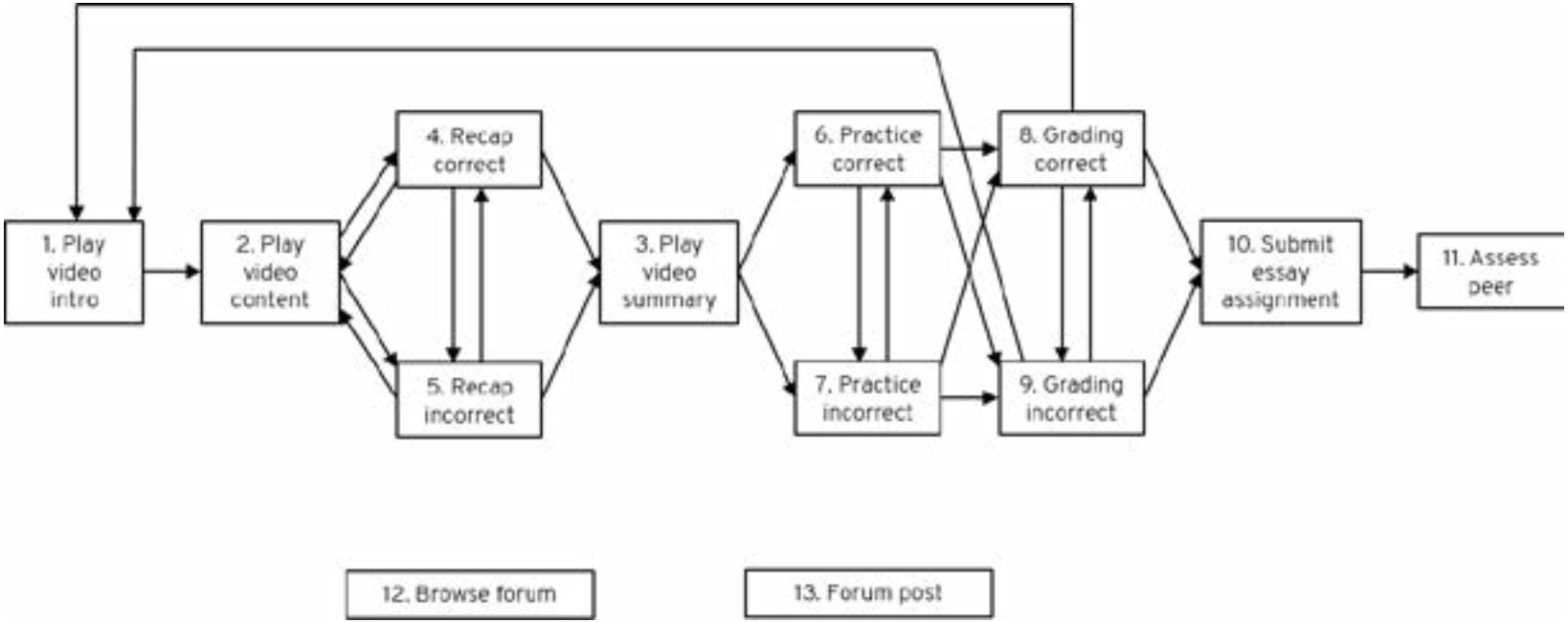

Figure 2 Process model of the course structure as intended by the course designers.

When following the intended process, a learner would start each module by watching the introductory video. A learner would continue with watching the first content video and answering the one or two associated recap questions. As there were two questions for most videos, and questions could be re-answered, the learner could move between correctly and incorrectly answering recap questions. The learner would continue watching content videos and answering recap questions until all content videos included in the module had been viewed. The learner would then watch the summary video and make the practice test. The practice test consisted of multiple questions and therefore the learner could transition between answering practice questions correctly and incorrectly. There were no consequences for answering a recap or practice question incorrectly, and the correct answer was shown as soon as the question was answered incorrectly. Therefore, the learner would know the correct answer to a recap or practice test question also after answering the question incorrectly. After the practice test, the learner would work on the graded test. This test also consisted of multiple questions, making it possible for the learner to have an incorrect question follow a correct question or reversed. After answering the final question, either correctly or incorrectly, the learner would start working on the next module by watching the introductory video. After finishing the graded test of the sixth module, the learner would hand in a peer-assessed essay. After handing in the essay, the learner had to grade the work of at least four others, before the learner's own grades would become available. If the learner's own work was peer-assessed to be a pass, the learner completed the course after grading four others.

Procedure

Learners could work with the course material in any order and at any pace they liked. The questionnaire on SRL was presented as a voluntary assignment at the end of module 2. Completion of the questionnaire took approximately 15 minutes. By completing the questionnaire on SRL, learners gave their informed consent and thereby gave permission to link their questionnaire responses to their trace data. The trace data were later retrieved from the edX server. As the current study focuses on the relation between interaction with course materials and reported SRL, only the trace data for those learners who filled out the SRL questionnaire were further analyzed. Permission for this study was attained from the institution's ethics committee.

Data analysis

In the current study, process models of groups with different self-reported SRL were compared to investigate how self-reported SRL is related to the order of learners' activities within the MOOC. As it is not feasible to compare the process models of all individual learners in the sample, learners first had to be clustered into groups with similar SRL before process models could be created.

Cluster analysis

Procedures as outlined in Mooi and Sarstedt (2010) were followed to conduct cluster analysis with a small sample. The scale scores (i.e., mean score per scale) of the five scales in the SRL questionnaire were used as the basis for clustering. The first step in cluster analysis was the exclusion of outliers. They are not part of any cluster and can severely influence the cluster solution (Milligan, 1980). It is therefore advised to remove these cases before conducting cluster analysis by using the single linkage Euclidian distance

algorithm (Mooi & Sarstedt, 2010). Seven cases were removed as outliers. Next, hierarchical cluster analysis was conducted with the remaining 62 cases using Ward's method (Mooi & Sarstedt, 2010). Cases are hereby segregated into clusters by combining cases that lead to the smallest increase in total variance per cluster. A four cluster solution led to the most equal distribution of learners over clusters and could also be best interpreted. The clusters were furthermore similar to the clusters found in previous studies in which learners were clustered based on their self-reported SRL (Barnard-Brak, Lan, & Paton, 2010; Dörrenbächer & Perels, 2016b; Ning & Downing, 2015). The four cluster solution was therefore selected as the final clustering. An overview of the clusters and the SRL scores of the learners within them can be found in Table 1.

The four clusters were labeled based on the reported SRL data. The first and largest cluster is a group of *average regulators*. Learners in this cluster reported average levels of SRL compared to the other clusters. The second group consists of *help seekers*. While learners in this group reported average levels of most SRL activities, it stands out that they indicated more engagement with help seeking behavior than the other clusters of learners. This indicates that these learners were aware of other learners in the course and that they wanted to engage with them to improve their learning. The third cluster is formed by the *self-regulators*. Learners in this cluster indicated the highest level of metacognitive skills, environmental structuring, and persistence. Their level of self-reported time management was almost as high as that of the average regulators, who indicated the highest score (4.47 versus 4.50). The self-regulators only scored lower on the help seeking scale than the help seekers. This, therefore, is a cluster of learners who indicated high *self*-regulated learning. The fourth and final cluster are the *weak regulators*. This cluster is exemplified by learners with lower scores than all other groups on the five SRL scales. Learners in this cluster appear to engage in the course without a clear strategy and without planning their study behavior.

Table 1 Descriptives of the Self-regulated Online Learning Questionnaire per cluster

	Average regulators (n = 22)	**Help seekers (n = 15)**	**Self-regulators (n = 10)**	**Weak regulators (n = 15)**
Metacognitive skills	4.44	4.95	5.52	3.93
Time management	4.50	4.38	4.47	2.62
Environmental structuring	5.32	5.01	6.42	4.99
Persistence	4.28	4.52	5.94	3.73
Help seeking	1.45	3.65	1.82	1.55

Note. All scales on a range from 1-7.

Process mining

After clustering the learners, process mining was used to analyze the trace data per cluster (Bannert et al., 2014; Maldonado-Mahauad et al., 2018). With process mining, process models are created to compare process data between individuals, or between groups of individuals. Thereby, process mining allows for the analysis of temporal patterns in the data. The typical transitions (i.e., edges) of learners between activities (i.e., nodes) within each cluster are visualized, while atypical, infrequent transitions are removed to handle noise in the trace data. We analyzed the trace data that related to interactions

focused on whole activities, such as watching a video. We did not zoom in on finer grained activities, such as pausing a video, or navigating between pages. The activities included are presented in Figure 2.

Process mining was conducted with ProM 6.6 and the fuzzy miner algorithm (see Bannert et al., 2014). The settings used for the fuzzy miner algorithm in the current study are similar to those used in the study conducted by Bannert and colleagues (2014). However, as we were interested in the transitions between the thirteen activities specified, no activities were removed from the models even if they appeared only very infrequently in the trace data; the node filter cutoff was set to 0 to retain all activities in the resulting models. Furthermore, Bannert and colleagues (2014) only retained the most significant and frequent relations (edge filter cutoff .200). We preferred a greater level of detail to result from process mining. We set the edge filter cutoff at .500 to retain more transitions in the model. Self-loops (i.e., one activity to the same activity) were present in the data, but were ignored while creating the process models. This was done as self-loops were so frequently occurring (switching between pause and play of a single video, answering multiple questions in a row), that they would make all other transitions too infrequent to be included in the process models. As we were interested in how learners' transition from one learning activity to another, self-loops were not considered when determining the importance of transitions for the process models.

Results

To analyze the relationship between learners' SRL and their behavior, we compared the behavior of learners within the clusters based on the thirteen learning activities specified in the method. Process models were created for each of the four clusters of learners with similar self-reported SRL. The four resulting process models can be found in Figures 3-6.

The process models showed that learners in all clusters generally followed the course activities in the order designed and intended by the course designers as presented in Figure 2; most of the transitions in Figure 2 were also visible in the four process models. In contrast, learners' engagement with the recap questions showed a deviation from the course structure in all clusters. In most cases, two recap questions were connected to a content video. The process models all showed that while learners may sometimes have answered the first recap question incorrectly after watching a content video, this transition was so infrequent that it was removed from the process models (activity 2 to activity 5). The most traversed path was from watching a content video, to answering a recap question correctly, to answering a recap question incorrectly (2-4-5). Transitions from recap question incorrect to recap question correct (5-4) were also observed and this could indicate students who corrected their wrong answer.

The transitions originating from incorrectly answered recap questions show the first major difference between clusters. Learners in all four clusters answered recap questions correctly before continuing with other learning activities (4-3). For learners in three clusters (i.e., average regulators, help seekers, and self-regulators) this is the only displayed transition after answering a recap question incorrectly. Learners in the weak regulators cluster however also had a frequently occurring path from incorrectly answered recap

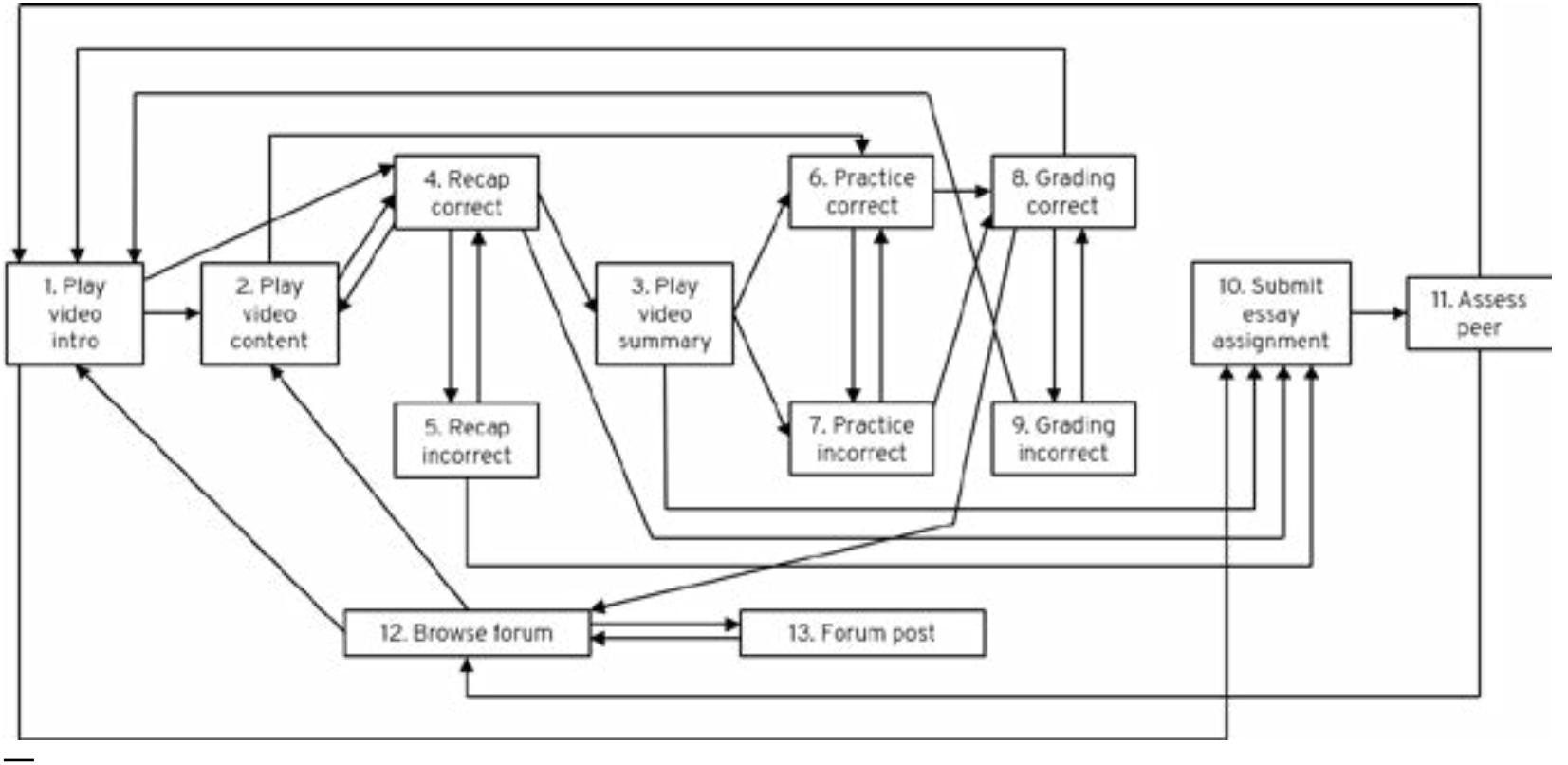

Figure 3 Process model for the cluster of average regulators.

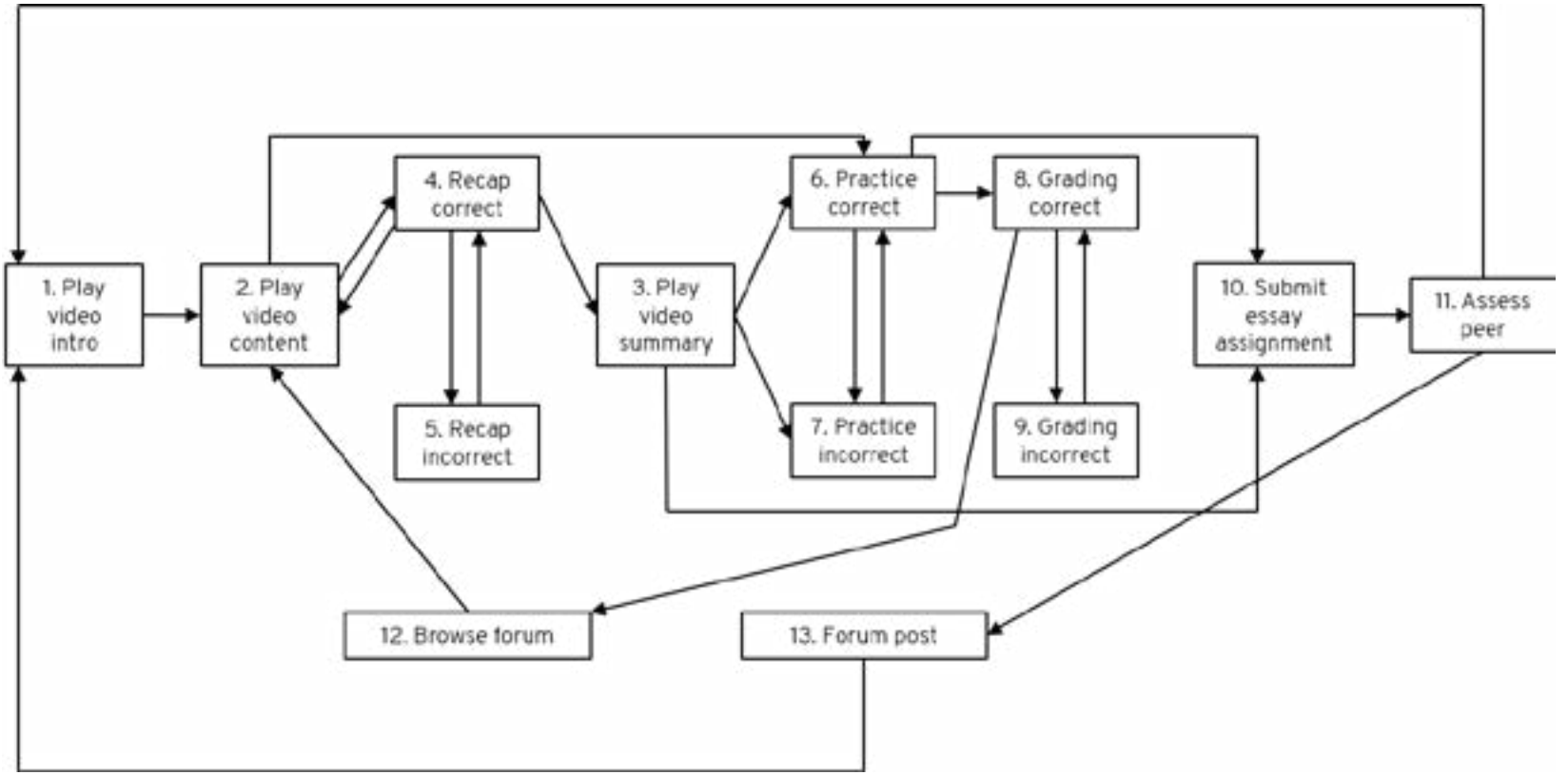

Figure 4 Process model for the cluster of help seekers.

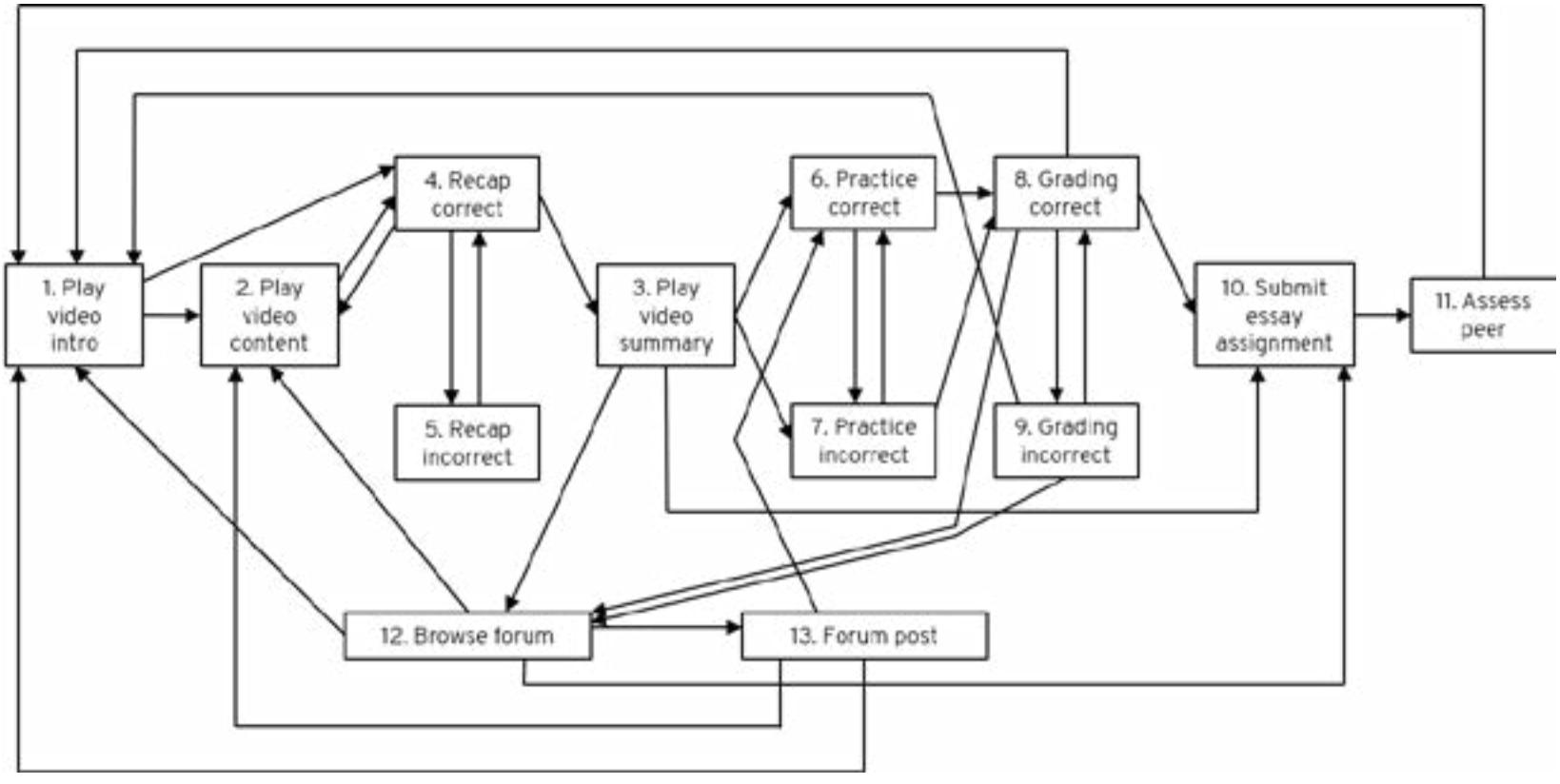

Figure 5 Process model for the cluster of self-regulators.

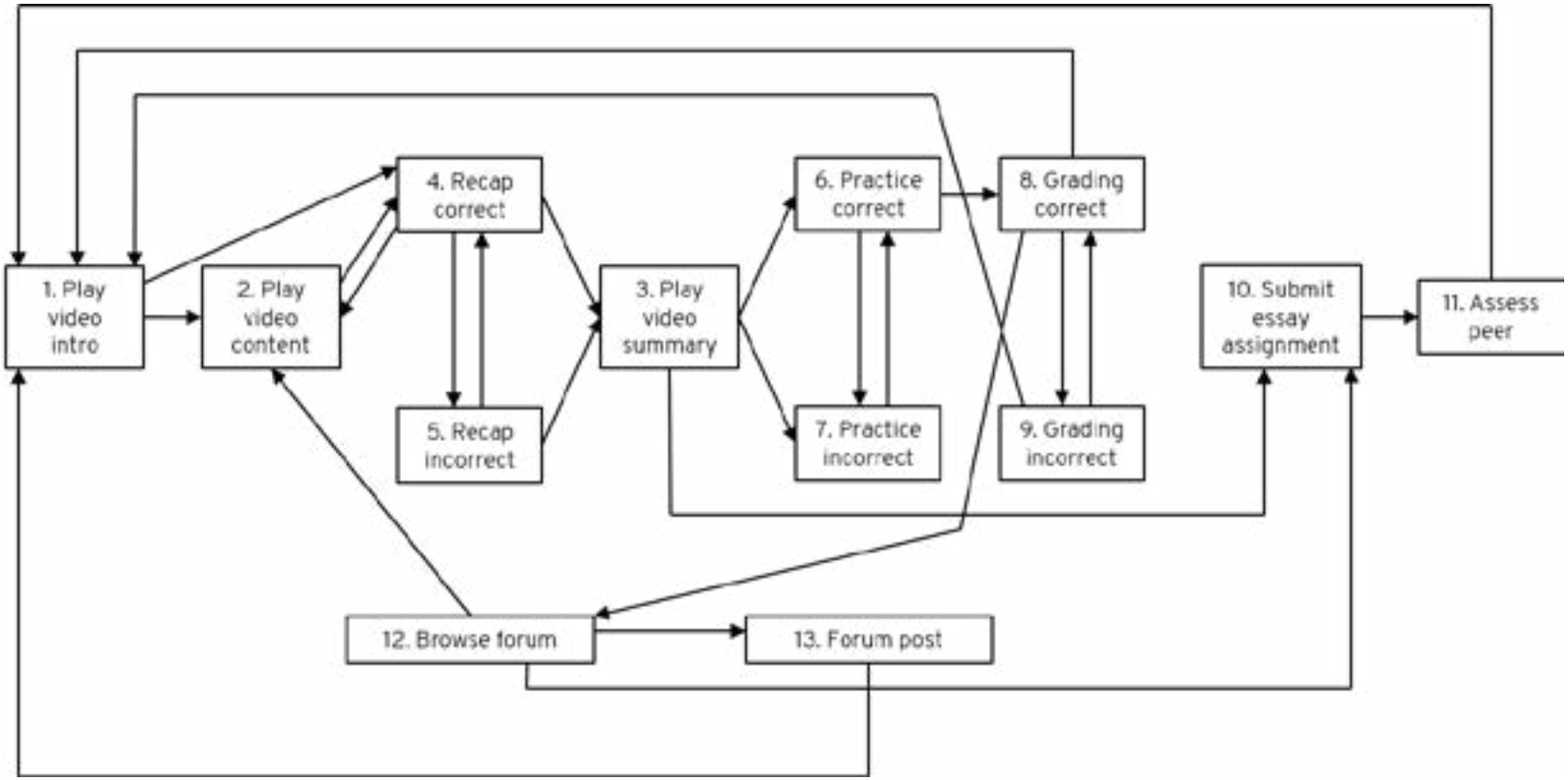

Figure 6 Process model for the cluster of weak regulators.

questions to watching a summary video (5-3). Learners in the average regulators and self-regulators clusters transitioned from answering a practice question incorrectly to answering a graded question correctly (7-8). As the correct answer to a recap or practice question was presented after answering the question incorrectly, transitioning from an incorrectly answered recap question or from an incorrectly answered practice question to a next activity, was therefore not better or worse than first answering the recap or practice question correctly before moving to the next activity.

The process models of several clusters also showed skipping of steps intended by the course designers. For average regulators and help seekers, transitioning from a content video to the practice test, thereby skipping the summary video was a frequent alternative (2-6). For average regulators, self-regulators, and weak regulators immediately answering a recap question after watching the introductory video was a frequent alternative to watching the content video first (1-4). While possible in the course design, none of the process models showed direct skipping of the introductory video, as there were no direct relations from answering the graded questions to watching the content videos (8-2 or 9-2). All process models did include transitions from answering graded questions correctly, to browsing the forum, back to watching content videos (8-12-2). Indirect skipping of the introductory video may thus have occurred.

When comparing the process models with the process intended by the course designers, it should also be noted that only for the self-regulators the transition from answering a graded test question to submitting the essay assignment was present (8-10). When following the order of the online course as designed, this was the order in which one should arrive at the final assignment. In all process models however, other transitions to this activity were present. All process models included a transition from watching a summary video to submitting the essay (3-10).

It was not mandatory for learners to browse or post on the forum in order to follow or finish the course, although engagement with other learners through the forum could be helpful. When we zoom in on learners' forum interactions, we first analyzed the help seekers. While help seekers only engaged in forum interactions after answering a graded test, and not at other moments in time, this transition is their only transition back from answering graded test questions (8-12-2). Learners in all other clusters transitioned directly from answering graded questions to watching an introductory video, likely of the next module (8-1 or 9-1). Furthermore, for all other clusters, posting on the forum solely occurred in response to browsing the forum. Learners in the help seekers cluster were the only group that had no transition between browsing and posting. For the self-regulators, browsing and posting on the forum were highly integrated in their learning process; their process model showed a large number of transitions from and to browsing and posting. For the average regulators and the weak regulators, forum activities were present, but these were less integrated in their learning process.

To sum up, two statements can be made concerning how the different clusters of learners interacted with the course materials. First, learners in all clusters generally followed the course in the order intended by the course designers. The intended course structure is visible in all four process models. This also explains why the process models of the four different clusters show similarities. Second, however, there were also differences between the process models of the clusters. The clearest differences occurred considering skipping of activities, and browsing and posting on the forum.

Discussion

In the current study, we explored the relationship between SRL and learner behavior in a MOOC. Process mining was used to compare learning processes. In order to conduct process mining, learners were first clustered based on their self-reported SRL. Four clusters emerged: average regulators, help seekers, self-regulators, and weak regulators. Next, the behavior of learners in the different clusters was compared by using the trace data stored in the online course environment. Specifically, we looked at their learning processes in terms of thirteen learning activities (Figure 2).

Two general conclusions could be drawn based on the comparison between the process models of the four clusters. First, the process models showed similarities between clusters. Learners in all clusters were guided by the course structure implemented by the course designers, and this intended course structure was visible in all four process models. The MOOC from which the learner data was analyzed in this study had a clear structure. Learners were guided in their learning process as all modules followed the same sequence and incorporated introduction and summary videos. Thereby the course design likely reduced the need for learners to regulate their learning.

However, SRL remained important as learners were still free to study what, where and when they wanted. The need for self-regulation is in line with the second general conclusion: differences between clusters were present, and these differences in process models could be interpreted in light of differences in SRL scores. The average regulators showed the greatest variety in the transitions present in their process model. Their SRL scores did not signal a particular (lack of) strategy and the behavior in their process model is diverse. The weak regulators, in contrast, followed the prescribed learning process almost to the letter; there were only few exceptions in the transitions present in their process model. The average regulators, weak regulators, and self-regulators all showed a nonconformity to the intended course structure in the form of a transition from watching the introductory video to answering a recap question correctly. The fact that skipping in all three cases occurred prior to answering questions correctly may suggest that these learners felt like they could already answer the question without further information and indeed were able to do so. The remaining learning process of the weak regulators was highly regulated by the course design. The learners in the self-regulators cluster, on the other hand, showed that they regulated their learning in a manner that suited themselves. This was in line with their self-reported SRL in terms of high scores on metacognitive skills, time management, environmental structuring, and persistence. Browsing and posting on the forum were clearly integrated in their learning process. It appears as if they used the forum as a source of help throughout their entire learning process; sometimes only browsing, but sometimes also posting after browsing. Finally, for learners in the help-seeking cluster, engagement with the course forum was not as integrated as for the self-regulators. This is somewhat counter-intuitive, as the help seekers reported the highest levels of help-seeking on the SRL questionnaire. For the help-seeking cluster however, forum engagement was the only transition after finishing a module and before starting the next module, making it an essential transition in their learning process. Browsing and posting on the forum fitted with their self-reported SRL strategy of looking for help when needed. It was, however, surprising that they did not browse the forum first as that could have been an easier way to find help compared to posting on the forum.

From these findings, we conclude that differences in SRL indeed relate to differences in learner behavior. Furthermore, differences in scores on specific SRL scales could be related to specific learning processes. We have thereby shown how SRL impacts learner behavior, providing evidence for the claim posited by Li and Baker (2018) that differences between learners influence course activity. Our results thus support Maldonado-Mahauad et al.'s (2018) suggestion that differences in learning processes are the result of differences in SRL.

Our study mostly resembled the work conducted by Kizilcec et al. (2017), but differed in two ways allowing us to extend their findings. First, we focused on SRL as a construct, taking the correlation between SRL scales into account. Kizilcec et al. (2017) found that learners who reported more SRL, more often revisited course materials (e.g., assessments, lectures) that they already completed. By clustering learners into SRL profiles before exploring the influence of SRL on behavior, we were able to show that high SRL is related to a much wider range of deviations from the course structure. In other contexts, such variety in learning activities has been found to be associated to increased achievement (Fincham, Gasevic, Jovanovic, & Pardo, 2018; Hadwin et al., 2007). Learners high in SRL thus seem better able to deal with the autonomy offered in the MOOC. A second difference between the study conducted by Kizilcec et al (2017) and ours is that we focused on learning as a process instead of a collection of transitions. By analyzing learners' online behavior through process mining we were able to identify the strong influence of the course structure on learner behavior: The course structure was visible in all process models. Identification of the influence of the course structure would have been much more complicated when analyzing individual transitions in learner behavior, showing the benefit of our approach for analyzing learner behavior.

Limitations and suggestions for future research

While the results of the current study increase our knowledge of the influence of SRL on learner behavior, the study is also subject to a number of limitations. The most prominent limitation of the current study is its sample: participants originated from a single MOOC, sample size was limited, and learners self-selected to fill out the questionnaire and thus to participate in this study. The generalizability of this study is limited due to these sampling issues. However, if participants would have studied in different MOOCs, with different structures, the impact of the course structure on learner behavior patterns would likely have been obscured if the data had been analyzed at once. It would be worthwhile to analyze the impact of SRL on learner behavior in future studies in diverse contexts and with larger samples. Thereby, it could for instance be determined if weak regulators also exhibit less variety in their behavior in other MOOCs. It would be especially interesting to study the influence of SRL on learner behavior in a less structured MOOC, as we found a strong influence of the course structure on learner behavior in the current study. If our findings can be replicated to different contexts, then SRL can explain (some of) the variability in online learner behavior.

Furthermore, process mining as a methodology to study learner behavior in MOOCs has great advantages: It enabled us to analyze the large amounts of event data and to create accompanying visualizations to make the data insightful. We however also identify two main limitations associated with process mining. First, data processing and process mining settings influence the results obtained. Transparent reporting of procedures and

the consequences of decisions made during analysis is thus essential. We have therefore reported on our data filtering (i.e., what activities in the trace data were retained) and our process mining settings in the current study. As it is not feasible to compare process models of all individual learners and compare those to their SRL scores, learners had to be clustered. We assumed that learners within each cluster would behave in a similar manner. The variety of transitions represented in a process model is then the result of the variety in learning processes *within* learners. However, the variety of transitions may also be (partly) resulting from a variety in learning processes *between* learners. Additional research studying the extent to which learners with similar SRL also behave similarly is needed. If learners with similar SRL vary in their behavior in a MOOC, then this variability in behavior may likely be the consequence of other differences between learners, for instance in motivation or prior knowledge. Zooming in on learners with similar self-reported SRL would help isolate the influence of SRL from the effects of other learner differences on learners' online behavior.

Second, the analysis of learner behavior with process mining is limited to the analysis of trace data. Learner behavior outside of the MOOC environment (e.g., consulting other sources) is not stored and can therefore not be analyzed. However, the storage of learner behavior into trace data in MOOCS is at a very fine granularity (every mouse click) and a long time span (the whole length of the course). MOOC trace data are thereby more complete than any other long term data collection, and as no learning could occur without interacting with the MOOC, all crucial learning activities were included by analyzing the trace data.

Practical implications

In MOOCs, learners are offered great autonomy over their learning process, making adequate SRL vital for learners (e.g., Azevedo & Aleven, 2013; Beishuizen & Steffens, 2011; Kizilcec & Halawa, 2015; Wang et al., 2013). Learners often struggle to successfully regulate their learning (e.g., Azevedo & Cromley, 2004; Bol & Garner, 2011). Many learners may therefore benefit from SRL support, as SRL support can lead to increased course completion and reduced learner dropout (Hew & Cheung, 2014; Kizilcec & Halawa, 2015; Yeomans & Reich, 2017). Unfortunately, many learners appear unable to successfully monitor their own learning needs and are unable to estimate the benefit they could have from using these tools. Low performing learners are especially unsuccessful at monitoring their need for support, while they are most in need of support and could thus benefit most (Clarebout & Elen, 2006; Clarebout et al., 2010). It has therefore been described that the use of such support tools should be encouraged by embedding the tools within the course environment, instead of providing them optionally (Clarebout & Elen, 2006; Clarebout et al., 2010). The results of the current study indicate that if SRL support would be integrated in the course structure, weak regulators – who likely have the greatest need for SRL support - are expected to come into contact with the support automatically and would thus, hopefully, benefit.

However, implementing SRL support requires balance between stimulating support use and respecting learners' autonomy. While many learners would benefit from SRL support, demanding compliance with an SRL intervention interferes with the open nature of MOOCs. Furthermore, high self-regulating students could be frustrated by mandatory support, leading to negative effects on their motivation and performance (Clarebout

et al., 2010; Narciss, Proske, & Koerndle, 2007). While learners in the other three clusters (average regulators, help seekers, self-regulators) deviated more from the intended course structure compared to the weak regulators, the course design was also visible in the process models of these three clusters. We therefore propose that an intervention should be designed in such a way that it may be ignored by learners, to not frustrate high-self regulated learners. Support that is integrated in the course in such a way that is automatically presented to MOOC learners, but that can be skipped when desired, would allow high self-regulating learners to stick to their personally preferred order of learning activities.

Of course, the option to skip support may also be used by learners that would highly benefit from it. Future studies might find it possible to identify learners in need of support based on their behavior in the online course environment. Potentially, learners in need of SRL support could then be identified during the course and interventions could be implemented only when needed, and tailored to the specific learners' needs. This would provide a solution for the presented conflict between embedding and obligating support for those unable to identify their need for support, and allowing those who are able to regulate their own learning to structure their learning in the way they desire.

Finally, the results of this study also indicate the practical benefit of process mining as a worthwhile addition to the toolkit of course designers. Process mining can provide educational designers with insight on whether learners are following the course structure they designed. For this purpose, process models could also be inspected at a greater level of detail. For instance, by analyzing the trace data at the level of individual videos instead of grouping all videos into introduction, content, and summary videos, course designers could identify points in the course where learners often deviate from the intended structure. Course designers could use this information to further develop their online courses.

Conclusion

In this study, we investigated the relationship between SRL and learner behavior in a MOOC. We did so by clustering learners based on their self-reported SRL and comparing the process models of their learning activities. Differences in learner behavior between the clusters were found, and these differences could be interpreted by using the clusters' SRL scores. Most importantly, weak self-regulated learners had a much more linear approach to studying compared to strong self-regulated learners. The results of this exploratory study show how SRL can influence learner behavior in a MOOC. We have thereby improved our understanding of the impact of learner heterogeneity on the variety in learner behavior online. While we acknowledge further research is necessary, our methods and results provide a valuable first step for others to build upon when investigating how SRL impacts learners' online study process.

5

Supporting Learners' Self-Regulated Learning in MOOCs

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This chapter is based on:

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Acknowledgement of author contributions:

RJ, AvL, JJ, and LK designed the study; RJ collected the data; RJ, AvL, JJ, and LK planned the data analysis; RJ and RC analyzed the data; RJ drafted the manuscript; all authors contributed to critical revision of the manuscript; AvL, JJ, and LK supervised the study.

Abstract

In MOOCs, learners are typically presented with great autonomy over their learning process. Therefore, learners should engage in self-regulated learning (SRL) in order to successfully study in a MOOC. Learners however often struggle to self-regulate their learning. We implemented an SRL intervention in three MOOCs. The intervention consisted of three short videos containing SRL instruction and study suggestions to improve learners' SRL. We tested the effects of the SRL intervention on both learners' course completion as well as on learners' SRL. Learners' SRL was measured with trace data variables indicating SRL activity. The results showed that the intervention positively affected learners' course completion. Furthermore, the learners who complied with the intervention also engaged in more SRL activities compared to the learners in the control condition: learners who complied showed more metacognitive activities before learning (planning), help seeking, and persistence. Intervention compliance was however low. Further analyses exploring potential causes of the low intervention compliance were conducted. The great majority of learners who did not comply with the intervention dropped out of the MOOC before they encountered the implemented intervention. We conclude that the SRL intervention has been successful in supporting both learners' SRL as well as their course completion. Implications include the importance of supporting learners' SRL as well as the necessity to conduct further research on how to improve intervention compliance.

Introduction

In online education, learners typically have more autonomy over their learning process than in traditional, campus-based education. This is especially so in Massive Open Online Courses (MOOCs), a specific form of online education. In MOOCs, learners have the freedom to decide over the pace, place, and time of their learning. This autonomy provided to learners in MOOCs requires that learners engage in self-regulated learning (SRL; Wang, Shannon, & Ross, 2013). Learners however often struggle to successfully regulate their learning process (e.g., Azevedo & Cromley, 2004; Bol & Garner, 2011; Dunlosky & Lipko, 2007; Peverly, Brobst, Graham, & Shaw, 2003). It is therefore important to support learners' SRL. In this study, we present an SRL intervention implemented in three MOOCs to improve learners' SRL as well as their course completion.

Self-regulated learning

In order to successfully deal with the autonomy offered in online education, learners have to engage in SRL. SRL entails that learners are actively involved in their learning, both metacognitively, as well as motivationally and behaviorally (Zimmerman, 2002). SRL is split into three phases: the preparatory, the performance, and the appraisal phase. In the preparatory phase, learners who self-regulate set goals and plan their learning. In the performance phase, learners work on the task, monitor their learning, seek help when needed and focus their attention. In the appraisal phase, learners reflect on their progress and the cognitive strategies they used (Puustinen & Pulkkinen, 2001; Zimmerman, 2002).

The influence of SRL on course outcomes and academic achievement has been studied extensively. Meta-analyses have shown that the relationships between SRL and academic achievement and SRL and course outcomes are significant and positive across educational levels (Boer, Donker-Bergstra, Kostons, & Korpershoek, 2013; Broadbent & Poon, 2015; Dignath, Buettner, & Langfeldt, 2008; Dignath & Büttner, 2008; Sitzmann & Ely, 2011): when learners engage more in SRL, their achievement is enhanced. However, students differ in their abilities to accurately regulate their learning (e.g., Azevedo & Cromley, 2004; Bol & Garner, 2011; Dunlosky & Lipko, 2007; Peverly et al., 2003). Therefore, scholars have invested much effort in exploring the effects of SRL interventions on SRL and achievement, reasoning that when interventions are successful in increasing students' SRL, their achievement will also increase. SRL interventions are, for instance, designed to inform learners about SRL strategies and the importance of SRL, or to prompt students to monitor and reflect on their learning, or to have learners track their learning in a diary (e.g., Berthold, Nückles, & Renkl, 2007; Dörrenbächer & Perels, 2016a; Rosário et al., 2010). The effects of SRL interventions have been integrated in a number of meta-analyses. These meta-analyses consistently show that SRL interventions are effective both in improving learners' SRL knowledge and activities, as well as their course performance and overall academic achievement (see Chapter 2 in this dissertation; Boer et al., 2013; de Bruijn-Smolders, Timmers, Gawke, Schoonman, & Born, 2016; Devolder, Van Braak, & Tondeur, 2012; Dignath & Büttner, 2008).

SRL in Massive Open Online Courses

SRL becomes of greater importance for learner success when the learning process is less externally regulated (e.g., by the teacher). Learners must then manage their learning

to a greater extent, making SRL more critical (Beishuizen & Steffens, 2011; Wang et al., 2013). Massive Open Online Courses (MOOCs) are a particular form of online education in which learners are provided with a great amount of autonomy (Hew & Cheung, 2014; Kizilcec & Halawa, 2015). MOOCs are courses often offered by universities on designated MOOC platforms (e.g., edX and Coursera). These courses are free of charge and available to anyone with an Internet connection. There usually are no prior knowledge requirements. Due to their open character, MOOCs often attract hundreds to thousands of learners. In MOOCs, learners are free to study what, where and when they like. To handle this autonomy, learners must engage in SRL to be successful in MOOCs (Azevedo, 2005; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017).

The necessity of SRL in MOOCs in combination with the increased number of MOOCs offered (Allen & Seaman, 2016) has made researching learners' SRL in this context topical and valuable. Initially, research on SRL in MOOCs and other forms of online education made use of questionnaires, showing positive correlations between self-reported SRL activity and course completion (Wang et al., 2013; Yukselturk & Bulut, 2007). Recently, however, trace data are increasingly used to study SRL. Trace data consists of information that is automatically stored as learners engage with the online course materials, for instance when they watch a video, submit their answer to a quiz question, or navigate to a page. This automatically stored log of all learner behavior in the MOOC learning environment forms a trace of learners' activities, hence the term *trace data*. Within the field of educational data mining, trace data have been used to identify variables related to student success (e.g., Lerche & Kiel, 2018; Theobald, Bellhäuser, & Imhof, 2018). Several researchers have attempted to use trace data as an indicator of learners' SRL. Kizilcec et al. (2017) for instance related learners' self-reported SRL to their trace data. The authors identified short sequences of activities (e.g., revisiting an assessment after completing a lecture) that occurred more commonly for learners that scored highly on their SRL scales (e.g., strategic planning, help seeking) compared to learners that scored low on that particular scale. Overall, they found that learners who reported stronger SRL skills were more likely to revisit course materials they had already completed. Unfortunately, the authors did not explain these correlations; information on why specific SRL scales and activity sequences are associated is missing.

Maldonado-Mahauad, Pérez-Sanagustín, Kizilcec, Morales, and Munoz-Gama (2018) took a different approach and made use of trace data only. They first identified the most common patterns of activity between when a learner started a learning session and when the learner finished the learning session. These learning patterns were then labeled based on the activities that occurred. For instance, one of the patterns was labeled *"video lecture complete to assessment try"*, as it involved the learner starting the session with watching a video and ending the session with working on an assessment. The authors then attempted to associate each of these six frequently occurring patterns to SRL strategies. *"Video lecture complete to assessment try"* was interpreted as self-evaluation, as the learner first studied material and then tested him/herself. While the labeling of the patterns is subjective, the results of the study do show that learners engage with the course materials in different ways and that SRL interpretations of these patterns are possible.

In contrast to Maldonado-Mahauad et al. (2018), Min and Jingyan (2017) and Cicchinelli et al. (2018) took a top down approach to their analyses. In both studies, researchers defined a priori how instantiations of SRL would be visible in trace data. Min and Jingyan

(2017) defined activities signaling each of the three phases of SRL, for instance, viewing the progress page was labeled as an instance of reflection, as course progress information helps learners review their performance. The majority of learners were classified as less-effective self-regulated learners as their trace data did not indicate activities in all three SRL phases. More effective self-regulated learners (i.e., those whose trace data showed activities in all three phases), showed greater persistence in the course and achieved higher course grades. Cicchinelli et al. (2018) related the frequency of learners' planning (e.g., viewing course organization information), monitoring (e.g., solving quizzes), and regulating (e.g., viewing content) activities to their course performance. The number of planning, monitoring, and regulating activities learners engaged in were all three strongly related to learners' course performance. In sum, these recent studies show that SRL can be identified in trace data. Furthermore, SRL detected in trace data seems to predict learners' success in these online environments.

Supporting SRL in MOOCs

The importance of SRL for successful MOOC learning has not only spurred research into measuring SRL with trace data; researchers have also started exploring the effectiveness of SRL interventions in this context. Kizilcec, Pérez-Sanagustín, and Maldonado (2016) asked 17 successful learners of a MOOC to write down study tips for those starting the MOOC. As an intervention, the tips were presented to half of the learners in a pre-course survey. These learners were asked to rate the usefulness of the tips. The learners in the control group were not presented the tips; they were presented the course topics and were asked to rate the usefulness of these topics for their career. To determine the effectiveness of the intervention, students' persistence (i.e., percentage of video lectures watched) and achievement (i.e., percentage of assignments completed with a passing grade) were measured. No differences were found between those learners who had and had not been presented the study tips in the survey. The authors provided several explanations for the lack of significant differences, including that the intervention may have been too small and insufficiently integrated with the rest of the course.

Yeomans and Reich (2017) also implemented an intervention in a pre-course survey. They measured the effects of the intervention on course completion, in line with Kizilcec et al. (2016), as well as on course verification (i.e., buying the course certificate). The intervention of Yeomans and Reich (2017) was more strongly related to the course content and required more input from learners. In the voluntary pre-course survey, learners were randomly assigned to a control condition or a planning condition. In the planning condition, learners were asked to describe any specific plans they had for learning the course content and completing quizzes and assignments. The implemented planning prompts increased completion and verification rates. The results thereby showed that SRL interventions in MOOCs can be effective; achievement was improved by linking the intervention to the course content and prompting learners to engage in SRL.

Davis, Triglianos, Hauff, and Houben (2018) made an even stronger connection between the course content and the intervention, by integrating the intervention in the course environment instead of integrating the intervention in a pre-course survey. The intervention was presented to all learners. The effects of the intervention were studied by comparing the learners who complied with the intervention with the learners who did not interact with the intervention (self-selected control group). The intervention consisted of asking

learners to express their motivation to follow the course. This motivation expression was presented back to learners while learners studied the course content. The intervention furthermore entailed asking learners to indicate how many videos they would watch, how many quizzes they would make, and how much time they intended to spend in the course in the upcoming week. Progression towards these self-set goals was visually depicted in the course environment. Those who complied with the intervention (i.e., submitted at least one weekly motivation expression and one weekly plan) engaged in the course to a much greater extent (e.g., time spend, videos watched, quizzes made), than those who did not comply. However, causality could not be established as all learners were presented with the intervention. Those learners who complied with the intervention may have differed from the learners in the self-selected control group before the intervention; for example, those who were more active in the course may have self-selected to also engage with the intervention.

From these studies measuring and improving learners' SRL in MOOCs, we identify several implications. First, research on SRL interventions in MOOCs is sparse and more research is needed to learn how SRL can be supported in these learning environments. Second, having learners comply with the intervention is challenging, which is a common problem in SRL support research (Clarebout & Elen, 2006; Clarebout, Horz, Schnotz, & Elen, 2010). Therefore, an intervention that is embedded in the course, that stimulates learners to think about and improve their SRL, is likely to be most effective. Third, while researchers are trying to identify instances of SRL in trace data, effects of SRL interventions have been measured in terms of simple interaction frequencies, course completion, and verification. We consider it worthwhile to combine these strands of research into SRL in the context of MOOCs. We thus propose measurement of the effects of an SRL intervention on SRL indicators obtained from trace data, in addition to measuring the effects of an SRL intervention on SRL with a questionnaire. Not only would such a study lead to greater insight into the effects of SRL interventions, but it would also shed light onto *why* SRL interventions improve course completion. Therefore, we propose a study in which the effects of an SRL intervention are measured on course completion *and* on SRL activity, with the latter measured with both a questionnaire as well as with trace data.

Current study

In the current study, we present the results and implications of an SRL intervention study. Learners in three MOOCs were randomly divided over a control and an intervention condition. The intervention focused on all three phases of Zimmerman's model of SRL, to improve the effectiveness of the intervention and to help learners understand the relations between the different phases (Schmitz & Wiese, 2006). We measured the effects of the intervention both on learners' SRL as well as on their course completion. Following suggestions for SRL research, we pay special attention to the coupling between SRL theory, the intervention and the SRL measures (Kizilcec et al., 2017; Pérez-Álvarez, Maldonado-Mahauad, & Pérez-Sanagustín, 2018). The following research questions were formulated:

1. Does an SRL intervention in a MOOC affect learners' SRL as (a) measured with a self-report SRL questionnaire, and (b) measured with SRL indicators in trace data?

2. Does an SRL intervention in a MOOC affect learners' course completion?

Method

Participants

Data were gathered in three MOOCs. The subjects of the MOOCs were Child Development, Clinical Epidemiology, and Human Rights. In each MOOC, participants were randomly divided over two versions of the course: an experimental version and a control version. In total, 2,426 learners enrolled in one of the three MOOCs. However, there is a large difference in the number of learners who enroll in a MOOC and the number of learners who actually log in to the course at least once and engage in any activity (Davis et al., 2018; DeBoer, Ho, Stump, & Breslow, 2014; Jordan, 2014). In our sample, 955 out of the 2,426 enrolled learners (39%) never engaged in any behavior within the MOOCs. These learners were excluded from further analyses. A distribution of the learners included in the analyses over conditions and MOOCs is presented in Table 1. As Coursera stopped the collection of demographic information with a voluntary survey in March 2015, demographic information is available for only 80 learners who enrolled in one of the MOOCs (44 of which were active learners). We therefore do not report learners' demographics.

Table 1 Distribution of learners over conditions and over MOOCs

		Child Development	Clinical Epidemiology	Human Rights
Enrollments (n = 2,426)	Control	721	148	337
	Intervention	723	160	337
Active learners (n = 1,471)	Control	438	98	175
	Intervention	469	114	177

Context

The experiment was conducted in three MOOCs offered by a Dutch university on Coursera. Although each MOOC covered a different domain (social sciences, medicine, law), the instructional design of the MOOCs was similar. In each MOOC, content was split into different course modules, each of which had a specific topic. All MOOCs had five modules containing the main content, and one final module containing a final exam. The MOOC on Clinical Epidemiology also had a separate introductory module at the start of the MOOC (total of seven modules). For the other two MOOCs, the first content module started with a course introduction (total of six modules). The content modules in all MOOCs contained a mixture of videos and readings. Course materials were alternated with quiz questions in all three MOOCs, and all content modules ended with a quiz on the content of the whole module. A distinction was made between graded quizzes and practice quizzes. Graded quizzes counted towards the course grade and were mandatory for students who wanted to obtain the course certificate. Practice quizzes were highly similar to graded quizzes, as they had a threshold to pass and a deadline, but they were voluntary and did not count towards a learner's course grade. The MOOCs on Clinical Epidemiology and Human Rights both had only one practice quiz, all other quizzes included in the MOOCs were graded. The MOOC on Child Development only included practice quizzes: both the short quizzes in between videos as well as the larger quizzes at the end of modules were not graded. All MOOCs also contained several peer-graded assignments which counted towards the course grade. In the MOOC on Child Development these peer-graded assignments were

the only graded components. Both graded quizzes as well as peer-graded assignments were assigned a weight by the course designer. The total weight of graded items always sums to 100%. Learners' course completion was calculated by summing the weight of the graded items (i.e., quizzes and assignments) they had passed.

The MOOCs had a fixed start date before which learners had to register. When registering for the MOOC, learners could access all materials of the first module. When the MOOC started, all other materials (module 2-6 or 2-7) became available for learners. Learners could then view all videos, access all readings, and work on quizzes and peer-assessed assignments. The suggested pace of the MOOCs was one module per week. This pace was enforced on learners as the quizzes and assignments all had deadlines. The deadline for the quizzes in module 1 was one week after the start of the MOOC; the deadline for quizzes and assignments in module 2 was two weeks after the start of the MOOC, and so on. Quizzes and assignments could however still be completed after their deadline had passed; their final (and real) deadline was the course end which was six or seven weeks after the course start. The deadlines thus solely functioned to help learners regulate their learning. Videos and readings were accessible all throughout the duration of the course. After the final deadline - six weeks after the start of the MOOCs with six modules and seven weeks after the start of the MOOC with seven modules - the courses closed.

All throughout the course, learners could access information about the course goals and structure through the Course Info page. Information on graded assignments (due date, weight, passing status yes/no, and grade) was always available through the Grades page.

Intervention

Learners were randomly divided over the control and experimental versions of the courses upon enrollment. The educational materials in both versions of the courses were identical. The intervention materials added to the experimental version of the course were the only difference between the two versions.

To support learners in all three phases of Zimmerman's model of SRL, the intervention consisted of three parts: part one on the preparatory phase, part two on the performance phase, and part three on the appraisal phase (Becker, 2013; Dörrenbächer & Perels, 2016a; Zimmerman, 2002). By supporting learners' SRL in all three phases, learners not only learned about SRL and SRL activities, but also about the interconnections between phases (Schmitz & Wiese, 2006). The phases were presented to learners as the *preparation phase*, the *action phase*, and the *reflection phase* to ease understanding. Each part of the intervention consisted of (i) a short video (3-4 minutes) with information on the three-phase model of SRL and several suggestions on how to improve SRL in the phase the video focused on. The presenter in the videos was a peer model who introduced himself at the start as a student who had previously taken the course. A peer model was chosen to increase the similarity between learners and the presenter, and to improve learners' belief in the usefulness and attainability of the suggestions (Bandura, 1994; Rosário et al., 2010; Wischgoll, 2016). As there were likely large differences with respect to learners' ability to regulate their learning, three or four different suggestions were given in each video. Thereby we attempted to appeal to the large diversity of learners (Masui & De Corte, 2005). After the video, (ii) learners were asked to rate the usefulness of each of the suggestions given on a 5-point Likert scale with the endpoints labeled "not useful"

(= 1) and "very useful" (= 5). These questions served a dual purpose. First, they required students to evaluate the advice and thus to reflect on it. Second, the questions served to determine if the intervention resonated with learners' needs. After the closed questions, learners were (iii) presented an open-ended question asking them to indicate how they could improve their learning in the SRL phase. This open question was a prompt for learners to apply the advice to their own learning process.

In the first video, three suggestions were given on how to improve one's learning in the preparation phase (SRL activity indicated in italics): (a) check the course content on the Course Info page to help you with goal setting *(goal setting)*, (b) set time for learning *(planning/time management)*, and (c) make your planning specific and concrete *(planning)*. The advice for the action phase was structured into two steps. Step one focused on monitoring and provided learners with two suggestions to monitor their learning: (a) note-taking or (b) taking quizzes *(monitoring)*. Step two focused on actions to take when a gap in knowledge is detected: (a) increase focus by taking a short break or by taking notes *(persistence)* or (b) seek help on for instance the course forum *(help seeking)*. The third video focused on the reflection phase. Three suggestions were given: (a) think about what you learned *(reflection)*, think about how you learned *(strategy reflection)*, and think about what you will do the next time you learn *(planning)*.

To help learners understand the relation between the three videos, the SRL model was presented at the start and at the end of each video. The presenter explained the relationship between the three phases and indicated the phase the current video focused on. The presenter furthermore referred to the other videos (e.g., *"in the next video I will be giving you some tips and tricks on the reflection phase, the last phase you encounter during learning"*). The SRL model and the SRL suggestions were depicted when they were mentioned, thereby presenting the information in two modalities to help learners comprehend the material (Low & Sweller, 2014). As with all videos in Coursera, transcripts of the videos were provided to learners. Screenshots of the SRL videos are presented in Figures 1a-b.

Figure 1a Screenshot of the SRL model presentation in the intervention video.
Figure 1b Screenshot of study suggestions given in the intervention video.

All intervention materials were embedded into the course structure to make sure learners automatically came across the videos and questions, as learners are unlikely to actively look for help (Clarebout & Elen, 2006; Clarebout et al., 2010; Davis, Chen, Van der Zee, Hauff, & Houben, 2016). The video and questions on the preparation phase were added to the first

content module (module 1 for the MOOCs on Human Rights and Child Development, and module 2 for the MOOC on Clinical Epidemiology). The intervention on the action phase was added to the second content module, and the intervention on the reflection phase was added to the third content module. The intervention materials were included after the final content materials of the module, but before the final quiz of the module.

The scripts of the intervention videos and the questions presented to learners are available as online supplementary material (bit.ly/dealingwithautonomy).

Measures

SRL questionnaire

Learners' SRL was measured with the Self-regulated Online Learning Questionnaire – Revised (SOL-Q-R; Jansen, Van Leeuwen, Janssen, & Kester, 2018) at the start and at the end of each course. Learners were invited to fill out the questionnaire as a voluntary activity within the learning environment. The questionnaire consisted of 42 items divided over 7 scales: metacognitive activities before learning (7 items, α = .87), metacognitive activities during learning (7 items, α = .80), metacognitive activities after learning (6 items, α = .85), time management (5 items, α = .69), environmental structuring (4 items, α = .81), persistence (7 items, α = .86), and help seeking (6 items, α = .92). A total of 193 learners filled out the SOL-Q-R, 96 learners in the control condition and 97 learners in the intervention condition.

Course intention

Learners were asked to indicate their course intention in the pre-course questionnaire, which furthermore contained the SOL-Q-R. Course intention was measured with a single item: "In this course I intend to ...". The answering options ranged from "browse" (= 1) to "participate in 100% of the learning activities and strive for a certificate" (= 8; Henderikx, Kreijns, & Kalz, 2017).

Course evaluation

The post-course questionnaire contained several questions measuring learners' course experience in addition to the SOL-Q-R. Learners were asked to grade the course on a scale of 1-10, to rate the course workload and course difficulty on a scale on a 5-point scale ranging from "too light" (= 1) to "too heavy" (= 5), and to indicate if the number of hours spent on the course was according to their expectations. Learners in the intervention condition were then asked for their opinion, both positive and negative, of the SRL videos. The final open-ended questions in the course evaluation, posed to both groups, were what they liked most about the course and what they liked least about the course. Since only 21 learners filled out the course evaluation, these data were not used for further analyses.

SRL indicators in trace data

All learners' activities in Coursera were stored on the platform's server. Activities stored include, but are not limited to, video interaction events (play, pause, stop, seek), quiz interaction events (open quiz, submit answers), marking readings as completed, submitting assignments and assessing peers, visiting and posting on the forum, and navigating between pages. Video interactions were stored every five seconds. This type of trace data is known as *heartbeat data*. Furthermore, progress records showed learners' scores on

quizzes and assignments, and the course materials they had completed. By keeping track of all these activities with a timestamp, the trace data formed a trace of a learner's path through the course.

By extracting variables from the trace data related to SRL, the influence of the intervention on learners' SRL was assessed. Below, the list of variables extracted in the current study is presented. In total, 12 variables were extracted from the trace data. For each variable, the aspect of SRL measured is indicated, as well as how the intervention may have influenced the variable measured.

Accessing overall course information. The Course Info page provided learners with general information on the course: the topics of the modules, a list of materials per module, and a list of graded elements per module. The Course Info page furthermore provided learners with an indication of the time required per module, the level of the course and more information on the requirements to pass the course. This information is valuable for learners as it helps them with goal setting and planning. Cicchinelli et al. (2018) found the frequency of accessing course information (both general info and detailed week by week info) to be significantly correlated to quiz scores ($r = .69$) and final exam scores ($r = .60$). In the video with suggestions for the preparation phase, learners were specifically instructed to visit the Course Info page to help them set goals. The number of visits to the Course Info page was therefore included as a variable indicating goal setting and planning, which are metacognitive activities before learning.

Accessing weekly course information. The weekly course information provided learners with a more detailed overview of the materials per week. In addition to a listing of the materials, quizzes, and assignments (which was also presented on the Course Home and the Course Info pages), an indication of the time necessary to complete each element was given. Accessing this information is related to achievement, as explained above (Cicchinelli et al., 2018). Information on the time needed to complete materials is necessary to make a specific, realistic and time-bound planning. Creating such a planning is known to be related to course completion and course verification (Yeomans & Reich, 2017). The number of times a learner accessed a weekly overview page was thus included to indicate goal setting and planning, both metacognitive activities before learning.

Pausing videos. By pausing the video, learners could control the pace in which information was presented to them (i.e., self-pacing principle; Van Merriënboer & Kester, 2014), and they could segment the video into meaningful units (i.e., segmenting principle; Mayer & Chandler, 2001; Mayer & Moreno, 2003; Van Merriënboer & Kester, 2014). As learners' working memory is limited, and overloading working memory hampers learning, segmenting and self-pacing may serve an important function in reducing learners' cognitive load. In addition, self-pacing and segmenting facilitate elaboration and deep processing. Learners are for example likely to take notes when they pause a video for a short amount of time. For this reason, pausing is considered a monitoring activity and beneficial for learning. In the action phase video, pausing videos and monitoring one's comprehension by taking notes were therefore recommended. The number of times a learner paused a video was included to indicate monitoring which is a metacognitive activity during learning. To control for differences between learners in the amount of time spent watching videos, the number of pauses was calculated as the average number of pauses per minute.

Handling failed quizzes. For each quiz, a predefined percentage of questions had to be answered correctly to pass the quiz. However, failing a quiz did not mean that the learner could not continue in the MOOC. Practice quizzes were voluntary and thus did not influence the learner's score. Graded quizzes influenced learners' performance, but learners could pass the course if enough other quizzes and assignments were passed. Nevertheless, failing a quiz did indicate that the learner did not sufficiently comprehend the material, as was explained in the action phase video. If learners restudied the material tested in the quiz, they acknowledged the gap in their knowledge. Learners were then likely to focus on those parts of the learning material that they had not understood correctly (Dirkx, Thoma, Kester, & Kirschner, 2015). The percentage of instances learners, after a failed quiz (either practice or graded), moved back to materials previously in the module, instead of continuing the course, was therefore considered an outcome of monitoring, a metacognitive activity during learning.

Accessing the course forum. The course forum provided learners an easy option to find help when they had trouble understanding the course materials or understanding the right quiz answers. Browsing and/or posting on the forum was therefore suggested as a help seeking strategy in the action phase video, especially considering that accessing the course forum is related to course completion (Kizilcec, Piech, & Schneider, 2013). The number of times a learner accessed the forum was analyzed to indicate help seeking, a variable that was independent of whether they browsed or posted as both activities are suitable for help seeking.

Accessing grade information. The course grade page provided learners with an overview of the graded quizzes and assignments in the course, the learner's grades and the learner's overall course progress. Metacognitive reflection involves reflecting on one's progress, and deciding on what still needs to be done in order to achieve one's goal (Winne & Hadwin, 1998; Zimmerman, 2002). Information on the goals to be attained and the current progress, as presented on the course grade page, could therefore be considered critical for reflection (Min & Jingyan, 2017). In the reflection phase video, learners were stimulated to think about what they learned and how they would continue the next time they worked on the course. Therefore the number of views of the course grade information was analyzed as indicating metacognitive activity after learning.

Completing course materials on time. The three MOOCs were designed for a pace of one module per week. Learners were thereby stimulated to engage in regular study behavior. Regular studying (i.e., staying on track) was found to be positively associated with course grade in previous online education studies (Cicchinelli et al., 2018; Goda et al., 2015; You, 2016). In order to engage in regular studying, learners must be able to adequately manage their time. The intervention was aimed at helping students plan, monitor, and reflect on their learning, thereby also supporting their time management. The ratio of materials (i.e., videos and readings) completed on time (in or before the week they were due) was included in the analyses as an indicator of learners' time management. To control for differences between learners in course completion, the ratio of materials completed on time was calculated by dividing the number of materials that were completed on time, by the total number of materials completed.

Passing quizzes and assignments on time. In each module, the videos and readings were combined with quizzes and assignments. In order to engage in regular studying, both

types of learning activities should be completed on time. The videos and readings however differed from the readings and assignments in two ways. First, quizzes and assignments had deadlines, while materials did not. Second, one could decide to attend the course without passing the quizzes and assignments. Furthermore, assignments and quizzes also differed from each other. Practice and graded quizzes were scored automatically and had to be passed. Assignments, in contrast, were peer-assessed and had to be handed in on time. Handing in assignments late is related to lower course achievement (You, 2016). Due to the differences between quizzes and assignments, we calculated variables for these two course components separately. The ratio of practice and graded quizzes passed on time (in or before the week they were due) and the ratio of assignments handed in on time (in or before the week they were due) were included in the analyses as additional indicators of learners' time management. To control for differences between learners in course completion, the ratio of quizzes passed on time was calculated by dividing the number of quizzes that were passed on time, by the total number of quizzes passed. For the same reason, the ratio of assignments handed in on time was calculated by dividing the number of assignments handed in on time, by the total number of assignments handed in.

Persistence. For successful learning, learners should focus their attention, and persist when they are struggling (Zimmerman, 2002). In the action phase video, learners were presented with strategies on how to keep focused (e.g., find help, take notes). If the intervention helped learners to regulate their effort, learners would be expected to complete a higher percentage of the videos and practice and graded quizzes they started. We did not expect them to pass the quizzes they started, but they should finish them. Therefore, the ratio of video persistence and the ratio of quiz persistence were included in the analyses to measure learners' persistence. To control for differences between learners in course completion, the ratio of video persistence was calculated by dividing the number of unique videos completed, by the number of unique videos started. For the same reason, the ratio of quiz persistence was calculated by dividing the number of unique quizzes finished, by the number of unique quizzes started.

If the intervention supported learners' persistence, then we would also expect learners to persist further in the course and thus to complete a greater number of videos and readings. The ratio of videos and readings completed is therefore incorporated in the analyses as course persistence, an additional measure of learners' persistence. To control for differences in the number of materials between the three MOOCs, the ratio of course persistence was calculated by dividing the number of unique videos and readings completed by the number of videos and readings in the MOOC.

Course completion

Problems with SRL are known to result in learners not attaining their intended goals (Kizilcec & Halawa, 2015; Zheng, Rosson, Shih, & Carroll, 2015). If the intervention successfully supported learners' SRL, more learners should have been able to attain their goal. Overall course completion should then be higher for learners in the intervention condition compared to overall course completion for learners in the control condition. Course completion was defined identically to the definition of course success in the MOOCs. Each graded course item (i.e., graded quizzes and peer-assignments) had a weight assigned by the course designers. The sum of the weight of all graded items in a MOOC is always 100%. Course completion was calculated by adding the weight of all passed assignments and graded quizzes. For instance, if a learner passed 3 quizzes, all with 8% weight, 2

peer-assessed assignments both with 10% weight, and the final exam with 30% weight, then the learner completed 74% of the course (3*8 + 2*10 + 30).

Analyses

In the performed analyses, we did not differentiate between learners in different MOOCs, as we were not interested in differences between courses. In all analyses, we only included data from learners who engaged in some activity in the course. Therefore in the first step, all learners who did not engage in any activity in the course were filtered from the data. These learners did not start watching a video, did not start a quiz, did not open a reading, nor did they look at the course information. In the second step, learners in the intervention and control conditions were compared on their SRL as reported with the SOL-Q-R at the start of the courses. No differences between the control and intervention group were found on any of the seven scales included in in the questionnaire. In the third step, the trace data variables described in the previous section were calculated. The script used to calculate the variables from the Coursera trace data is available as online supplementary material (bit.ly/dealingwithautonomy). While the script contains all information necessary to replicate calculation of the trace data variables, we would like to mention several details of the calculations here, as they are important for a correct interpretation of the results presented.

When counting the number of visits to the course forum, only visits to the content pages of the forum were included. We excluded visits to the "introduce yourself" page of the forum and to pages discussing "technical difficulties". As introducing yourself and posing technical problems with the MOOC itself do not constitute seeking help with comprehending the content of the MOOC. Videos were counted as completed by the learner if the learner watched at least 80% of the video. Learners' video watching behavior was calculated with the heartbeat data. A so-called *heartbeat* was stored for every five seconds a learner watches or pauses a specific video. The heartbeat data thereby allows for accurate calculation of amount of time spent watching videos and the number of videos completed (defined as ≥ 80% in the current study). Intervention videos were not included in the number of videos started or completed, nor were they included in the total number of videos in the MOOC, nor in the amount of time spent watching videos, as the inclusion of the intervention videos would lead to differences in the total amount of videos available between the intervention and the control condition, and potentially also to differences in the total amount of videos started, videos completed, and time spent watching videos.

In the fourth step, the extent to which learners in the intervention condition complied to the intervention (i.e., if they watched the intervention videos) was calculated. The amount of time spent watching the intervention videos was calculated by using the heartbeat data, as explained above. Intervention compliance was very low. Therefore, we considered all learners who watched at least one of the intervention videos for more than 50% "intervention compliers" (n = 76). We thus did not differentiate between watching one, two, or three intervention videos. As all intervention videos contained information about the three phase model of SRL (preparation, action, reflection) at the start and the end of the video, all learners watching 50% of one of the videos would have, at least, been introduced to this model. Furthermore, after watching one of the videos for ≥ 50% the learner would also have, at least, been given several study suggestions for the SRL phase the video focused on. In Table 2, an overview is given of the statistics concerning intervention

compliance. The low intervention compliance is further analyzed with explorative analyses in the Results section.

Table 2 Frequency distribution of the number of intervention videos watched by learners in the intervention condition

Number of intervention videos watched for 50% or more	**0**	**1**	**2**	**3**
n	684	41	20	15

Subsequently, two types of analyses were conducted to test whether the SRL intervention affected learners' SRL as measured with SRL indicators in the trace data. In the fifth step, the trace data variables were compared between the intervention and control group. These are called "intention to treat" (ITT) analyses, as they also include learners in the intervention condition that did not adhere to the intervention (Lamb, Smilack, Ho, & Reich, 2015). Bootstrapping was used to conduct the independent samples *t*-tests, as the data were highly zero-inflated and thereby strongly deviated from a normal distribution (Field, 2018). In the sixth step, "treatment on treated" (TOT) analyses were conducted (Lamb et al., 2015). Here, only learners who complied with the intervention were included from the intervention condition. The trace data variables were compared between these compliers and all learners in the control condition. It was not tested whether the SRL intervention affected learners' SRL as measured with the SOL-Q-R since only 21 learners filled out the post-course questionnaire.

To answer the second research question, the seventh step entailed analysis of learners' course completion. Course completion was compared both between the control and the intervention group (ITT analysis) as well as between the control group and those who complied with the intervention (TOT analysis). In both cases, independent samples *t*-tests with bootstrapping were conducted.

Results

RQ 1: Does the SRL intervention affect learners' SRL?

We attempted to measure the effect of the SRL intervention both on learners' self-reported SRL as measured with a questionnaire, as well as on SRL indicators in the trace data. As the post-course SRL questionnaire was filled out by only 21 learners, we did not have sufficient data to compare pre- and post-course scores, and we do not further report on these results.

To determine whether the SRL intervention affected learners' SRL as measured with SRL indicators in the trace data, the trace data variables described in the Method section were calculated. Whether learners moved back to material previous in the MOOC after failing a quiz, was described as an indicator of monitoring behavior. However, failing quizzes occurred very infrequently. In the control group, 32 learners had failed a quiz and in the intervention group 25 learners had failed a quiz. Therefore, the variable "handling failed quizzes" could be calculated only for a small group of learners. This sample size was too small to conduct bootstrapping analyses. The variable "handling failed quizzes" was therefore not incorporated in the analyses conducted.

Table 3 Results of the ITT and TOT analyses of the SRL indicators in the trace data and learners' course completion data

	Comparison control – intervention (ITT)						Comparison control – comply (TOT)					
Indicator	**Mean diff.**	***df***	***t***	***p***	**Hedges' *g***	**95% CI**	**Mean diff.**	***df***	***t***	***p***	**Hedges' *g***	**95% CI**
Course info (c)	0.07	1469	0.97	.36	0.05	[-0.08;0.22]	-1.30*	78	-3.60	.01	-0.80	[-2.03;-0.66]
Weekly course info (c)	-1.19	1435	-1.04	.30	-0.05	[-3.45;0.98]	-37.61**	77	-6.01	<.01	-1.51	[-50.32;26.99]
Pauses/min video (r)	-0.02	720	-0.21	.86	-0.02	[-0.19;0.16]	0.01	426	0.05	.96	0.01	[-0.26;0.22]
Forum (c)	-0.14	1310	-1.49	.14	-0.07	[-0.31;0.03]	-2.21*	76	-4.05	.01	-1.14	[-3.40;-1.22]
Grade info (c)	-0.36	1131	-2.04	.07	-0.10	[-0.71;-0.03]	-4.29	76	-3.21	.05	-1.04	[-7.29;-2.01]
Materials on time (r)	-0.02	1211	-1.52	.14	-0.09	[-0.05;0.01]	0.04	681	1.33	.14	0.16	[-0.02;0.10]
Quizzes on time (r)	-0.02	262	-0.41	.69	-0.07	[-0.13;0.08]	-0.05	111	-0.83	.42	-0.14	[-0.18;0.07]
Assign. on time (r)	-0.07	187	-1.09	.27	-0.16	[-0.20;0.06]	-0.13	104	-1.78	.08	-0.30	[-0.29;0.02]
Video persistence (r)	-0.02	720	-0.70	.50	-0.07	[-0.09;0.04]	-0.20**	146	-4.67	<.01	-0.47	[-0.28;-0.12]
Quiz persistence (r)	-0.00	1075	-0.20	.86	0.00	[-0.05;0.04]	-0.40**	89	-7.78	<.01	-1.09	[-0.50;-0.30]
Course persistence (r)	0.00	1469	0.32	.77	0.05	[-0.02;0.02]	-0.38**	80	-9.26	<.01	-1.80	[-0.46;-0.30]
Course completion	-0.02*	1416	-2.13	.04	-0.15	[-0.041;-0.002]	-0.37**	77	-7.40	<.01	-1.18	[-0.47;-0.27]

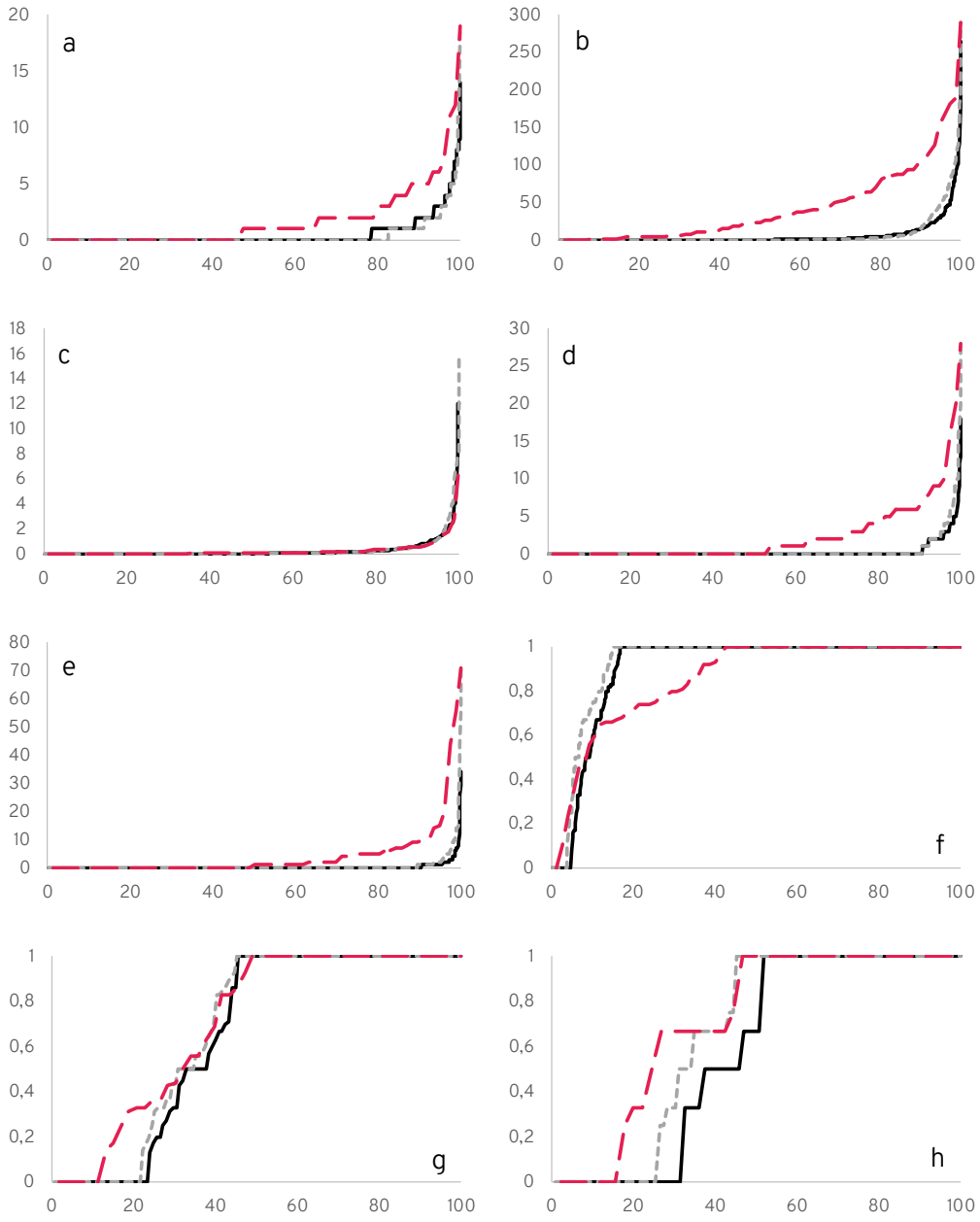
Note. Variables marked with 'c' concern counts of activities; variables marked with 'r' concern ratios. Bootstrapping analyses conducted with 1000 samples. * $p < .05$, ** $p < .01$

Figures 2a-k present graphical overviews of the SRL indicators in the trace data for the control group, the intervention group, and the compliant group (a subset of the intervention group). Since the groups are highly dissimilar in size, the x-axis does not represent the number of learners, but the distribution quantile. The graphs show that large numbers of learners engage in the MOOC only minimally. The graphs also indicate that those who comply with the intervention self-regulate their learning to a greater extent than the intervention and control groups. The descriptives of the SRL indicators for the three groups are available as online supplementary material (bit.ly/dealingwithautonomy).

ITT analyses were performed comparing the SRL indicators between learners in the intervention and control conditions as described in the Analyses. The results of the ITT analyses are presented in columns 2-7 in Table 3. Columns 8-13 of Table 3 contain the results of the TOT analyses that were performed to compare the SRL indicators between learners in the control group and the intervention compliers. No significant differences were found for the SRL indicators in the trace data between the learners in the intervention and the control conditions (ITT analyses). However, significant differences in the SRL indicators in the trace data were found when comparing the learners in the control condition to only those learners in the intervention condition that complied with the intervention (TOT analysis). Learners who complied with the intervention visited the course info page (metacognition before learning), the weekly course info pages (metacognition before learning), and the forum (help seeking) more often than learners in the control condition. Learners who complied with the intervention also completed a greater proportion of the videos and quizzes they started (persistence). Furthermore, compliers completed a greater proportion of the videos in their course (persistence). These results all point to higher frequencies of SRL activities for learners who complied with the intervention.

RQ 2: Does the SRL intervention affect learners' course completion?

Course completion was calculated by summing the weight of all graded quizzes and assignments passed by the learner, as described in the Method section. Thus, learners could pass between 0 and 100% of graded course items. Learners' course completion in the control and intervention conditions, as well as the course completion of the intervention compliers, is visualized in Figure 2l. The descriptives of learners' course completion are available as online supplementary material (bit.ly/dealingwithautonomy). To determine whether the SRL intervention affected learners' course completion, course completion was compared both between the control and the intervention group (ITT analysis), as well as between the control group and those who complied with the intervention (TOT analysis). The results of these analyses are presented in Table 3 (bottom line). Both analyses indicate that the intervention significantly improved learners' course completion.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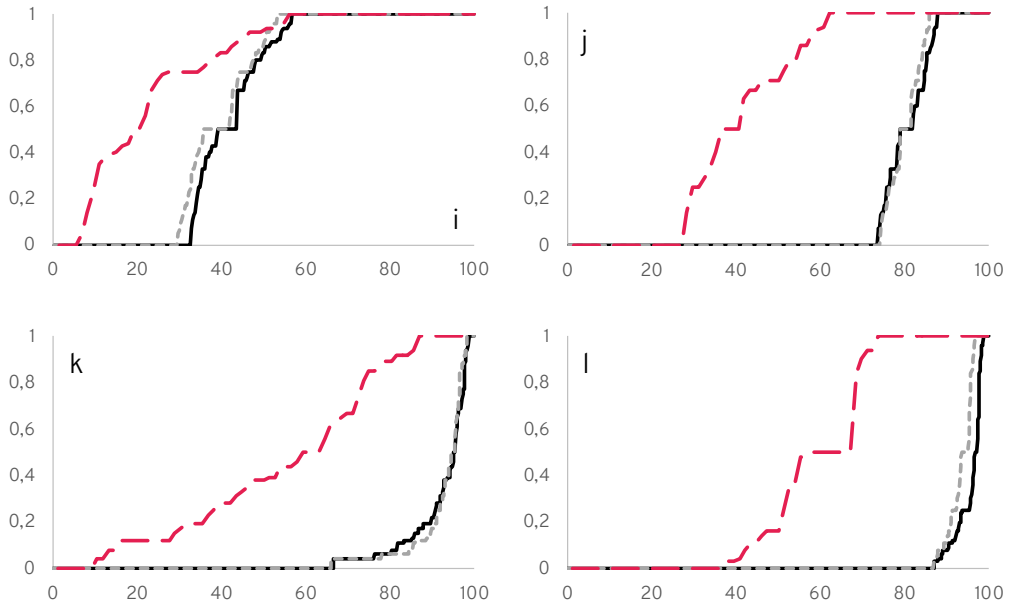


Figure 2a-l SRL activity ordered by distribution quantile (0-100% of learners within the control/intervention/comply condition). Control, Intervention, Comply.

a Number of visits to the course info page (metacognition before learning).

b Number of visits to the weekly course info pages (metacognition before learning).

c Ratio of pauses per minute of video watched (metacognition during learning).

d Number of visits to the course forum (help seeking).

e Number of visits to the grade info page (metacognition after learning).

f Ratio of materials completed on time (time management).

g Ratio of quizzes passed on time (time management).

h Ratio of peer-assignments handed in on time (time management).

i Ratio of videos completed that were started (persistence).

j Ratio of quizzes finished that were started (persistence).

k Ratio of videos present in the course that were completed (persistence).

l Course completion.

Low intervention compliance

Intervention compliance was low: only 10% of the learners in the intervention condition who engaged in any behavior in the course watched one or more of the intervention videos for at least 50%. To better understand the low intervention compliance, we performed five additional, exploratory analyses. Only learners in the intervention condition who engaged in some behavior in the course are included in the exploratory analyses, and we compare the learners who complied with the intervention (*compliers*) with the learners who did not comply with the intervention (*non-compliers*).

First, learners' self-reported SRL at the start of the course was compared between the compliers and non-compliers to determine if differences in SRL already existed before the start of the course. The SRL scores did not differ significantly between the compliers and the non-compliers on any of the seven scales included in the SOL-Q-R. It is thus unlikely that non-compliance with the intervention was the result of pre-existing differences in SRL.

Second, learners' course intentions were compared between the compliers and non-compliers to determine if differences in intentions existed at the start of the course. Course intention was greater for learners who complied with the intervention than for learners who did not comply with the intervention (M_{comply} = 7.35; $M_{non\text{-}comply}$ = 6.50; $t(df)$ = -3.37(116), $p < .01$). Learners course intentions might therefore explain why some learners in the intervention condition complied with the intervention while others did not. To test whether course intentions influenced our results, we conducted the TOT analyses for the SRL indicators and course completion for a second time, only this time with groups matched on course intention. For compliers, the minimum reported course intention was 4 ("participate in 40% of the course"). For the matched group analyses, all intervention compliers who filled out the questionnaire (n = 37) were compared with those in the control group who reported course intention ≥ 4 (n = 133). The differences between the control group and intervention compliers remained significant for the following SRL indicators: visiting the course info (metacognition before learning; $t(df)$ = -2.95(40), p = .01), visiting the weekly course info (metacognition before learning; $t(df)$ = -3.73(42), p < .01) and visiting the course forum (help seeking; $t(df)$ = -2.63 (39), p = .49). Furthermore, significant differences remained in quiz persistence ($t(df)$ = -3.93(70), $p < .01$) and course persistence ($t(df)$ = -5.39(168), $p < .01$). The only SRL indicator that no longer differed significantly between the control group and the compliers was video persistence (i.e., ratio of videos started that are completed; $t(df)$ = -1.81(92), p = .07). Course completion also remained significantly greater for those who complied with the intervention than for the learners in the control group, after matching the groups on course intention. We therefore conclude that, while the intervention compliers had greater course intentions than the learners in the control group and those who did not comply with the intervention, the differences in course intentions do not explain the differences in SRL indicators and course completion found with TOT analyses.

The third and fourth exploratory analyses both attempted to determine if the advice that was given in the intervention videos had been helpful for the learners. The number of learners who started watching the intervention videos was determined. If a large number of learners started the intervention videos, but stopped before watching 50%, this could signal that learners stopped watching the videos because the videos in some way did not match their needs. We also calculated the average usefulness of the study suggestions in

the videos as rated by the learners. The results of both analyses indicated that the intervention videos were useful for the learners. The great majority of learners who started watching an intervention video also continued watching the intervention video for 50% or more. The average usefulness rating of the videos was 4.09 for the preparation phase, 4.11 for the action phase, and 4.08 for the reflection phase on a scale of 1 to 5. Tables 4 and 5 present an overview of these results. Thus, a lack of usefulness of the intervention videos was not a likely explanation for non-compliance either.

Table 4 Number of learners who started and completed watching the intervention videos

		n
Preparation phase	Started watching (5 sec)	86
	Completed video (≥ 50%)	67
Action phase	Started watching (5 sec)	47
	Completed video (≥ 50%)	31
Reflection phase	Started watching (5 sec)	38
	Completed video (≥ 50%)	28

Table 5 Average usefulness rating of the study suggestions presented in the intervention videos

	Study suggestions	**Average (*SD*) usefulness rating (1 = "not useful", 5 = "very useful")**
Preparation phase (*n* = 35)	Check the course content	4.29 (0.93)
	Set time for learning	3.94 (1.08)
	Be concrete in your planning	4.03 (0.99)
Action phase (*n* = 20)	Monitor your comprehension at regular times	4.15 (0.59)
	Monitor your comprehension with an activity	4.10 (0.72)
	Try to get your focus back	4.20 (0.70)
	Look for help	4.00 (1.08)
Reflection phase (*n* = 16)	Think about what you learned	4.06 (1.00)
	Think about how you learned	4.00 (1.10)
	Decide how you will continue	4.19 (1.05)

A final potential explanation for the low intervention compliance is that learners never came into contact with the intervention because they dropped out of the course too early. We therefore checked if the furthest video in the course watched for minimally 80% by the non-complying learners was before or after the intervention videos. The results of this analysis are presented in Table 6. The results indicate that only 29 of the 648 learners who did not comply with the intervention completed a video further in the MOOC than the first intervention video (preparation phase). A massive number of learners who did not comply with the intervention did not complete a single video (*n* = 494) or dropped out before the first intervention video (*n* = 161). We therefore conclude that the main reason for non-compliance is that learners did not come into contact with the intervention because they had already dropped out of the course.

Table 6 Location in the MOOC of the furthest video completed by learners who did not comply with the intervention

Location furthest video	n
No video completed	494
Furthest video < preparation video	161
Furthest video > preparation video but < action video	11
Furthest video > action video but < reflection video	4
Furthest video > reflection video	14

Discussion

Learners in open online education need to self-regulate their learning in order to be successful (Beishuizen & Steffens, 2011; Wang et al., 2013). However, learners often struggle to engage in successful SRL (e.g., Azevedo & Cromley, 2004; Bol & Garner, 2011; Dunlosky & Lipko, 2007; Peverly et al., 2003). To support learners' SRL in open online education, we implemented an SRL intervention in three MOOCs and tested the effects of the intervention on both learners' SRL (RQ 1) as well as on course completion (RQ 2). To answer research question 1, the effects of the SRL intervention on learners' SRL could only be investigated for the SRL indicators extracted from the trace data, since the response rate for the SRL questionnaire at the end of the MOOCs was too low to be included in the analyses. When testing the effects of the SRL intervention on learners' SRL, no differences were found between the control and the intervention group (ITT analyses), leading to the conclusion that the intervention did not result in more SRL. However, only a small portion of the learners' in the intervention condition complied with the intervention to at least some extend (i.e., watched one of the intervention videos ≥ 50%). When comparing the SRL of learners in the control group with learners who complied with the intervention (TOT analyses), significant differences were found for a number of SRL indicators: intervention compliers engaged in more SRL. Specifically, they engaged in more metacognitive activities before learning (visiting the course info and weekly course info), they engaged in more help seeking behavior (visiting the forum), and they showed greater persistence (completed a greater proportion of videos and quizzes started, and completed a greater proportion of videos in the course) compared to learners in the control condition. To answer research question 2, we tested the effects of the SRL intervention on learners' course completion. Learners in the intervention condition completed a significantly greater proportion of the graded items of the MOOC than learners in the control condition (ITT analysis). The difference between the control and the intervention condition was enlarged when comparing the control condition with the learners who complied with the intervention (TOT analysis).

Theoretical implications

From the results, we conclude that even a small intervention, as implemented in the current MOOCs, positively affects learners course completion. The value of the intervention is even greater if the increased SRL of learners who complied with the intervention is due to the implemented SRL intervention. However, since learners in the intervention group self-selected to comply with the SRL intervention, we cannot establish if the SRL intervention caused the differences in SRL between the control group and the compliers.

We conducted a number of analyses to determine whether the differences found with the TOT analyses could be explained by other factors (e.g., suitability of the intervention). Among other explorative analyses, we tested two learner characteristics that potentially could have influenced the decision of learners to comply with the intervention: SRL and course intentions. These learner characteristics however did not influence the results. There may be other learner characteristics, not tested in the current study, that may influence learners' decision to comply with the intervention and their SRL activity. These factors may, for instance, include learners' self-efficacy or learners prior experiences with online education as both are known to be related to course completion (Greene, Oswald, & Pomerantz, 2015; Wang et al., 2013). But since these factors were not measured in the current study, further research is necessary.

The finding that differences between the control group and the compliers cannot be explained by differences in learners' self-reported SRL or course intention, points us in the direction that the differences between the compliers and the control group in SRL were due to the intervention. Due to the low intervention compliance we were forced to already count a mere 50% of a single intervention video watched as intervention compliance. This relatively small intervention improved learners' course completion and likely also improved learners' metacognitive activities before learning, their help seeking and their persistence. Our results are thereby unlike the results of previous studies in online and higher education in which a small SRL intervention was implemented (Greene, Hutchison, Costa, & Crompton, 2012; Hodges & Kim, 2010; Kizilcec et al., 2016; Sitzmann, Bell, Kraiger, & Kanar, 2009). In these studies, no differences between the intervention and the control groups were found on course completion, course achievement, and SRL. While several differences between the current study and the previous studies can be identified, a vital difference appears to be that these previous intervention studies only prompted students to engage in SRL activities: students were stimulated to engage in SRL activities, but were not explained how or why they should do so. In contrast, learners in the current study were mostly instructed about the three phase model of SRL and the importance of SRL for successful learning in open online education. Study suggestions were provided to support the SRL instruction and to give students practical advice. Instructing students on the importance of SRL and how to engage in successful SRL thus appears to be key when implementing an SRL intervention in open online education. The positive effects of SRL instruction in open online education are in line with results found with (larger) interventions containing SRL instruction in higher education. In these studies, SRL instruction was found to have positive effects on both learners' achievement as well as on their SRL activity (e.g., Azevedo & Cromley, 2004; Bannert, Hildebrand, & Mengelkamp, 2009; Bol, Campbell, Perez, & Yen, 2016; Lee, Shen, & Tsai, 2008; Rosário et al., 2015). By testing the effects of alternative (small) interventions in MOOCs in future studies, it can be established if the incorporation of SRL instruction indeed causes a small SRL intervention to be effective. Future intervention studies would furthermore increase insight in other factors important for the implementation of a successful SRL intervention.

Practical implications

The positive effect of the SRL intervention leads to the practical implication that the implementation of SRL instruction is beneficial for learners in open online education. Not only does an SRL intervention improve learners' course completion, but it likely also supports learners' SRL activity during learning in the MOOC. However, an intervention

cannot be effective if learners do not come into contact with it. Therefore, the low intervention compliance remains problematic. In previous studies, it was suggested that intervention compliance could be improved by (more) strongly integrating an SRL intervention in the course (see Chapter 4 in this dissertation; Clarebout & Elen, 2006; Clarebout et al., 2010; Kizilcec et al., 2016). We therefore paid extra attention to the way the intervention was implemented in the current study: the intervention was integrated in the course itself (not in a pre-course survey), in multiple weeks at the start of the course, and between the videos and the quiz. Our strong integration of the intervention in the MOOCs however still led to low intervention compliance: only 10% of learners in the intervention condition watched at least 50% of one of the intervention videos. Low intervention compliance thus appears to be a persistent problem in SRL intervention research in open online education.

We conducted further analyses to determine why intervention compliance was low. We found that the low adherence was not due to the intervention being irrelevant to learners; rather the opposite appears to be the case with usefulness ratings of the study suggestions ranging between 3.94 and 4.29 (scale of 1 to 5). A large number of learners had already dropped out of the course before they came into contact with the intervention video. Of the 1220 learners who were assigned to the intervention condition, 760 learners engaged in the course in some way. Of these 760 learners, only 266 completed one or more videos and 76 complied with the intervention. To increase intervention compliance, it thus appears most important to implement an intervention earlier in the learning process. It may therefore be interesting to consider the possibility of implementing an intervention when learners enroll for a MOOC. Learners may, for instance, be provided with more information about the course content and the time investment required when they express the intention to enroll for the MOOC. Prompting learners to reflect if this information is in line with their own goals before finalizing their enrollment might be helpful. Such an intervention might lead to lower enrollment numbers, but to a greater percentage of enrolled learners engaging in the course and completing the course. Another suggestion to increase intervention compliance would be to require learners to engage with the intervention (e.g., watch an intervention video) before they can engage with the course materials. This is however not in line with the open-ended nature of MOOCs, and might result in resistance from learners.

Limitations and directions for future research

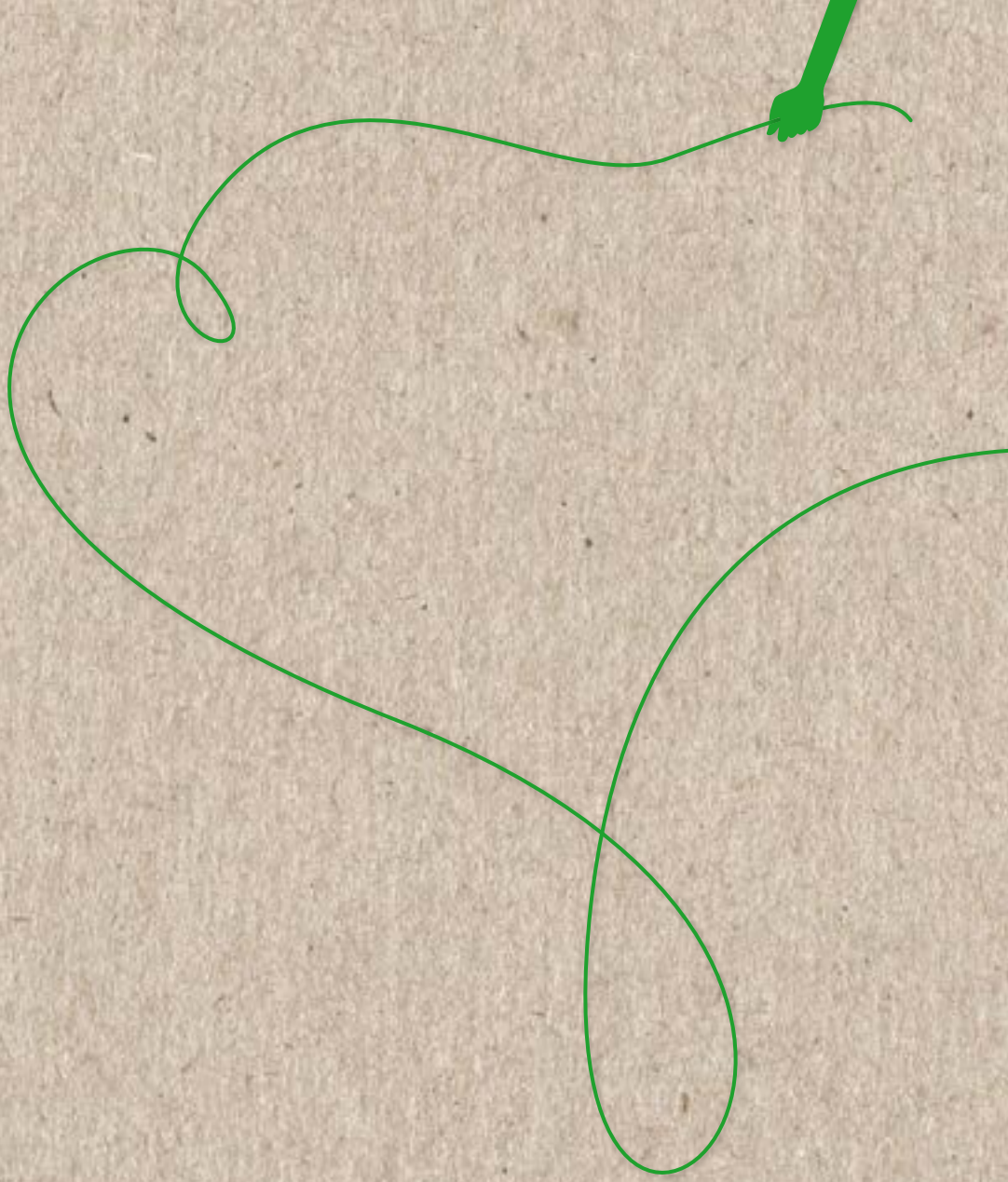
In this study, we calculated intervention compliance as the proportion of learners who engaged in the course in some manner and who watched at least one intervention video for 50% or more (10%). However, one could also calculate intervention compliance as the proportion of learners who were assigned to the intervention condition and who watched at least one intervention video for 50% or more (6.23%). Other alternatives would be to set a different bar for what behavior is considered 'compliant' or to only include learners who have been exposed to the intervention (Yeomans & Reich, 2017). These different calculations naturally lead to different results. Decisions concerning which learners to include and what activities to include, not only influence statistics concerning intervention compliance, but also the numbers of (SRL) activities engaged in and the results of analyses. We have been careful throughout the manuscript to report which (groups of) learners were considered and how variables were exactly calculated, not only to make replication of the study possible, but also to support accurate interpretation of the data. The different results of the ITT and TOT analyses for SRL activity provide a principal

example of the influence group selection can have on results. In ITT analyses, the random allocation of learners to conditions is preserved. ITT analyses can therefore be used to establish causality of effects. In this study, the ITT analyses showed that the SRL intervention improved learners' course completion, but did not affect learners' SRL. At the same time, low intervention compliance makes it hard to find significant differences between conditions, as a large number of learners in the intervention condition were not compliant with the intervention. This problem is remedied with TOT analyses in which only learners who complied with the intervention are included in the analyses. In this study, significant differences were found both for learners' course completion as well as several aspects of SRL activity with TOT analyses. However, as learners decided themselves whether or not they complied with the intervention, causality cannot be established with TOT analyses. By combining ITT and TOT analyses, and exploring factors that might have influenced intervention compliance, we have attempted to resolve the disadvantages of both analyses as well as possible.

By analyzing the effect of the SRL intervention on not only course completion, but also on SRL activity, we were able to determine which aspects of SRL activity were likely influenced by the intervention. The finding that SRL indicators differed between compliers and the control group, after controlling for course completion by calculating ratios, is unique in itself. Future research could investigate the correctness of these indicators: are they indeed a measure of the SRL activity for which we have considered them an indicator based on theory and empirical knowledge? Furthermore, since we cannot establish if the differences in course completion are caused by the better SRL of compliant learners, this may be an interesting suggestion for further research. It might for instance be worthwhile to determine which of the SRL indicators influences learners' course completion.

Conclusion

To conclude, the implemented SRL intervention has been successful in improving learners' course completion and has likely also been successful in improving learners' SRL activity. SRL activity was measured with variables calculated from learners' trace data and indicated differences between the control group and the intervention compliers in metacognitive activities before learning, help seeking, and persistence (both in terms of finishing materials that are started and finishing more materials in the course as a whole). The results thereby provide evidence for the benefit of implementing SRL support in MOOCs. More research into the effects of different SRL interventions, and how to best implement SRL support to improve intervention compliance, is necessary. The current study provides a valuable base to build on.



6

A Mixed Methods Approach to Studying Self-Regulated Learning in MOOCs: Combining Trace Data with Interviews

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RJ, AvL, JJ, and LK designed the study; RJ recruited participants and collected the data; RJ, AvL, and JJ planned data analysis; RJ analyzed the data; RJ drafted the manuscript; all authors contributed to critical revision of the manuscript; AvL, JJ, and LK supervised the study.

Abstract

To be successful in online education, learners should be able to self-regulate their learning due to the autonomy offered to them. Accurate measurement of learners' self-regulated learning (SRL) in online education is necessary to determine which learners are in need of support and how to best offer support. Trace data are gathered automatically and unobtrusively, and are therefore considered a valuable source to measure learners' SRL. However, measuring SRL with trace data is challenging for two main reasons. First, without information on the how and why of learner behavior it is difficult to interpret trace data correctly. Second, SRL activities outside of the online learning environment are not captured in trace data. Building on earlier mixed methods studies, we propose a mixed methods approach with a sequential design to address these two challenges. We present a pilot study in which we combined trace data with interview data to analyze learners' SRL in online courses. In the first part of the interview, cued retrospective reporting was conducted by presenting learners with visualizations of their trace data. In the second part of the interview, learners' activities outside of the online course environment were discussed. The results show that the mixed methods approach is indeed a promising approach to address the two described challenges. Suggestions for future research are provided, and include methodological considerations such as how to best visualize trace data for cued retrospective recall.

Introduction

Online learning has increased rapidly over the past years (Allen & Seaman, 2014, 2016). Not only are online learning materials increasingly included in campus-based education, the number of courses offered fully online has also expanded rapidly. Massive Open Online Courses (MOOCs) have become increasingly common in higher education. MOOCs are offered fully online, they are accessible to anyone with an Internet connection without requirements regarding prior knowledge, and in most cases there are no costs involved to access the learning materials. In these online courses, learners are free to decide when, where, and what they study. This increased autonomy in online education requires learners to self-regulate their learning to a greater extent compared to students in traditional campus-based education (Azevedo & Aleven, 2013; Beishuizen & Steffens, 2011; Broadbent, 2017; Hew & Cheung, 2014; Wang, Shannon, & Ross, 2013). It is therefore of high scientific as well as practical relevance to measure, analyze, and support self-regulated learning (SRL) in the context of online education.

To do so, researchers have increasingly focused their attention on trace data as a means to examine students' SRL (Van Laer & Elen, 2018; Winne, 2010). In online education, all learner behavior in the online learning environment (playing videos, submitting assignments, browsing on the forum) is stored. These so-called traces of learner behavior are stored as time stamped events, providing an overview of all learner behavior within the online learning environment. Using trace data as an indicator for learners' SRL is considered a promising approach because the data are gathered automatically, unobtrusively, and over longer durations of time. Using data mining techniques, trace data could be used to automatically measure and support SRL, for example by automatically detecting when students show a lack of self-regulation and subsequently offering feedback, suggestions, or other forms of interventions. Because MOOCs typically have thousands of subscribed learners, the idea of being able to offer automated support on a large scale would be a solution for the impossibility of personal interaction between instructors and learners. To obtain this goal, it has to be possible to interpret trace data in terms of SRL in a reliable and valid way.

However, interpreting learners' SRL based on trace data is challenging for multiple reasons. First, while trace data show what and when learners study, it does not provide information on how and why learners engaged with the learning material the way they did (Jovanović, Gašević, Dawson, Pardo, & Mirriahi, 2017; Min & Jingyan, 2017; Phillips et al., 2011). Second, trace data are limited to capturing learners' behavior in the online learning environment only, and thus does not include other learner behavior, such as browsing websites or taking notes on paper. These two reasons combined mean that translating trace data into conclusions about learners' SRL is challenging because of the possibility of misinterpreting certain events or overlooking relevant events. It has therefore been argued that a mixed methods approach, in which trace data are combined with other methods to measure SRL, is useful and necessary to draw valid conclusions from the trace data (Cicchinelli et al., 2018; Howard-Rose & Winne, 1993; Jovanović et al., 2017; Karabenick & Zusho, 2015; Reimann, Markauskaite, & Bannert, 2014).

In this methodological chapter, our aim is to demonstrate that interview data could be a valuable addition to trace data to measure and analyze learners' SRL in online education. Through interviews, researchers are able to examine learners' reasons behind their

activities, as well as to gather an overview of learners' activities outside of the online learning environment, thus offering the possibility to overcome the challenges outlined above. In this chapter, we present a pilot study in which we combined trace data with interview data, and discuss the methodological possibilities and challenges of our approach concerning the aim to understand learners' SRL in online education.

Measuring SRL with trace data: affordances and challenges

Self-regulated learners are defined as motivationally, metacognitively, and behaviorally active in their own learning process (Zimmerman, 1986). Self-regulated learners engage in a number of activities, including goal setting, planning, monitoring, reflection, attention focusing, time management, environment structuring, and seeking help when needed (Panadero, 2017; Puustinen & Pulkkinen, 2001). Thus, the extent to which learners adapt to changes in the task and learning context is a critical component of SRL (Azevedo & Cromley, 2004; Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007). As SRL is considered a process, any measurement of SRL must take into account changes in learner behavior over time (Azevedo et al., 2013; Winne, 2010). As outlined above, trace data allows for the capturing of learners' activities unobtrusively over time at a very fine granularity. Trace data provide a reliable measure of when students engaged in the online learning environment and with what materials they engaged, and offer information about temporal and sequential characteristics of activities, making it a readily available and valuable data source to study learners' SRL (Cicchinelli et al., 2018; Fincham, Gasevic, Jovanovic, & Pardo, 2018; Hadwin et al., 2007; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Maldonado-Mahauad, Pérez-Sanagustín, Kizilcec, Morales, & Munoz-Gama, 2018; Winne, 2014). Several authors have used trace data to attempt to locate learner behavior that is representative of SRL activities (Van Laer & Elen, 2018). For example, in the study of Kizilcec et al. (2017), SRL questionnaire data were coupled to learner behavior information stored in trace data to identify learner activities related to SRL. Similarly, Min and Jingyan (2017) also used trace data as a measure of SRL. Before their data collection, Min and Jingyan defined sequences of learner behavior that, in their view, were indicative of SRL. Learners whose trace data included sequences indicative of all defined SRL activities had greater persistence in the course and achieved higher course grades. These exemplary studies show trace data may be beneficial for studying SRL in online education: trace data are gathered unobtrusively, can be analyzed automatically for large groups of learners, and may in the future even be used for real time support of learners (Van Laer & Elen, 2018).

However, these same studies also demonstrate the challenges of using trace data as a measurement of SRL. The most striking problem is that while trace data shed light on learners' behavior in the online learning environment, there is doubt on how to interpret this behavior in terms of SRL (Cicchinelli et al., 2018; Jovanović et al., 2017; Min & Jingyan, 2017; Phillips et al., 2011; Rovers, Clarebout, Savelberg, de Bruin, & Van Merriënboer, 2019). SRL activities are for a large part covert in nature; they constitute the regulating activities that shape and guide the observable learning activities (Nelson & Narens, 1990). The consequence is that interactions and interaction sequences with the learning material are ambiguous; there are usually multiple plausible explanations from the perspective of SRL (Jovanović et al., 2017; Phillips et al., 2011). For example, watching the same video in the online environment twice may indicate that the student found the material hard to understand and is therefore re-watching the video (an indication of comprehension monitoring).

It may however also be the case that the student did not remember already watching the video (problems with effort regulation), and therefore watches the video twice. Learner behavior captured by trace data thus needs to be interpreted before it can be labeled as originating from a student's self-regulating behavior, which makes interpretation of the results of trace data analyses complicated (Maldonado-Mahauad et al., 2018; Schraw, 2010). This difficulty in interpreting learner behavior in terms of self-regulating behavior, may thus also compromise the validity of the results obtained in studies that employ this methodology. More insight is thus needed into the how and why of learners' activities to understand the reasons underlying learner behavior and the meaning of learner behavior in terms of SRL (Cicchinelli et al., 2018; Jovanović et al., 2017; Min & Jingyan, 2017; Phillips et al., 2011). Authors such as Kizilcec et al. (2017) therefore make use of questionnaire data to identify learner activities related to SRL (see also the section on mixed methods). In the sections below, we argue why we think interviews are more suited for this purpose.

A second challenge in measuring SRL with trace data is that some SRL activities take place outside of the online learning environment (Min & Jingyan, 2017). Winne and Jamieson-Noel (2002) for instance argued that scrolling of learners through a text-document indicated planning, planning activities may however also have occurred (mostly) in learners' heads (Rovers et al., 2019). Veletsianos, Reich, and Pasquini (2016) studied learners' activities outside of the online learning environment and identified additional activities in three domains. In each of these domains, SRL activities may take place: behaviors at the learners' workplace (SRL activities: note-taking, making a planning, picking the study location), learners' activities online, but off-platform (SRL activity: looking for help by browsing the web), and learners' activities in the wider context of their lives (SRL activity: dilemma's in time management due to other priorities). Thus, trace data may be helpful in providing insight into learner behavior, and this behavior may be interpreted in terms of SRL, but there is reason to suspect that trace data does not capture *all* of learners' SRL activity.

Trace data measurement of SRL should thus be supplemented with a measurement method that enables a) understanding the reasons underlying learners' behavior, and b) measuring and understanding learners' SRL activities outside of the online learning environment. In the present chapter, we propose that combining trace data with interviews, i.e., using a mixed methods approach, could help to solve these two challenges. In the sections below, we reflect on what mixed methods research entails, and then elaborate on the mixed methods approach of measuring SRL by combining trace data with interviews.

Measuring SRL with mixed methods research

In mixed methods research, qualitative and quantitative research methods are combined (Creswell, 2008; Johnson & Onwuegbuzie, 2004). Mixed methods research can be classified on two dimensions: the time order decision and the paradigm emphasis decision (Creswell, 2008; Johnson & Onwuegbuzie, 2004). The time order is either sequential or concurrent depending on whether one method informs the other, or if both methods are used concurrently to gather data. The paradigm emphasis decision is either equal status, if quantitative and qualitative methods are of equal importance, or dominant status, if either the quantitative or qualitative data collection is given more weight. By classifying mixed methods research on these two dimensions, four types of designs emerge. The most suitable design depends on the purpose of the mixed methods study, which could for example

be triangulation, complementarity, or expansion. Independent of the design, a mixed methods approach will generally provide a more valid measurement of the construct studied than any single method can provide (Creswell, 2008; Johnson & Onwuegbuzie, 2004; McGrath, Martin, & Kulka, 1981).

In the context of SRL, several researchers have employed a mixed methods design in various combinations of time order and paradigm emphasis for various empirical goals (Ben-Eliyahu & Linnenbrink-Garcia, 2015). For instance, Littlejohn, Hood, Milligan, and Mustain (2016) aimed to obtain more in-depth information about five sub-processes of SRL that are commonly measured with self-report questionnaires, namely motivation and goal setting, self-efficacy, task strategies, task interest value, and self-satisfaction and evaluation. To do so, learners filled in a questionnaire within a MOOC environment, and a selection of questionnaire respondents was later interviewed. The authors thus combined two self-report measurement methods in a sequential mixed methods design, where quantitative data was used as input for the qualitative data collection, with paradigm emphasis on the qualitative interview data (Creswell, 2008; Johnson & Onwuegbuzie, 2004). The interview data yielded several insights, for example that learners with high scores on SRL were less focused on obtaining the certificate compared to learners with low scores on SRL, and more focused on professional development and the relevance of the learning material for their job.

Other work relevant to the present study is the paper by Kizilcec et al. (2017), in which trace data was combined with questionnaire data to identify sequences of learner behavior correlated to high or low scores on specific SRL scales. This is another example of a study combining instruments in a concurrent time order. The authors correlated learners' scores on the SRL questionnaire with specific transitions in behavior. The results included the finding that learners who reported higher SRL skills were more likely to revisit earlier materials instead of starting new materials after completing a part of the course. The authors thus aimed to specify behaviors that correlate with self-reported SRL. As stated earlier, one of the main challenges associated with interpreting trace data in terms of SRL is that learner behavior is sometimes ambiguous. The study by Kizilcec et al. (2017) shows that trace data can indeed be coupled to SRL, but does not completely solve this challenge, because multiple SRL scales were found to be correlated to the same behavior, leaving open the question how to interpret specific instances of behaviors. Additionally, because their starting points were the scores on the SRL questionnaire, not all behavior found in the trace data was 'matched' with one of the SRL scales. In terms of time ordering in mixed methods studies, we therefore want to propose a sequential methodology that has the trace data as its starting point.

In the present chapter, our goal is to build on these earlier mixed methods studies that have aimed to increase our understanding of trace data in terms of SRL. We propose to employ a mixed methods design in which trace data are complemented with interview data. Interviews allow researchers to explore and understand how people behave and think (Alshenqeeti, 2014). In contrast to questionnaires, interviews also allow for follow-up questions that emerge from the dialogue to probe for further information and improve understanding of learner behavior (DiCicco-Bloom & Crabtree, 2006). They are therefore suitable to gain insight into learner behavior in a flexible way, both concerning behavior inside and outside of the online learning environment. In the section below, we reflect on how interviews could be used to address the two challenges of interpreting trace data.

Combining trace data with interviews

The first challenge associated with interpreting trace data in terms of SRL concerns the trace data's ambiguity. To understand why a learner performed a specific action at a specific time, the interview technique of verbal protocols, in which a participant verbalizes his or her thoughts and actions (Ericsson & Simon, 1993), could be a solution. Several types of verbal reporting exist, including concurrent reporting (verbalizing during the task), retrospective reporting (verbalizing after the task), and cued retrospective reporting (verbalizing after the task, induced with a cue; Ericsson & Simon, 1993; Van Gog, Paas, Van Merriënboer, & Witte, 2005). With cued retrospective reporting, learners report on their thoughts and activities after the task, but receive a cue to help them remember the process correctly (e.g., eye movements). Cued retrospective reporting thereby attempts to minimize errors of omission and fabrication, which may occur with retrospective reporting, and without risking to alter the primary process (i.e., reactive invalidity), which may occur with concurrent reporting (Russo, Johnson, & Stephens, 1989; Van Gog et al., 2005). Learners' trace data could be visualized and presented to them as a cue during an interview to help the learner remember and reflect on his/her learning process. The learner could be asked about specific activities and transitions in the trace data, and thereby be a tool to understand learners' behavior in terms of SRL. Of course, the numerous events in a learners' trace data, and therefore also numerous transitions, make it impractical and unrealistic to have learners explain and reflect on *all* of these events and transitions in the form of cued retrospective reporting. The researcher therefore has to make a selection of specific events and transitions that are presented as a cue during the interview, so that learners can remember and reflect on their learning process. Combined with follow-up questions from the researcher, the cues could then be used to help learners understand which activities, and which transitions, the interviewer is informing about. By incorporating elements of cued retrospective reporting in such a way, knowledge about specific activities and transitions can be obtained, while also increasing knowledge on the interpretation of these activities, which in traditional verbal reporting is the sole responsibility of the interviewer (Ericsson & Simon, 1993).

The second challenge associated with interpreting trace data is capturing not only the online SRL activities within the online learning environment, but also those outside of it. Again, we argue that interviews could be a tool to address this issue. For this specific challenge, the more traditional form of interviews could be employed, in terms of the researcher asking overarching questions about the participants' learning process without presenting a cue. For this interview format, three types are distinguished: structured, semi-structured, and unstructured interviews (Alshenqeeti, 2014; DiCicco-Bloom & Crabtree, 2006). Structured interviews are most like a verbal questionnaire and often produce quantitative data (Alshenqeeti, 2014; DiCicco-Bloom & Crabtree, 2006). Since the current aim is to understand learner behavior and move beyond sole quantitative data, structured interviews provide too little freedom and they are therefore unsuitable for the current purpose. In contrast, unstructured interviews may provide too much freedom. During unstructured interviews, the questions asked often arise during the interview itself and these sessions are thereby more like guided conversations (DiCicco-Bloom & Crabtree, 2006). This approach is valuable when interviewers want to minimalize their influence on the interviewee or when little is known about the topic at hand. However, when measuring SRL, it is important to measure all aspects of the construct. Over time, SRL has been defined in a number of ways, but all entail roughly the same activities that together form SRL activities (Jansen, Van Leeuwen, Janssen, Kester, & Kalz, 2017; Puustinen & Pulkkinen, 2001). To get

a full grasp of learners' SRL, it is worth discussing this predetermined list of SRL activities with the learner (e.g., goal setting, time management). In a semi-structured interview, the SRL activities can be used as topics for which pre-determined questions are created. A checklist can be used to make sure all topics are discussed (Alshenqeeti, 2014). At the same time, a semi-structured interview allows for follow-up questions that emerge from the dialogue to be asked, to probe for further information and improve understanding of the learner's activities (DiCicco-Bloom & Crabtree, 2006). A semi-structured interview is therefore a suitable method to gather data on learners' SRL activities outside of the online learning environment, by asking them about each SRL component.

The present study

To summarize, SRL is of high importance in online education, which makes measuring this construct of high theoretical and practical value. Trace data obtained in online education provides a detailed, objective listing of learners' activities over time and is argued to be a valuable source to measure learners' SRL. However, measuring SRL with trace data is challenging for two main reasons. First, trace data does not provide information on the how and why of learner behavior, making it challenging to interpret trace data correctly. Second, learner behavior outside of the online learning environment is not captured in trace data. Building on earlier mixed methods studies, in this chapter we propose a mixed methods approach with a sequential design to address these two challenges. We present a pilot study in which we augment trace data with interview data to analyze learners' SRL in online courses. Trace data from several online learners were analyzed. These learners were later interviewed about the regulation of their learning during the course they were enrolled in. In the interview, cued retrospective reporting was conducted by presenting learners with visualizations of their trace data. In the second part of the interview, learners' activities outside of the online course environment were discussed in a semi-structured interview format. We present our methodology for a subset of our data, so that we are able to thoroughly explain our procedures for data collection and interpretation. Our aim is therefore to make a methodological contribution to measuring learners' SRL in online education. We conclude the chapter by discussing the benefits and possible improvements of our approach.

Method

Design

A mixed methods research study was performed as a methodological illustration of how to measure SRL in online education, in which quantitative trace data were analyzed in conjunction with qualitative interview data (Johnson & Onwuegbuzie, 2004). The interview served two main goals. The first goal was to gain a better understanding of learners' trace data in terms of SRL. The second goal was to gain insight into learners' SRL outside of the online learning environment. Therefore, the time order of this mixed methods study was sequential; the trace data was analyzed and then used as input for semi-structured interviews. Dominant status (paradigm emphasis decision) was given to the interview data, as we were interested in the additional information that can be extracted from *adding* interviews to trace data.

Participants

Four students who completed the exam associated with a SPOC (Small Private Online Course) were interviewed. The participants were all students of the same Dutch university, but took different courses. The SPOCs were identical in setup to a Massive Open Online Course (MOOC): all educational materials were offered online, but credits could be received for following the online course by taking a traditional exam (with a fixed time and location) after finishing the MOOC. The educational materials all had to be accessed through edX (an online learning platform), were the students taking the SPOC could not be distinguished from the students attending the regular MOOC; they were in the same learning environment. The only difference between the MOOC and SPOC learners was thus that the SPOC students registered for and attended the exam.

All students that registered for a SPOC exam in the Spring of 2018 were invited to be interviewed. Five students indicated they were willing to be interviewed, and gave consent for the analysis of their trace data. One student had taken the exam already in the Fall of 2017 and was therefore excluded. The data of four students were therefore used (1 male; M_{age} = 22.0, range 19-24). The students were interviewed by the first author. Participants received a monetary compensation for their participation.

Trace data

All learners' activities in the online learning environment were automatically stored, leaving a trace learners' behavior (hence the term *trace data*). This trace data included a time stamped log of all their activities, including videos played and paused, self-test questions answered correctly and incorrectly, and exam questions answered correctly and incorrectly. As the data were time stamped and related to a learners' user id, the order in which a learner engaged with the learning materials is known. The trace data can be analyzed in a number of ways, for instance by looking at absolute or relative frequencies of activities, transitions from one activity to another, or patterns of activities per session or over the entire learning period. Depending on the aim of the research, different analyses are suitable. For instance, to identify activities or sequences of activities related to learner achievement, analyses counting activities and sequences would be fitting. Currently, the aim is to gain insight in participants' learning processes and to identify potential SRL activities present in their trace data. For this aim, participants' trace data were analyzed in a number of ways. The timing of learners' study sessions was analyzed, indicating when and how long a learner studied in the online course environment. Furthermore, attention was paid to the frequency of activities and potential skipping of learning activities. Finally, the order of learners' activities in the online learning environment was inspected.

To stimulate learner recall of their learning activities, a visualization of the learning process was considered most suitable, since it provides learners with an overview of their learning process and such a visualization can be understood rather easily without prior knowledge of the data gathered. Therefore, for each participant, a visualization of their learning activities within the online learning environment was created. To aid understanding of these trace data visualizations, an excerpt of the flow chart of P4 is presented in Figure 1. More information about the analysis of the trace data, and the interpretation of the flow charts can be found in the sections "Analysis" in the Method and "Trace data interpretation" in the Results.

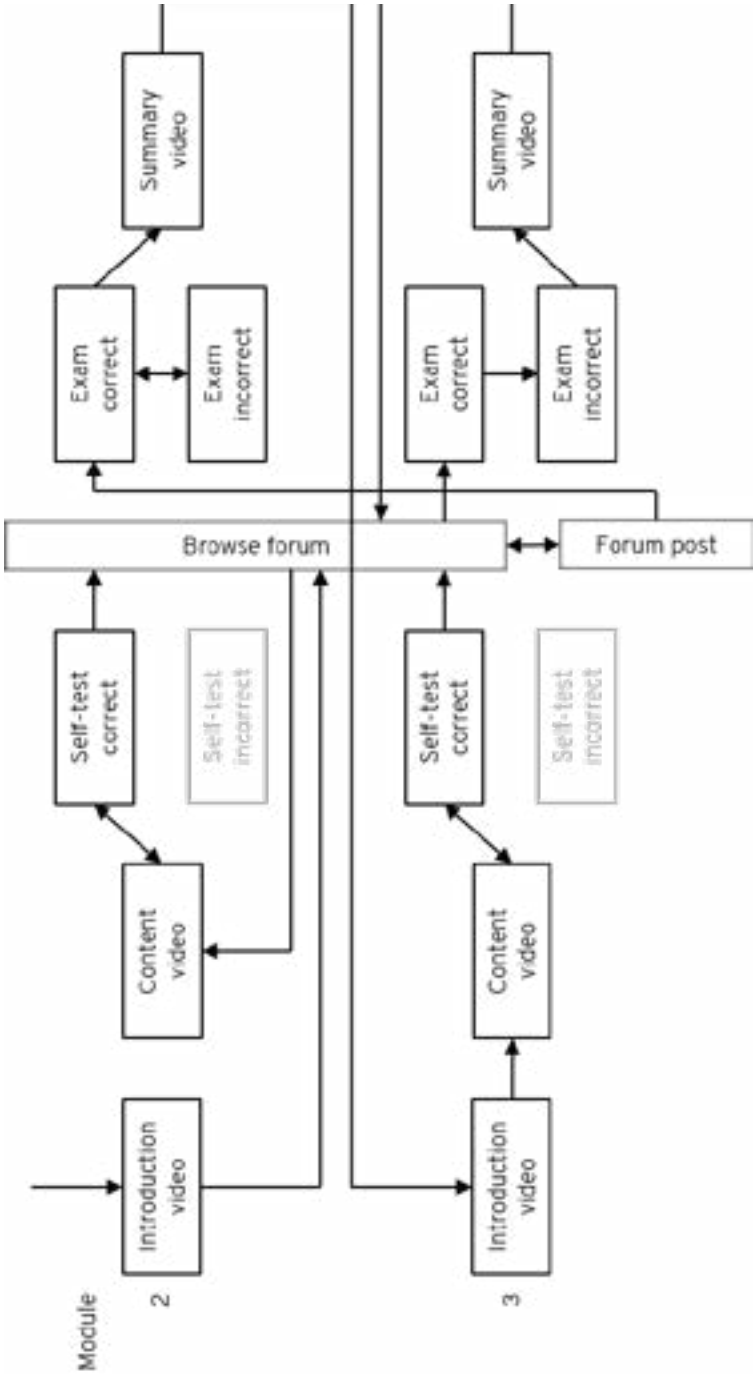

Figure 1 Excerpt of the flow chart of P4. The flow chart visualizes the order in which P4 engaged with the learning materials of module 2 and 3.

Interviews

A semi-structured interview guide was developed with a descriptive/interpretive focus to gain insight into the explanations of learners' online behavior and their SRL outside of the online learning environment (McIntosh & Morse, 2015). A visualization of students' trace data was used during the interview as a cue for recall of the learning process. The interview guide consisted of four segments and is available as online supplementary material (bit.ly/dealingwithautonomy).

First, the interviewer explained the interview goal and asked several introductory questions. The introductory questions included asking the participant about the title and topic of the SPOC the student followed and how the participant had learned about the opportunity to take a MOOC for credit. The questions were constructed to learn some basic information about the participant and to create rapport between the interviewer and the interviewee.

Next, learners' activities were discussed at a micro level, meaning that learners were asked about their behavior in the learning environment. The aim was to gain an SRL-themed explanation for learners' trace data. To help learners remember their learning process, a visualization of their trace data was presented to learners as a cue (see Figure 1 for an example). This segment thereby had similarities to cued retrospective reporting. However, not all activities and transitions in the visualization were discussed, not only because the learning process was simply too complex to do so, but also because some of the activities were conducted months before the interview. More importantly, the aim of the interview also was not to understand *all* transitions and activities, but to gain an understanding of learners' overall learning process, how they managed their learning, and the reasons underlying their behavior. Learners were therefore not only presented the trace data visualization, but were also interviewed about their learning process in general and about the way they engaged with the specific elements of the course (e.g., introductory videos, content videos, self-test questions, exam questions), to better understand with what intent the learners engaged with these materials (e.g., content learning, comprehension check). Learners were furthermore interviewed about the timing of their learning sessions (i.e., when they worked on the course), to understand the (ir)regularity of their studying and their time management.

Third, learners' activities were discussed at a macro level. Learners were interviewed about SRL activities not visible in the trace data and their behavior outside of the learning environment. Learners were for instance asked about the location where they studied, potential help-seeking, and their planning. It was made sure that all aspects of SRL, as described in the articles of Jansen, Van Leeuwen, Janssen, and Kester (2017) and Puustinnen and Pulkinnen (2001) were discussed with the participant at a micro and/or at a macro level. Finally, learners were interviewed about any challenges they had encountered during learning, and if they had suggestions for improving the course, especially related to SRL.

The interviews were conducted in Dutch as it was the mother tongue of both the interviewer and all interviewees. The interviews lasted between 1 hour and 1 hour and 15 minutes each. At the start of the interview, participants signed an informed consent for the interview to be audio and video taped. The video camera was directed at the table to record the trace data materials shown to participants and any pointing to specific activities and transitions on these materials (e.g. "during *this* module", or "when I moved from *here* to *here*").

Procedure

After registering for a SPOC exam, students were emailed information about the present research study. They were given the option to supply their contact information if they were willing to be interviewed. Students were informed that their trace data would be analyzed if they indicated their interest in participating. The trace data of interested students was analyzed a) to determine the number of learners' activities in the online learning environment, b) to determine the length and number of learning sessions, and c) to create a flow chart of learners' activities. The interview was structured by following the interview guide described above. Learners could be invited to participate in the interviews only after registering for the SPOC exam, and only after agreeing to participate could their trace data be analyzed. As trace data analysis itself is time consuming, interviews were scheduled approximately two months after the SPOC exams.

Analysis

The trace data were inspected to gain knowledge on the timing and length of learners' sessions, the frequency of their activities, and the order of their learning activities. The activities of each learner were visualized in a flow chart. While the participants followed different courses, the main elements of all courses were the same. Therefore their flow charts also contained the same elements. Per module, the following activities were visualized in the flow chart: introduction video, content video (there were usually multiple content videos per week, interactions with either of the videos were aggregated to this label), self-test question correct, self-test question incorrect, exam correct, exam incorrect, and summary video. Furthermore, browsing the forum and posting on the forum were visualized in the flow chart, but on a course level and not on a module level. Next, each learner's transitions were added to the course model. As only a small sample of learners participated in the current study, this was done by hand. Furthermore, per learner an overview was made of when the learner was active in the course. Additionally, a description was made of the overall learning process of the student, including any activities or transitions that were considered remarkable or interesting. It was then attempted to distill SRL activities from the trace data analyses.

The flow charts visualizing the learning process of the participants were used during the interviews as a cue for recall (see Figure 1). After conducting the interviews, the interviews were first transcribed. Next, statements that helped interpret the trace data, especially in terms of SRL, and statements that indicated SRL activities not visible in the trace data were identified in the transcripts. These statements were then labeled with the trace data or SRL activity they provided information about. For each theme, statements of the different participants were then grouped, and a description of the information gathered from the interviews was written per theme.

Results

The results are presented in three parts. First, case descriptions of the four participants are given. The case descriptions contain, per participant, information about the course followed, their study intentions, and the timing of their learning sessions. Next, we present the trace data of one of the participants (P4) and attempt to interpret the trace data in

terms of SRL. While the trace data provide an objective overview of the learner's behavior, no definitive conclusions regarding SRL activities could be made based on trace data alone for P4, nor for the other participants. The trace data of P4 are used to illustrate the data available and to illustrate the opportunities and challenges of using the data, especially for understanding and interpreting the data in terms of SRL. Last, the interview findings are presented in which we focus on the additional insights gained from interviewing learners in addition to analyzing their trace data. We first indicate in what way the interviews improved our understanding of the trace data. Second, we describe the SRL activities of learners not visible in the trace data.

Case descriptions

The four interviewees followed different SPOCs. The exams for all SPOCs took place mid-February. Below, more information per participant is provided about the course they followed, their study intentions, and the information obtained from their trace data.

Participant 1 (P1)

P1 followed the course "Food access" which she finalized with a grade of 7.5 (out of 10). She had time to spare next to the regular curriculum which she wanted to utilize in a meaningful manner. She started the SPOC out of interest in the topic of the course and decided on taking the exam after completing a large part of the course. The SPOC was her first experience with a fully online course. In total, 1146 activities were logged for P1, distributed over 20 days in a time span of five months. Figure 2 shows the timing of the learning sessions.

Figure 2 Timing of learning sessions P1. Pink bars indicate activities were logged on that day.

Participant 2 (P2)

P2 followed the course "Food risks" which he finalized with an 8.0. The SPOC was part of a so-called *"micromaster"* which contains three SPOCs which together serve as a replacement for a traditional campus-based course. P2 had already taken the other two courses in the micromaster, and thus started this SPOC with the intention to finish the course, pass the exam, and receive the credits. In total, 1407 activities were logged for P2, distributed over 28 days in a time span of six months. Figure 3 shows the timing of the learning sessions.

Figure 3 Timing of learning sessions P2. Pink bars indicate activities were logged on that day.

Participant 3 (P3)

P3 followed the course "Food risks", the same course as P2, which she finalized with an 8.0. P3 was abroad for a month during the study year and planned on attending this SPOC and two others to gain elective credits while away. However, as she had much less time available for studying while abroad, and there were technical difficulties with the internet connection, she did not complete any of the SPOCs while abroad. After returning home, she completed the SPOC on "Food risks"; the other SPOCs were dropped. This was her first experience with studying online. In total, 1012 activities were logged for P3, distributed over 22 days in a time span of two months. Figure 4 shows the timing of the learning sessions.

Figure 4 Timing of learning sessions P3. Pink bars indicate activities were logged on that day.

Participant 4 (P4)

P4 followed the course "Animal behavior", which she finalized with an 8.5. She started the course out of interest in the topic, and only later learned about the opportunity to take an exam and receive elective credits. It was her first experience with studying online. In total, 1296 activities were logged for P4, distributed over 14 days in a time span of 6 months. Figure 5 shows the timing of the learning sessions.

Figure 5 Timing of learning sessions P4. Pink bars indicate activities were logged on that day.

Trace data findings

Before interviewing the students, their trace data were analyzed. For all four participants, the trace data provided a good overview of their learning process, and activities could be identified that might be indicate of SRL activities. However, interpretations of the data

were ambiguous for all four participants. To illustrate the information gathered from the data, a description of the trace data gathered for P4 is provided, including potential SRL interpretations.

When analyzing the activities stored in the trace data, the trace data for September only showed interactions with the introductory module of the course and the first few videos of module 1 (the first video with actual content). During the sessions in October and November the learner completed all other course materials (videos, readings, exams and assignments). In the two sessions in February, right before the course exam, P4 engaged linearly with the introduction and content videos of all modules. This may indicate strategic studying behavior. It is however not known if the participant also used other materials to study for the exam. The finding that she completed all materials well before the exam may indicate good time management abilities.

In Figure 1 (in the Method) an excerpt of the flow chart of P4 was presented, showing the activities of P4 in modules 2 and 3 of the course. The excerpt is exemplary for the entire learning process of P4. P4 engaged with the videos, self-test questions, and exam questions mostly in linear order. However, watching videos was regularly alternated with browsing and posting on the forum. The regular forum interactions of P4 may indicate help seeking. The trace data of the video interaction activities of P4 included frequent pausing (and then continuing playing) videos, especially with content videos. The trace data furthermore regularly included seeking a specific time point in the video. Pausing the video may indicate note-taking, while seeking in the video may indicate that she noticed a gap in her understanding (comprehension monitoring) or missing notes and that she then attempted to gather the missing knowledge. Finally, as is also the case in the excerpt of the flow chart presented in Figure 1, the participant answered most self-test questions correctly. In the few cases that she answered a question incorrectly, P4 first answered the question correctly before continuing with other course materials. However, P4 did not consult the associated course materials before re-answering the question, at least not in a way visible in the trace data. She may have guessed the correct answer, as all self-test questions are multiple choice, or she may have consulted her notes if she made them. This activity order cannot be interpreted based on trace data alone.

In sum, the trace data provide information on the learning process of P4. However, understanding the reasons underlying the activities, and interpreting them as the result of SRL activities, is not possible without ambiguity remaining. The trace data analysis results in assumptions of SRL activities and potential explanations, but doubt on the accuracy of these explanations remains. This was no different when attempting to interpret the trace data of the other three participants. The trace data description of P4 is therefore an illustration of the difficulties in using trace data to measure SRL for all participants. In order to measure and understand learners' SRL, more information was necessary for all four participants. Below, we describe how the four interviews extended and improved our understanding of learners' SRL activities.

Interview findings

In the following sections we present several strands of information which were collected by adding interviews as a measurement method to trace data analyses. While we by no means imply that our results provide a complete description of all potential SPOC learners,

our results do show the benefit of incorporating interviews, instead of solely analyzing trace data to measure learners' SRL. Our results can be considered an illustration of the results that can be obtained from the methodological approach advocated in this chapter. The findings are structured around two themes: (1) interview findings that improve our understanding of the trace data, and (2) interview findings that teach us about learners' SRL outside of the online learning environment. Quotes of the interviewees are incorporated to support our findings.

Understanding trace data

In the first part of the interview, participants were questioned about their behavior in the online learning environment. The insights they provided have led to a better understanding of the how and why of learner behavior in the online learning environment.

Linear learning behavior. The trace data of all participants showed a rather linear approach to learning in the SPOCs; meaning that the participants – to a large extent - worked with the course materials in the same order as it was designed by the course designers. In the interviews, participants explained why they approached their learning in a linear fashion. Linear studying was more a habit out of convenience than a conscious decision. As P3 commented *"I always just clicked 'resume course '"*. P1 said *"it seemed logical that they would have a structure for offering materials"*, which was also given as a reason for linear studying by P4. P4 furthermore added *"By studying linearly, you know what you have done and you don't need to search for where to continue. You know where you left off and what you still need to do"*. Linear studying thereby thus had benefits for monitoring progress and made it easier to continue working at a later moment in time. In conclusion, the interviews provided an explanation for why the students followed a linear, regular pattern while studying in the SPOCs.

Lack of engagement with the course forum. P4 was the only participant who regularly engaged with the course forum. She introduced herself on the forum, posted her answers to questions when invited to, and asked for help on the forum. The other participants hardly engaged with the course forum, or not at all. When asked about the course forum their first response was that it did not seem useful to them (P1 *"I didn't see any added value in using the forum"*); they followed the course for their own learning and were not interested in the experiences of other learners around the world. The forum however does not solely have a social function; it can also be used for seeking help. All participants indicated that they had had some problems with understanding the course materials. Their barriers to asking for help on the forum included not knowing how long it would take to get an answer, finding it too much effort to type out mathematical formulas, and being too stubborn (P2 *"I was too stubborn to share my questions, I would then just look back at the video once more"*). In sum, the interviews helped to understand the lack of help seeking on the forum indicated by the trace data. The interviews also revealed that visiting the forum and posting questions might have been an effective strategy for learners in some cases.

Engagement with videos. The trace data showed that the participants watched (almost) all videos. The trace data also showed regular, short pausing of the videos. This likely indicated pausing to take notes, which was confirmed in the interviews, as P1 said *"I typed notes while watching the videos, and I paused the video when it went too fast"*. The notes were useful for studying for the exam, as all participants indicated using their notes as their main study material for the exam, only supplemented with questions and videos when

their notes were not fully clear. The interviews thus supported the hypothesis derived from the trace data: short pauses while watching the videos were caused by students taking notes.

The courses contained different types of videos. Each module consisted of an introductory video, multiple content videos, and a summary video. Participants indicated having different approaches for these different types of videos. They watched the introductory and summary videos *"in a more laid-back manner"* (P3). For instance, *"the introductory videos were really an introduction, which meant that I often did not take serious notes"* (P2) and *"I watched the summary videos, but I didn't do anything with them. I had just seen all the content, so the summary did not really add anything"* (P4). While note-taking was thus a common activity for the content videos, it was much less so for the introductory and summary videos. This difference can also be detected in the trace data, as the content videos were paused more often than the introductory and the summary videos.

However, the lack of note-taking does not imply that the videos were not useful for the participants. While some watched the introduction and summary only because they feared they would miss something important if they did not (P1 *"I will watch them [the introductory videos] anyway, because maybe they will say something important"*), the videos helped participants orient on what was to come and to reflect on the content of the past module. As P4 said about the summary videos *"If something was mentioned that I did not remember hearing about, I looked it up in the previous videos. Even though I was already putting my stuff away while the summary video was playing"*.

Engagement with questions. Participants were clearly aware that answering the self-test questions helped them monitor their comprehension. P4 indicated *"I used the questions to check if I had paid attention, and that was almost always the case"*. Participants thus engaged in metacognitive monitoring when answering the self-test questions.

SRL requires learners to be adaptive in their learning strategy, especially when they face adversity. It is therefore interesting to better understand learners' strategies when they find questions difficult and/or answer questions incorrectly. These strategies are not (always) visible in the trace data. As P1 explained *"Questions that I did not answer correctly, or that I found difficult, I wrote down in my notes, together with the correct answer. So that I would understand that information the next time I studied"*. P2 had a different strategy. He tried to answer the question. If his answer was incorrect, he first looked back in his notes to work out what went wrong. If that did not answer his question, only then did he go back to the associated video. The trace data thereby thus only showed a part of the strategy of P2 to deal with wrongly answered questions. In sum, the interviews helped to further enlighten the SRL processes students were engaged in; they specifically shed light on learners' engagement with self-test questions and the relation between answering questions and comprehension monitoring.

Timing of sessions. The timing of learners' activities (Figures 2-5) was diverse; some learners worked on the course for an extended period of time and others only had a few, very active, days. Some participants also showed a burst in activity the days before the exam (see Figure 1 and 4). The interview provided more information about the timing of learners' activities. For instance, P2 spread working on the course materials over a large portion of time. He explained *"I knew I had to take this course next to other courses*

at some point (...) so I better started in September, then I still knew some of the knowledge I gained in the previous two SPOCs, and that would leave me with the biggest chance to finish in February". For P1 other obligations, such as campus-based courses, resulted in large stretches of time between working on the course. P3 had planned on studying online abroad, but as she had less time available than expected, studying was postponed until she was back in The Netherlands. The trace data showed that the first couple of sessions (while abroad) were much shorter in length than the later sessions. The sprint in studying in the two weeks before the exam is thereby visible in the trace data (see Figure 4). In these cases, the interviews helped understand learner behavior and provided explanations for the irregular timing of participants' learning sessions.

Associated with the timing of learning sessions are different segments in learners' studying. For some participants, the trace data showed a clear distinction between completing the course materials and, later in time, studying for the exam. This distinction was visible in the timing of the sessions (paced studying throughout most of the course, and then a few days of high intensity right before the exam), but the ordering of activities also showed a distinction. The participants completed the course materials in a linear fashion. After finishing all materials, they looked back at specific materials: they moved from content video to content video, ignoring the introductory and summary videos, and viewed only some of the questions. The assumption that these behaviors were associated with different segments of the study process could be verified in the interviews. When discussing the exam preparations, P1 commented *"I looked at the exams again, to see what kind of questions they asked. And for the things that I did not understood, what I found complicated, for those things I watched the videos again"*. Here too, the interviews helped to better understand the difference in behavior of the participating students between the phase where they followed the course and the phase where they were studying for the exam.

SRL outside of the online learning environment

The second part of the interview focused on learners' SRL outside of the online learning environment. The interviews thus supplemented the trace data by focusing on activities for which no indicators can be found in the trace data.

Planning and goal setting. Participants' intentions for taking the SPOC differed: while P2 needed the credits associated with the course, P3 was interested in the credits but they were not necessary, and P1 and P4 took the course completely out of general interest and only decided on taking the exam after completing part of the course. However, besides the overall goal of course completion that all participants had sooner or later in the course, they did not set goals. Furthermore, they also did not have any plans, or had general plans which they failed to stick to: *"I knew I wanted to go through the course linearly, but only when it suited me to work on the course. I did not really have a plan or something (...) I had so much time to finish the course, I just worked on the course when it was convenient"* (P1) or *"I knew I would not be able to finish a module per week, so I tried to finish half a module per week, but that also did not work and I ended up just studying an hour now and then, without any clear structure"* (P2). All participants finished their SPOC successfully, suggesting that the courses are attainable also without a clear planning. However, participants' learning might have benefitted from better planning and goal setting. In any case, trace data alone are insufficient to determine which students are in need of support for planning and goal setting. More information, for instance through interviews, is needed.

Comprehension monitoring and attention focusing. Participants indicated that they engaged in note-taking not only to improve their remembrance of the information presented, but also to support comprehension monitoring and attention focusing. Note-taking was thereby an important cognitive activity for participants. As P2 indicated *"If you pause the video to take notes, and you don't know where to start, then that is a moment of reflection; maybe you have to start over or continue the next day"*. P1 explained *"I get distracted easily, for instance by Facebook, causing me to miss information. If I take notes, then I really have to pay attention to identify the main message"*. The trace of pausing videos could be associated with taking notes. This trace may thus be interpreted not only as a cognitive activity (i.e., taking notes), but also as a metacognitive activity (e.g., comprehension monitoring) or attention focusing. The interview data allowed for the validation of the interpretation of pausing videos as an SRL activity.

Reflection on learning. The trace data indicated that participants often ended a session with an exam and the associated closing video, which may indicate reflection. The interviews provided evidence that participants ended after an exam on purpose *"If I was working on the course, then I wanted to complete the whole module"* (P4). Participants were asked to what extent they reflected on their learning strategies and their progress, for instance at the end of a learning session. Participants indicated hardly any reflection: *"I think it was just a closing [video] indeed, and then it was simply done"* (P3) and *"And then [after the closing video] it was just done, then I was allowed to stop"* (P4). Based on the trace data alone, it could not be established if learners engaged in the SRL activity reflection; it could only be established that they engaged in activities that may be associated with reflection. In the interview, learners could be directly asked about any reflection on their learning. Learners indicated not to reflect on their learning, and the usefulness of their learning activities. Thus, while the trace data was ambiguous concerning the SRL activity reflection, the interviews provided clear information that the learners did not (consciously) engage in reflection.

Time management. Participants repeatedly indicated problems with time management. Participants did not orient themselves on the amount of work per module: *"I found it difficult to estimate how long one module would take. So, if I planned on doing modules 3 and 4 that day, I had no clue how much time that would cost me"* (P3). The lack of orientation led to an underestimation of the amount of work involved: *"I don't know how long I expected that it would take. [On the website] it said that it would take 6 to 8 hours per week. But I thought 'only videos, that can't take that long'"* (P1). In addition, P4 indicated underestimating the time she would need to finish the course as a result of her prior experience with studying, since *"I thought that – as I am already enrolled in university – I know how to study, so I will need a few hours less than they say"*. Consequence of learners' lack of planning and insufficient time management, was that they were stressed and pressed for time when finishing their course; *"eventually you get stressed and that is a shame, because it is absolutely not necessary"* (P3). While the trace data showed bursts in activity in the days before the final exam, this could not be interpreted as problematic. The interview data allows us to better understand learners' time management and taught us that learners underestimate the amount of time needed.

Help seeking. Participants hardly used the course forum, as already described in the section "lack of engagement with the course forum". During the interviews, it became clear that learners overall hardly ever needed help. When asked if there was material

that was hard to comprehend, learners responded with *"No, I thought it was all just clearly designed"* (P2) and *"The theory was not complicated"* (P3). There was limited external help seeking, as P3 indicated *"I may have googled two terms when preparing for the exam, of which I thought 'what was this again?'"*. However, it also became clear that participants sometimes did need help when they were unsure about the answer of an exam question. Participants found different solutions, including re-watching videos, or skipping the material under the assumption that one would not need to understand everything to pass the course (P3 *"I thought, if I understand seven out of eight [modules], then it must be alright"*). It was already indicated in the section on forum engagement that P2 preferred re-watching the videos over posting on the forum, and P4 indicated: *"I would look back in my notes, or in the transcript, or in the video, in that order"*. In sum, the trace data indicated very little engagement with the course forum, and the inference that learners are not searching for external help appears to be correct. However, learners do occasionally need help, and the interview results showed a number of solutions employed by learners to seek help outside the course forum.

Environment structuring. Participants consciously decided on where they studied for their SPOC and they made use of the autonomy in study location offered by online education (P1 *"I appreciated that I could study everywhere. That you were not bound to a specific location"*). P1 and P2 studied in varying locations: *"I sometimes worked on the course when I went home to my parents, sometimes in my student dorm room, and sometimes in the university library"* (P1) and *"I switched between the university library and at home. (...) And if I am in the train, I try to do something useful, so then I also regularly worked on it"* (P2). P2 further clarified *"If I studied in the train, then I often just watched videos, knowing that I would have to watch them again later (...) or I watched specific videos a second time"*. Studying in the train was thereby in addition to studying at home or the university library, not a replacement. P3 and P4 deliberately choose to study at home, as P3 remarked *"I like having the option to study at home, since I can then make a nice cup of tea when I want to, and I am not surrounded by annoying people the way you are in the university library"*. Overall, the interview data provided clear information for all participants on where they studied, and the reasons underlying their choice of location. As environment structuring cannot be extracted from trace data, but is part of SRL, the interviews helped get a more comprehensive measure of learners' SRL.

Discussion

In this study, we used a mixed methods approach combining trace data and interview data to study SRL in online education. To be successful in online education, learners must be able to self-regulate their learning due to the autonomy offered to them (Azevedo & Aleven, 2013; Beishuizen & Steffens, 2011; Broadbent, 2017; Hew & Cheung, 2014; Wang et al., 2013). Accurate measurement of learners' SRL is necessary to determine which students are in need of support and how to best offer support. Trace data have been used previously to measure learners' SRL, since trace data can be gathered unobtrusively from all learners (e.g., Cicchinelli et al., 2018; Hadwin et al., 2007; Kizilcec et al., 2017; Van Laer & Elen, 2018). We identified two main problems with measuring SRL with trace data, which we tried to solve by combining trace data with interviews in a mixed methods study.

First, the interviews helped to remove ambiguities in the interpretation of the trace data. For instance, all learners indicated that the short pauses in watching the content videos were used for note-taking, and that their viewing behavior of the introduction and summary videos was markedly different (i.e., more laid-back) from their viewing behavior of the content videos. The interviews were thereby helpful for accurate interpretation of learners' trace data. Using interviews to interpret trace data could be a valuable addition to existing studies that aim to measure SRL in online education. For instance, interview data could be useful in studies that correlate SRL activities measured with questionnaires to sequences found in trace data, as reported for example in the study by Kizilcec et al (2017). in that study, sequences of activities could be related to multiple SRL constructs, thus leaving open the option for multiple SRL interpretations. In such situations, interviews may be helpful to determine the correct SRL interpretation of transitions for individual learners. Interviews may also be useful to determine accurate indicators of SRL activity in trace data. Cicchinelli et al. (2018) defined trace data indicators for several SRL activities. The frequency with which these indicators were present in learners' trace data was used as a measure of learners' engagement in SRL activities during learning. In such situations, in which trace data are used to measure SRL activity, it may be useful to conduct interviews before collecting trace data to support the selection of accurate trace data indicators of SRL activity.

The second problem identified was that learners' behavior outside of the learning environment is not captured in trace data. The interviews helped gain insight into learners' SRL activities that occur outside of the online learning environment. Learners for instance indicated that they studied in different locations, and some learners' study strategy also differed based on their study location (e.g., only re-watching videos in the train). The interviews showed that while some SRL activities occur both inside and outside of the online learning environment (e.g., comprehension monitoring), others solely take place outside of the online learning environment (e.g., environment structuring), This finding means that researchers might draw incorrect conclusions about how learners self-regulate their learning if they only rely on measurements of learners' SRL activities within the online learning environment. Researchers may for instance conclude that learners who do not take self-test questions do not monitor their learning. However, learners may also engage in note-taking to monitor their comprehension of the key points; behavior which is not visible in trace data directly. Furthermore, the interviews showed that learners who are able to self-regulate their learning inside the online learning environment, may still struggle with SRL outside of the online learning environment. It may then incorrectly be assumed that these learners are not in need of SRL support. Many learners however struggle with time management due to conflicting responsibilities in the rest of their lives (Hew & Cheung, 2014); an issue that is hard to measure with trace data only. Measurement of learners' SRL activities outside of the online learning environment as we have done with interviews is thus important to obtain a complete overview of SRL activities and to provide learners with adequate support.

Using trace data in combination with interview data in a mixed methods study thus proved a useful approach for addressing the two identified problems with using trace data as a mono-method to measure learners' SRL. However, interviewing learners is much more time consuming and labor intensive than collecting trace data. The main benefits of trace data, unobtrusive collection and measurement of *all* learners, no longer apply when combining trace data with interviews. While we currently consider it important to combine

trace data with another data source due to the problems described, we also acknowledge that combining trace data with interviews is not attainable at a large scale. Fortunately, we also do not consider this necessary, as we see other potential solutions for the identified problems in the future.

After repeated multi-method studies in which trace data are combined with interviews for larger, and more diverse samples, it will likely be possible to interpret at least part of the trace data unambiguously in terms of SRL. The trace data variables that can be interpreted reliably in the future may then be used without combining them with another data source. For instance, answering test questions indicated comprehension monitoring for all learners in this pilot. If this interpretation is replicated, then quiz taking may be used as an indicator for the SRL activity comprehension monitoring. Researchers who are interested in the measurement of the SRL behaviors that can be interpreted reliably from trace data, will thus be able to use trace data as a mono-method in the future. Furthermore, in studies in which trace data is the only available data source, it is then clear what trace data can be interpreted validly and reliably. Hereby, we argue, we will be able to reap the benefits (and simultaneously: be aware of the limitations) of unobtrusive, large-scale measurement of SRL with trace data in the future.

As learners' behavior outside of the online learning environment is not captured in trace data, we will never be able to measure this behavior with trace data as a mono-method. Repeated measurement of learners' behavior outside of the learning environment could help determine what SRL activities are overlooked when solely measuring SRL with trace data in online education. If trace data are then used as a mono-method in research, it will be clear what aspects of SRL are not measured. Additionally, the measurement of learners' SRL activities outside of the learning environment will allow for categorization of these activities if enough learners, from diverse samples, have been interviewed. It is therefore anticipated that a questionnaire to measure learners' SRL activities outside of the learning environment can be developed based on the united interviews findings of multiple studies. While questionnaires measuring learners' SRL outside of the learning environment already exist (e.g., Barnard, Lan, To, Paton, & Lai, 2009; Jansen et al., 2017), these have been developed based on theoretical knowledge of SRL and experiences of learners in offline learning environments. Participant input to make sure the right SRL behaviors are inquired in the questionnaire is therefore currently missing and would make a worthwhile addition to the questionnaires to increase their validity. While measurement of learners' SRL outside of the learning environment with a questionnaire is not unobtrusive, questionnaire data can be gathered on a large scale more easily than interview data.

Methodological reflection

The results of this study have improved our understanding of learners' activities in SPOCs. By focusing the interviews on both participants' reflections on (1) the trace data itself and (2) their SRL outside of the learning environment, we were able to better understand both aspects of learners' activities. In order to measure both the micro and macro aspects of learners' activities, we made use of interviews, since they allow asking questions on a range of different granularities. We feel this is valuable, as it provided a richer understanding of learner behavior. However, as it was the first study of its kind within this domain, a reflection on the methodology used is in order.

When combining trace data with interview data, three issues that need specific attention can be identified. The first issue concerns the selection of participants. As is the case in all research, the sample included influences the results found and the generalizability of those results. The interviews conducted in the current study formed a pilot sample to show the benefits of the presented methodology. If researchers want to use our proposed methodology to draw conclusion and add to theory development, they should attempt to obtain a larger sample. The current sample of four interviewees was rather homogeneous in characteristics, yet the interviewees already differed in their reported SRL. This diversity indicates that a much larger, and more diverse, sample is necessary to determine valid interpretations of learner behavior. Likely, an iterative approach of interviewing and analyzing data is necessary to reach data saturation (Morse, 2010; Strauss & Corbin, 1994), especially when one is interested in measuring and understanding the SRL of a more diverse group of learners. Since trace data provides insight in learners' learning process, analysis of the trace data of learners may be helpful for purposive sampling (Robinson, 2014). Trace data may be used to identify a diverse set of learners to be interviewed or to identify specific cases one is interested in, such as learners who quit the course early or who finished the complete course. Purposive sampling may thus contribute to reach data saturation.

The second methodological issue concerns the time span between the learning activities and the interview. Interviewing students early, potentially even during the course they are attending, results in richer data that is likely more reliable than verbal reporting collected later. Retrospective reporting may lead to both errors of omission (forgetting SRL activities) as well as to errors of fabricating (reporting SRL activities that did not take place, or were not as deliberate as they are reported; Russo et al., 1989). Nevertheless, waiting with selecting interviewees until the course is over as happened in this study also has advantages. First, learners' behavior in the course is then not influenced by the interview, which may be the case when interviewing during the course (reactive invalidity; Russo et al., 1989). Second, trace data for the full course can then be used to select an adequate sample. For instance, learners that quit the course cannot be selected early on, as they may continue learning in the SPOC or MOOC (much) later. In this pilot, the time between studying and the exam on the one hand, and the interview on the other hand, was two months. This likely hampered learners' recall of their activities and the reasons underlying their activities. The flow charts we made for every participant alleviated this problem to some extent, as they helped interviewees remember their learning activities (i.e., cued retrospective recall). However, we acknowledge that approaching potential interviewees at an earlier point in time would likely have resulted in richer data.

The third methodological consideration influencing our findings, is the presentation of trace data to participants. The trace data visualizations are used as a cue for cued retrospective reporting. The formatting of the cue, and the information that is and is not included, likely influences learners' reporting. Researchers should therefore carefully decide on the formatting of their trace data cue and be aware of the consequences of their decisions. Trace data visualizations in the form of flow charts, as they were used in the current study, helped learners to remember all activities present in the course. They furthermore helped learners to explain both the linearity in their learning behavior as well as the deviations in this linearity. However, the flow charts are limited by the fact that if multiple arrows move out of an activity, one cannot determine which one of the out arrows should be followed at which moment in time. For instance, in Figure 1 the learner may have

posted on the forum every time after browsing the forum, however, the learner may also have posted only once in response to browsing. This difference is not visible in the static flow chart. In this study, the listing of all activities was used as supportive information during the interviews. A dynamic flow chart, in which arrows are added over time, thereby including temporal information, could solve this problem.

Conclusion

We have presented a methodological approach to measuring SRL in online education by combining trace data with interview data. While there is surely room for improvement, for which we have provided suggestions in this discussion, the results of this study already show the potential of this combination of methodologies. Currently, trace data are already interpreted in terms of SRL (e.g., Cicchinelli et al., 2018; Fincham et al., 2018; Maldonado-Mahauad et al., 2018). However, the interview results show that interpretation of trace data is often ambiguous. More research should be conducted to establish what components of trace data can be validly labeled, and how they should be labeled (Rovers et al., 2019). In addition, we can conclude from the interview data that not all SRL activity is visible in the trace data. Therefore, more research is also necessary to establish which aspects of SRL can and which aspects of SRL cannot be measured with trace data, as the results of such research are necessary to reliably determine what aspects of SRL are overlooked when measuring SRL with trace data. More research into learners' SRL activities outside of the online learning environment will furthermore enable the development of a questionnaire to measure learners' SRL activities that are not captured in the trace data. Hopefully, in the future, we can validly measure learners' SRL with unambiguous interpretations of unobtrusively collected trace data from all learners, in combination with large scale measurement of learners' SRL outside of the learning environment with a valid questionnaire.

7

General Discussion

In open online education, learners are given autonomy over how they organize their learning process (e.g., Azevedo, 2005; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Wang, Shannon, & Ross, 2013). Learners are free to decide on the topic they want to study, but also on the time, place, and pace of learning. To be successful in open online education, learners have to deal with this autonomy. Learners should therefore engage in self-regulated learning (SRL; e.g., Azevedo & Aleven, 2013; Kizilcec et al., 2017; Wang et al., 2013). Self-regulated learners are metacognitively, motivationally, and behaviorally active in their learning process (Zimmerman, 1986, 2002). They plan their work, monitor and reflect on their progress, seek help when needed, and manage their time, effort, and environment. While the ability to self-regulate one's learning process is essential for success in open online education due to the freedom provided, it is known that learners often lack the capability to engage in successful SRL (e.g., Azevedo & Cromley, 2004; Bol & Garner, 2011; Dunlosky & Lipko, 2007; Peverly, Brobst, Graham, & Shaw, 2003). It can therefore be considered worthwhile to provide learners with adequate SRL support in open online education to improve their learning process. However, as open online education is a relatively new educational context, little is yet known about how best to offer SRL support to learners in open online education. One of the aims of the current dissertation was therefore to improve our understanding of learners' SRL in open online education, and more specifically, how to support learners' SRL in open online education.

Related to the study of SRL support in open online education, is the measurement of SRL in open online education. Accurate measurement of SRL can be considered a prerequisite for offering adequate support. Accurate measurement of SRL is necessary to determine learners' need for SRL support and to evaluate the effects of SRL support on learners' SRL activity. The measurement of SRL is however not without problems (e.g., SRL should be measured as an event instead of as a state; e.g., McCardle & Hadwin, 2015; Winne, 2010; Winne & Perry, 2000). The new context of open online education puts forward new opportunities for the measurement of SRL due to the automatic collection of trace data. All learner behavior within the online learning environment is stored in trace data, such as video interactions, answering questions, and navigating between pages. The availability of trace data, together with the importance of accurate SRL measurement, led us to explore several methodological issues surrounding the measurement of SRL in open online education. The overall research question addressed in this dissertation was therefore: *"How to measure and support learners' SRL in open online education?"*.

In this general discussion, we first summarize our findings on the first part of the research question, namely how to support learners' SRL in open online education (Chapters 2, 4, and 5). We integrate these findings, present limitations of our research and provide suggestions for future research. Next, we summarize our findings on the second part of the research question, namely how to measure learners' SRL in open online education (Chapters 3, 4, and 6). We here also integrate our findings, present limitations of our research, and provide suggestions for future research. In these sections, we focus on overarching limitations and future research directions, based on the more specific limitations and future research directions of the individual studies. After discussing the two main research questions, we reflect on the research conducted from a broader perspective when we present our overarching impressions regarding the future of MOOCs and research on SRL support.

How to support learners' SRL in open online education?

In the studies presented in Chapters 2, 4, and 5, we explored how learners' SRL can best be supported in open online education. In Chapter 2, we reviewed existing empirical research on SRL interventions in higher education. We included the effects of SRL interventions on SRL activity as well as on achievement. We conducted meta-analytic structural equation modeling (MASEM) to test whether the positive effects of SRL interventions on achievement were mediated by SRL activity. The results indicated that the effects of SRL interventions on achievement were only partially mediated by SRL activity ($\beta = .05$, $p < .05$). We therefore concluded that while SRL interventions are effective in improving both SRL activity and achievement, the effects of SRL interventions on achievement are mostly due to other factors than improvements in SRL activity. Examples of such factors could be students' time on task and task motivation. We furthermore conducted separate meta-analyses of the effects of SRL interventions on academic achievement, the effects of SRL interventions on SRL activity, and the relationship between SRL activity and academic achievement. The overall effect sizes found were $d = .49$ for the effect of SRL interventions on achievement, $d = .50$ for the effect of SRL interventions on SRL activity, and $r = .28$ for the relationship between SRL activity and achievement. Since the effect sizes differed significantly between studies, we tested a range of study-, measurement-, and intervention characteristics as potential moderators of the effect sizes. The results of the moderator analyses did not provide specific indications of how to best develop SRL support. Based on these results, we concluded that SRL support is effective both to support students' SRL activity as well as their achievement. The results thereby underline the importance of implementing SRL interventions to support both students' SRL activities as well as their achievement.

In Chapter 4, we explored how learners' SRL influenced their learning process in a MOOC. We hereby attempted to link learners' covert SRL to their overt learning behavior. Learners were first clustered based on their self-reported SRL at the start of the MOOC. Four clusters of learners emerged: average regulators, help seekers, *self*-regulators, and weak regulators. Next, for each cluster of learners, learners' process through the MOOC was analyzed with process mining (see Bannert, Reimann, & Sonnenberg, 2014). With process mining, learners' transitions between the main learning activities in the course were visualized in process models. These process models showed that learners in all clusters generally adhered to the course structure intended by the course designers, yet there were also remarkable differences between the process models of the four different clusters. Learners who reported weak SRL showed few deviations from the intended course structure, while learners in the other three clusters showed much more diversity in their behavior. The results of this study imply that SRL interventions should be integrated in the course structure to provide support to weak self-regulating learners.

In Chapter 5, we evaluated the effects of an SRL intervention in three MOOCs. The SRL intervention consisted of three short videos containing SRL instructions and study suggestions for learners on how to improve their SRL. The intervention videos were integrated in the course structure; they were presented to learners between the course content videos and the weekly quiz. The effects of the SRL intervention were tested on learners' course completion, as well as on their SRL activity. Learners' SRL was measured with a number

of variables calculated from the trace data, including visiting the weekly course information (to indicate planning) and finishing videos and quizzes that were started (to indicate persistence). The results indicated that the SRL intervention significantly improved learners' course completion. Furthermore, when comparing the SRL activity of learners who complied with the intervention with the SRL activity of learners in the control condition, learners who complied with the intervention showed significantly higher SRL activity in terms of metacognitive activities before learning (e.g., planning), help seeking, and persistence. These differences in SRL activity could however not be established when comparing the control group to the intervention group as a whole, presumably because intervention compliance was low. Explorative analyses indicated that the low intervention compliance was likely due to the fact that most learners who started the course had already dropped out before encountering the first intervention video at the end of week 1. From the results we concluded that the implemented SRL intervention successfully improved learners' course completion and likely also supported learners' SRL activity.

Together, the findings of the studies presented in Chapters 2, 4, and 5 lead to the following conclusions and implications. First, SRL interventions are effective for improving SRL activity and achievement in higher education. SRL interventions are furthermore effective for improving SRL activity and course completion in open online education. It is therefore advisable for instructional designers to implement SRL support for learners in their courses, to help learners regulate their learning and successfully cope with the autonomy offered to them. Second, the different effects of SRL interventions on SRL activity and achievement highlight the necessity for researchers to measure and report the effects of SRL interventions on both outcome measures. Using both SRL activity and achievement or course completion (dependent on the context) as outcome measures helps determine to what extent SRL interventions are effective in improving these outcomes. The findings presented in Chapter 5 for instance indicate that learners' course completion improved, but learners' SRL activity only improved for some aspects of SRL. Measuring and reporting the effects of SRL interventions on both SRL activity as well as on achievement or course completion has a second benefit for research. Reporting the effects of SRL interventions on both outcome measures also helps in understanding if and how improvements in SRL activity are related to improved achievement or course completion. None of the studies included in the meta-analyses of Chapter 2 tested the mediation of SRL activity on the effects of the SRL intervention on achievement. In Chapter 2, we tested this mediation and found evidence that SRL activity only partially mediates the effect of SRL interventions on achievement. If more researchers test the effects of their SRL intervention on both SRL activity and on achievement, and include mediation analysis, then our understanding of how SRL interventions improve achievement will be improved. Finally, we conclude that researchers and instructional designers should carefully consider how they present their SRL support to learners. Based on the findings presented in Chapter 4 and previous SRL intervention studies, the SRL intervention in Chapter 5 was strongly integrated into the courses. Yet, SRL intervention compliance was still low. It is likely that learners who needed support had already dropped out before they encountered the intervention. Hence, we conclude that strong SRL intervention integration in the course structure is not sufficient for learners to adhere to the intervention. Implementing an intervention even earlier (e.g., at enrollment) might be a solution to this problem.

Limitations and suggestions for future research

In Chapter 5, we found that intervention compliance was low. This finding led to the suggestion to integrate SRL interventions earlier (or differently) in the course design. Low intervention compliance also represents a limitation of our research into the effects of SRL interventions. Low intervention compliance complicated the analyses of the effects of the SRL intervention in Chapter 5 and may also have played a role in the heterogeneity of effect sizes found in the meta-analyses in Chapter 2. We could not test whether intervention compliance was a significant moderator of the effects of SRL interventions on SRL activity and achievement in the meta-analysis, as it was not reported in the primary studies. Future studies should therefore measure and report intervention compliance to determine if and how intervention compliance influences the effects of SRL interventions. We furthermore consider the improvement of learners' intervention compliance an important direction for further research, since learners can only reap the benefits of an SRL intervention if they comply with the intervention. The results of Chapter 5 indicated that the content of the intervention did not cause the low intervention compliance. To improve intervention compliance, researchers should instead focus on reaching students that were currently not exposed to the intervention, for instance, by integrating the intervention earlier in the course or potentially even at enrollment. A related interesting question for future research is which factors (e.g., students' course intentions, prior SRL knowledge) influence whether learners do or do not comply with an intervention, as these differences may provide indications if learners who do not comply are actually not in need of support or if these learners are in need of earlier and/or different support.

Additionally, the definition of SRL used in this dissertation, and the components that we did and did not include in our definition and measurements of SRL, impacted the results of our studies. We defined self-regulated learners as metacognitively, behaviorally, and motivationally active in their learning process (Zimmerman, 1986, 2002). We thereby included metacognitive and resource management activities in our definition and measurement of SRL. Metacognitive activities could occur before (e.g., planning), during (e.g., monitoring), and after (e.g., reflection) learning. Resource management activities entailed time management, environment structuring, help seeking, and persistence. Learners' task motivation was thereby outside of the scope of our research. Task motivation is usually split into task value, goal orientation and self-efficacy (Pintrich, 1999). We considered these motivational aspects precursors of SRL (Efklides, 2011; Pintrich, 1999). However, as described in the discussion of our literature review (Chapter 2), learners' task motivation may influence the effects of SRL interventions. Indications of this relationship between task motivation and effects of SRL interventions have been found in several empirical studies (Duffy & Azevedo, 2015; Sitzmann, Bell, Kraiger, & Kanar, 2009). Learners who are more motivated for a learning task, may be more motivated to improve their learning process and might thus be more susceptible to SRL interventions. We hypothesize that task motivation may influence the effects of SRL interventions in two ways. First, task motivation may influence who complies with an intervention. Second, task motivation may moderate the effects of an SRL intervention on achievement (i.e., larger effect of the intervention for those with greater task motivation). It would thus be interesting to take this diversity in learners into account by measuring learners' motivation for the task in future SRL studies. The potential influence of task motivation on intervention compliance could then be tested, as well as the possible influence of task motivation on the effectiveness of the SRL intervention. Alternatively, one could consider testing the effects of an

SRL intervention on learners with high task motivation, as they have the willingness to learn and may therefore also comply with the intervention to a greater extent. An SRL intervention could for instance be implemented in a small private online course (SPOC). SPOC learners can usually receive credits for their achievement in the online course and may therefore have greater task motivation than MOOC learners. Either way, we consider exploring the influence of task motivation on the effects of SRL support an interesting avenue for future research.

Learners' engagement in cognitive learning activities was also outside of the scope of the research conducted. We focused on how learners (struggle to) regulate their engagement in cognitive activities, not on learners' engagement in cognitive activities itself. However, learners' SRL and their engagement in cognitive activities are tightly intertwined (Nelson & Narens, 1990). Sufficient knowledge of and experience with a variety of cognitive strategies can be considered a prerequisite for adequate SRL: without a repertoire of cognitive activities, learners have little to choose from when regulating their learning (Hattie, Biggs, & Purdie, 1996; Paris & Paris, 2001). By measuring learners' cognitive activities, for instance with trace data or with a questionnaire, it can be established whether learners meet this prerequisite for successful SRL. If learners cannot engage in a sufficient variety of cognitive activities, SRL support may need to include cognitive activity support in order to successfully improve learners' achievement. Focusing on learners' cognitive activities is also interesting when measuring the effects of an SRL intervention. Cognitive activities differ in their effectiveness for learning. Dunlosky, Rawson, Marsh, Nathan, and Willingham (2013) for example report that self-explanation and practice testing are more effective learning techniques than summarization. Successful self-regulated learners may display a higher relative engagement in such effective cognitive activities. By evaluating the effects of an SRL intervention on learners' engagement in cognitive activities, this hypothesis could be tested. These research suggestions provide examples of how the relationship between cognitive activity engagement and SRL can be studied if cognitive activity engagement is included in SRL research. Thereby, empirical evidence on the relationship between cognitive activities and SRL could be extended.

How to measure learners' SRL in open online education?

In Chapters 3, 4 and 6 we focused on the challenges involved in measuring learners' SRL in open online education. We attempted to validly and reliably measure learners' SRL. In Chapter 3, we developed a questionnaire to measure learners' SRL in open online education. Based on several existing SRL questionnaires, we developed and tested a questionnaire specifically suited to the context of open online education. That is, we developed a questionnaire without questions relating to the context of face-to-face lectures or a fixed planning, but with questions relating to the freedom to decide on the time, pace, and place of learning. This questionnaire was named the Self-regulated Online Learning Questionnaire (SOL-Q). We revised the questionnaire in a second study, most importantly to improve the measurement of learners' metacognitive activities. The questionnaire resulting from this revision was also evaluated and contained 42 items divided over seven

scales: *metacognitive activities before learning, metacognitive activities during learning, metacognitive activities after learning, time management, environmental structuring, persistence,* and *help seeking* (SOL-Q-R).

In Chapter 4, we focused on the coupling of learners' self-reported SRL with their learning activities within a MOOC. The main aim of this study was to increase our theoretical understanding of how SRL relates to differences in learner behavior. However, this study also led to methodological insights which we report here. After clustering learners based on their self-reported SRL, process models indicating the learning process of each group of learners were created. The process models of these four groups showed clear differences. This diversity in behavior could be related to learners' self-reported SRL scores. For instance, for learners in the "help seekers" cluster, the only transition from one module to the next module was through browsing or posting on the course forum. We therefore concluded that the influence of SRL activities on students' learning process is visible when analyzing learners' overt learning activities in open online education.

In Chapter 6, we utilized a mixed methods approach to better understand learners' SRL in open online education. In the study, we identified two main challenges with the use of trace data to measure learners' SRL. First, trace data provides information about the what and when of learners' activities, but not about the how and why of these activities. Second, learner behavior outside of the online learning environment is not captured in trace data. We therefore conducted a mixed methods study in which we combined trace data with interview data to improve our understanding of the SRL of four students. In the interviews, we employed a form of cued retrospective recall. Students were provided with visualizations of their trace data as a cue to help them recall their learning activities. The results of the mixed methods study indicated that combining trace data with interview data indeed helped us interpret learners' behavior (as captured in the trace data) in terms of SRL. Second, the interviews also provided information about learners' SRL activities that were not captured in the trace data (e.g., environment structuring). We therefore considered combining trace data with interview data a promising approach to measuring SRL in open online education.

Based on the results of the studies presented in Chapters 3, 4, and 6, we conclude that the measurement of SRL in open online education requires different measurement techniques compared to the measurement of SRL in traditional, face-to-face, education. Since learners need to regulate different and more aspects of their learning process, specific research instruments are necessary. This is exemplified in the findings of the interview study presented in Chapter 6. In that study, learners for instance explained how they regulated the timing of their learning. This is a regulatory activity that is, at least in part, planned for learners when engaged in a traditional, campus-based course, through the planning of lectures. We have furthermore shown that trace data can be used as an indicator of SRL activities. We have provided indications of the connection between learners' covert SRL activities and their overt learning behavior in Chapter 4. In Chapter 5, we have made use of this connection as we used variables calculated from learners' trace data to measure learners' SRL. While we remain hesitant to consider trace data a valid monomethod of measuring learners' SRL (as described extensively in Chapter 6), the data definitely allows for the measurement of aspects of learners' SRL activities. The studies in this dissertation have thereby advanced research on how to use trace data, the result of learner behavior, as an indicator of learners' SRL activities.

Limitations and suggestions for future research

As described in the Introduction of this dissertation, it is important to take the covert nature of SRL activities into account when measuring learners' SRL (Veenman, 2007; Winne, 2010). SRL activities mostly occur at a meta-level and can therefore not be observed directly. The link between regulatory activities and cognitive activities is theoretically clear: with the regulatory activities, learners control their learning activities, and the learning activities are in turn used as input for further regulation (Nelson & Narens, 1990). In Chapter 4, we showed that covert SRL activities are indeed related to overt learning activities. In Chapter 5, we measured the effects of an SRL intervention on learners' SRL. We used trace data variables as indicators of learners' SRL activities. This approach is however not without risks, as there often is ambiguity in the interpretation of learners' trace data in terms of SRL. For instance, pausing a video can signal that a learner is taking notes, but it may also signal that the learner is distracted and is engaging in an activity not related to the MOOC. Trace data furthermore only captures learner behavior inside the online learning environment; activities outside of the online learning environment are not measured (see Chapter 6). We attempted to minimize the risks of using trace data to measure SRL activities by explicitly grounding our trace data variables in theoretical knowledge of SRL and in previous empirical studies in which trace data were used. Additionally, we attempted to measure SRL with a combination of trace data and questionnaire data. Nevertheless, more information on how the coupling between SRL and learner behavior is visible in data is needed. As already emphasized in the discussion of Chapter 6, more research is necessary to improve our interpretation of trace data in terms of SRL and to better understand what SRL activities are not included in trace data measures of learners' SRL.

Next to the covert aspects of SRL, the temporal dynamics of SRL activities are also important for accurate measurement of SRL (Molenaar & Järvelä, 2014; Sonnenberg & Bannert, 2016). Temporal analysis is considered important for the accurate measurement of SRL, as successful SRL is argued to be adaptive to the context at hand (Panadero, 2017). Two types of temporal analysis can be distinguished: sequentiality and temporality. Sequentiality focuses on the order (i.e., sequence) of learners' activities within the online learning environment. Temporality focuses on the timing of events and the elapsing of time (Knight & Friend Wise, 2017; Molenaar & Järvelä, 2014; Van Laer & Elen, 2018).

With temporal analysis, it can for instance be analyzed if learners engage differently with simple compared to complex materials. This would signal adaptation to the task, which is part of adequate SRL. In Chapter 6, interviewees reported different engagement with content videos (complex) compared to introduction and summary videos (simple). Learners reported more pausing and note-taking with content videos, compared to introductory and summary videos. These differences in engagement would have been visible with either form of temporal analysis. With temporality, the duration of play video would be longer for the simpler videos, as video play would not be interrupted by video pause. Sequentiality would show iterative cycles of play and pause for content videos but not for introduction and summary videos, as engagement with these videos would be play video only. This example indicates that both sequentiality as well as temporality, while different in focus, allow for the measurement of changes in learner behavior over time. These changes in behavior may be helpful in designing successful personalized SRL support for learners. For instance, learners who engage in a course on a regular basis during the first weeks, but then stop engaging, may need support to keep them on track. We will come back to these questions concerning the design of SRL support later.

In Chapter 4, we studied how learners' SRL relates to learners' overt learner behavior. In this study, we conducted temporal analysis in the form of sequentiality. We showed that SRL influences students' learning processes at a broad granularity. The examples described above indicate that learners' SRL may also influence the temporality of learner behavior as well as the sequentiality of learner behavior at a smaller granularity. These forms of temporal analysis could thus improve our understanding of the influence of SRL on learner behavior. Thereby, theoretical knowledge on the influence of SRL on learner behavior would be expanded. Furthermore, if stable connections between SRL and learner behavior can be established, then this behavior could be used as a proxy for learners' SRL in the future.

In Chapter 5, we used learners' trace data to calculate variables indicative of SRL activities. By calculating variables from the trace data, we ignored the temporal aspects of learner behavior that were stored in the data. Analysis of the temporal information would have allowed us to look for changes in learner behavior before and after learners' exposure to the SRL intervention. This is particularly interesting in intervention studies conducted in open online education, as the timing of learners' engagement with the intervention was not set. The implementation of the intervention at the end of weeks 1, 2, and 3 of the MOOC makes it probable that learners engaged with the intervention videos at the start of their learning process. However, learners were free to move through the course at any pace and in any order they liked. It is therefore possible that some learners first engaged with all regular learning materials, and afterwards watched the intervention videos. With temporal analyses, the timing of learners' engagement with the intervention videos could have been established. Analysis of the sequentiality and temporality of learner behavior would furthermore have allowed us to answer additional questions regarding the influence of the SRL intervention on learners' SRL activities.

Concerning sequentiality, we attempted to analyze how learners continued with learning after failing a quiz (sequentiality). However, since only few learners failed a quiz, there was too little data available to analyze the effects of the SRL intervention on how learners handled failing a quiz. It may be possible to identify other sequences in learners' activities that are indicative of SRL activity. For instance, Kizilcec et al. (2017) reported that learners high in SRL were more inclined to revisit materials compared to learners low in SRL. With sequential temporal analysis, the impact of an SRL intervention on such behavioral sequences can be studied. Concerning temporality, we only analyzed whether learners completed the course materials, quizzes, and assignments on time to indicate learners' time management. However, it might have been possible to extract additional SRL variables from the trace data if more attention had been paid to the temporal information stored in the data. For instance, the duration of a video pause could provide an indication of the behavior engaged in by the learner: short pauses may have been used for note-taking (indicating comprehension monitoring), while longer pauses may indicate that the learner was engaged in an activity not related to the online learning environment.

Researchers increasingly use trace data when studying learning in online or blended education. However, in most cases, variables are calculated from the trace data. To fully exploit the research opportunities trace data have to offer, there is still much ground to cover concerning temporal analysis (Knight & Friend Wise, 2017). The suggestions for future research described above provide valuable ways in which the temporality and sequentiality of learner behavior can be studied to improve our understanding of learners'

SRL in open online education. Furthermore, to improve the clarity surrounding the measurement of the temporal dynamics of SRL, we recommend that researchers incorporate the terms *sequentiality* and *temporality* within their discourse (Van Laer & Elen, 2018).

A final limitation concerning the measurement of SRL we would like to note here, is that trace data analyses are always impacted by the decisions made by researchers. The analyses conducted in this dissertation are no exception. Trace data may appear objective, but the filtering of the data and the decisions on what traces to ignore or to group, and at which level, all influence the frequencies and sequences of activities in the resulting data set. Van Laer and Elen (2018) provided a clear call for a methodological framework on the use of trace data to measure SRL. We believe that in order to further the field and to improve our understanding of the impact of the decisions made during analyses, researchers should explain their decisions and report them transparently. We have attempted to do so throughout this dissertation by reporting our methodological decisions, as well as by providing the scripts used for data analysis as supplementary material. Only with transparent reporting, can we continuously refine our methodologies and improve our understanding of SRL research methods.

Overarching reflections

Within this dissertation we have studied SRL in open online education. In the previous sections we have presented our findings, and the limitations and implications of the conducted studies. At the end of this research project, we present our overarching impressions regarding the future of MOOCs and research on SRL support.

The future of MOOCs

The increase in MOOCs over the past decade has been accompanied by the promise that MOOCs were going to provide free, accessible education to all, thereby influencing educational equality around the world and providing new opportunities for lifelong learning (Friedman, 2013; Pappano, 2012). The hype was quickly followed by a call for more research on the MOOC phenomenon (Fischer, 2014). Over the past years, significant research has been conducted on MOOCs. The studies conducted within the SOONER research project provide prominent examples hereof (The Structuration of Open Online Education in the Netherlands; NWO funding 405-15-705). Now that the hype has subsided, and empirical evidence on the benefits and challenges of MOOCs at a micro, meso, and macro level is accumulating, researchers are starting to question the future of MOOCs in their current form (Reich & Ruipérez-Valiente, 2019). Enrollment numbers in MOOCs are decreasing and there still appears to be no profitable business model for the development of MOOCs by universities (Al-Imarah & Shields, 2018; Fischer, 2014; Pilli, Admiraal, & Salli, 2018; Reich & Ruipérez-Valiente, 2019). It therefore seems likely that something must, and will, change in the years to come.

In this dissertation, we focused on how learners self-regulate their learning process in open online education in order to deal with the autonomy offered to them. Throughout this dissertation we found that SRL support can be beneficial to improve learners' achievement and their course completion. Learners can thus benefit from SRL support. However,

the low intervention compliance reported in Chapter 5 indicates that supporting SRL will only lead to a small increase in the percentage of learners who complete MOOCs. Large numbers of learners did not engage with the MOOCs at all after enrollment, or they had already quit the MOOCs before they encountered the SRL intervention. Thus, while SRL can be considered an obstacle for learners in open online education, SRL interventions will probably not lead to drastic increases in the numbers of learners completing MOOCs. As a result, SRL support will likely only lead to a small increase in the number of course certificates sold. This increase in revenue from sold certificates will be too small to make the selling of course certificates a profitable business model for MOOCs. MOOC producers will therefore likely resort to other ways to make the development of MOOCs profitable.

A possible solution is the integration of online courses in traditional curricula (Fox, 2013; Reich & Ruipérez-Valiente, 2019; UNESCO Institute for Information Technologies in Education, 2013). Increasingly, MOOCs are offered in the form of SPOCs and are thereby integrated in traditional, campus-based, curricula (White, Davis, Dickens, León, & Sánchez-Vera, 2015). SPOC learners receive credits if they successfully complete the course exam. SPOCs may thereby, for instance, offer a flexible way for learners to gain elective credits. In Chapter 6 we studied how several SPOC learners regulated their learning. The integration of MOOCs into traditional campus curricula can be done without conflict to the open nature of MOOCs, as courses may be offered both fully open online and have a separate track for private learners.

The inclusion of MOOCs into traditional curricula influences MOOCs at a macro (organizational) level. This transition will also influence the micro (learner) level. If MOOCs are incorporated in traditional curricula, then learners are accredited if they complete the course. Accreditation of MOOCs may also be provided by employers if MOOCs are incorporated in workplace training programs. The provision of accreditation will provide learners with a clear incentive to finish the course successfully, thereby increasing learners' external motivation to complete the online course. However, even though learners will be more motivated to complete the course, they will likely still struggle to engage in adequate SRL. Learners' struggles to adequately regulate their learning are not unique to open online education, and the autonomy offered to learners will mostly stay intact in SPOCs. We already saw indications of this in the interviews presented in Chapter 6, in which learners reported that they sometimes struggled to regulate their learning in the SPOCs, even though they were motivated to obtain the elective credits.

To conclude, MOOCs will likely be more integrated in traditional curricula in the future. Successful completion of online courses will thereby become more important than it is nowadays, as quitting a course will no longer be without consequences. Thereby, the need for learners to self-regulate their learning in online education will become even more vital. Since learners' need for help to engage in adequate SRL will remain, the implementation of SRL support will remain an important research topic in the future. In the next section, we reflect on SRL support research and present various directions for future research.

Supporting SRL

The results of the literature review presented in Chapter 2 present a clear indication of learners' need for SRL support: SRL is correlated with achievement, and SRL interventions improve both learners' SRL activity as well as their achievement. The review has

thereby confirmed and extended existing SRL research showing the importance of SRL for achievement, and the effectiveness of SRL interventions on SRL and achievement at all educational levels (e.g., Boer, Donker-Bergstra, Kostons, & Korpershoek, 2013; Broadbent & Poon, 2015; Dignath, Buettner, & Langfeldt, 2008; Dignath & Büttner, 2008; Hattie, Biggs, & Purdie, 1996). The difficulties learners often have with SRL (e.g., Bol & Garner, 2011), combined with the importance of SRL for achievement and the impact of SRL interventions, provide a clear answer to the question why learners should be offered SRL support. There also is a vast amount of research on the design of SRL interventions. However, the results of these studies are less clear-cut. In this section we identify several facets of SRL intervention design in need of more systematic research. Greater scientific clarity on these aspects of SRL interventions would support educational designers in developing more effective SRL support tools. In the paragraphs below, we reflect on aspects of SRL support that re-occurred throughout the studies in this dissertation, namely the content of the intervention, the influence of learner characteristics, identifying those in need of support, the implementation of SRL support, and the timing of SRL support. After considering these aspects, we end with a section about the possibilities and challenges of providing personalized and adaptive SRL support.

Content of the intervention

SRL support can come in a large variety of shapes and sizes. What kind of support to offer to learners is the most explored aspect of SRL interventions in review studies. Reviews for instance explore the effect of providing SRL instruction or prompts and the effect of the theoretical model the intervention is based on. The importance of providing students with knowledge on self-regulatory strategies and their benefits has been reported for SRL interventions in primary and secondary education (Boer et al., 2013; Dignath et al., 2008; Dignath & Büttner, 2008). In our review on SRL support in higher education, we could not identify intervention design factors that significantly influenced the effects of SRL interventions on either SRL activity or on achievement. However, the results of the SRL intervention study presented in Chapter 5 suggest that SRL instruction is equally important in open online education as it is in primary and secondary education. Yet, more systematic research on what makes an SRL intervention effective in open online education is necessary. Questions to be answered include: Do learners in online education also benefit from SRL instruction? What is the minimal duration of an SRL intervention? And is the support of some SRL activities more beneficial for achievement than the support of other activities? When studying SRL support in open online education, researchers should take into account that part of learners' self-regulation in open online education takes place outside of the online learning environment. Time management and sufficiently prioritizing work in an online course are such SRL activities that are conducted outside of the online learning environment. These activities are considered the biggest challenges for learners to overcome for successful online learning (Eriksson, Adawi, & Stöhr, 2017; Hew & Cheung, 2014; Zheng, Rosson, Shih, & Carroll, 2015).

Influence of learner characteristics

What kind of SRL intervention is effective in improving learners' achievement and learners' SRL activity may be intertwined with the question who is supported. That is, what SRL intervention is most effective is likely depends on characteristics of the learners (i.e., aptitude-treatment interactions; Snow, 1991). This question is especially critical in open online education, as the learners enrolling in this type of education are known to be highly heterogeneous in their characteristics (Breslow et al., 2013; Kizilcec, Piech, &

Schneider, 2013; Li, 2019). Already in 1990, Zimmerman & Martinez-Pons reported significant relationships between learner characteristics (i.e., age, gender, and giftedness) and SRL. Furthermore, the influence of learner characteristics in the form of internal factors is described in several SRL models (cf., Boekaerts, 1992; Winne & Hadwin, 1998; Zimmerman, 2002). Nevertheless, there is little research on the influence of learner characteristics on the effectiveness of SRL interventions in online education (Wong et al., 2019). The results of studies that are available indicate that learner factors can markedly influence the effects of SRL interventions. Learner factors such as goal orientation (Duffy & Azevedo, 2015), prior knowledge (Yeh, Chen, Hung, & Hwang, 2010), cognitive ability, and self-efficacy (Sitzmann et al., 2009) have been found to influence the effectiveness of SRL interventions on achievement. Additionally, interventions that are effective for some learners may even decrease the performance of others, as was found by Pieger and Bannert (2018): while text learning was improved with the inclusion of metacognitive prompts for learners low in reading competence, text learning was impeded by metacognitive prompts for learners high in reading competence.

Cognitive load theory may present a theoretical framework helpful in explaining the differential effects of SRL interventions for various learners (De Bruin & Van Merriënboer, 2017). The necessity to engage in SRL activities to regulate the learning process induces extraneous load in learners. SRL support tools are developed to help learners with their self-regulation and thereby to reduce cognitive load. However, if learners find the learning task itself already challenging, then engagement with SRL support may overload their working memory and thereby deteriorate performance. SRL support may thereby only be beneficial for learners with sufficient cognitive resources available. Cognitive load theory would predict that learners with insufficient cognitive resources to engage with SRL support, may be better off without SRL support, or in a learning environment that itself is more regulated. Learners would then be able to expend all their efforts on understanding the learning material. In sum, cognitive load theory contains interesting links to SRL research, and SRL support research. Cognitive load theory may be useful in interpreting the findings of SRL support studies, as well as provide interesting further research ideas (De Bruin & Van Merriënboer, 2017; Sweller, Van Merriënboer, & Paas, 2019).

Identifying those in need of support

In order to provide learners with adequate SRL support, it must be determined which learners should be supported. Not all learners are in need of support; some learners are able to adequately regulate their learning (see Chapter 4 in this dissertation; Barnard-Brak, Lan, & Paton, 2010). According to the expertise-reversal effect, these learners may only be frustrated and distracted by SRL support (Clarebout, Horz, Schnotz, & Elen, 2010). The expertise reversal effect is built on cognitive load theory. It states that cognitive support may have differential effects based on learners' prior knowledge: while support is beneficial for learners low in prior knowledge, the support is redundant for learners high in prior knowledge and only overloads their working memory (Schnotz, 2010). Such an expertise reversal effect may also exist for SRL support. This would mean that learners with insufficient SRL skills benefit from SRL support, while learners who are capable of accurately regulating their learning are impeded by SRL support. Support is distracting from the learning task for adequate self-regulated learners. If an expertise reversal effect exists for SRL support, then the effects of SRL support would differ between learners high and low in SRL skills.

Within open online education, dropout may provide an answer to who is in need of support. Some consider early course dropout an indicator of learners' need of SRL support (e.g., Kim et al., 2017). However, learners in open online education differ drastically in their course intentions (DeBoer, Ho, Stump, & Breslow, 2014; Henderikx, Kreijns, & Kalz, 2017; Milligan & Littlejohn, 2017). Intentions may range from just wanting to see what a MOOC is, to completing all assignments and obtaining the MOOC certificate. The diversity in learner intentions might make it necessary to distinguish subgroups of learners. Broadly speaking, two groups of learners may be identified within the group of learners that drops out of the MOOC early. For one group of learners, quitting the course may be a deliberate decision. For example, because the course did not fit with their expectations or because they learned what they wanted to. Another group of learners however, may quit because they struggled to adequately regulate their learning. For these learners, their inability to self-regulate their learning may impede them from accomplishing their course intention. For this second group of learners, SRL support may be beneficial. The likely existence of such subgroups of learners has several implications. First, not all learners are in need of nor interested in SRL support. The development of personalized support may therefore be worthwhile. Personalized support would enable supporting learners who are willing to receive support, while not unnecessarily overloading other learners. Second, if the group of learners that quits deliberately is large, then the effects of an SRL intervention implemented in a MOOC will underestimate the true benefits of the intervention for learners in need of support.

The implementation of SRL support

After determining who needs what kind of support, the question becomes how to present the SRL support to learners: embedded or non-embedded (Clarebout & Elen, 2006). Learners are often inaccurate in determining their support needs and thereby often make insufficient use of support that is offered (Clarebout & Elen, 2006; Clarebout et al., 2010; Narciss, Proske, & Koerndle, 2007). Requiring learners to engage with support tools however leads to more superficial use of the support. In turn, low quality support use leads to less favorable effects on learning outcomes compared to high quality support use (Clarebout et al., 2010). Requiring learners to engage with SRL support tools may furthermore induce extraneous, redundant cognitive load in learners who do not need the support. The performance of high SRL learners would then be impeded by embedded support. More research is therefore needed to find the right balance on how to offer support tools to learners.

Support can be offered not only in a variety of ways, but also in a variety of locations. Where to offer SRL support to learners therefore needs consideration. For instance, SRL support in online education has been offered through e-mail (e.g., Hodges & Kim, 2010; Kizilcec, Schneider, Cohen, & McFarland, 2014), in a pre-course survey (e.g., Kizilcec, Pérez-Sanagustín, & Maldonado, 2016; Yeomans & Reich, 2017), or embedded in the course (e.g., Chapter 5 of this dissertation; Davis, Triglianos, Hauff, & Houben, 2018). It is likely that most learners are reached by the intervention, if the intervention is embedded in the course. Yet, even with an embedded intervention, our study presented in Chapter 5 showed it is hard (if not impossible) to reach all those in need and willing to receive support. Some of the learners who would have benefitted from SRL support to (better) achieve their course intention had already dropped out of the course before encountering the support. The low compliance that we reported for our SRL intervention highlights the difficulty educators face when trying to support learners in online education.

Where to implement SRL support is further complicated by the variety of ways learners can progress through an online course. In open online education, learners have the freedom to decide on the order in which they engage with course materials. That is, while a course structure is often present which learners mostly adhere to (as presented in Chapter 4), there also is great diversity in the ways in which learners engage with online learning materials, both in amount and in order (e.g., Goda et al., 2015; Jovanović, Gašević, Dawson, Pardo, & Mirriahi, 2017; Maldonado-Mahauad, Pérez-Sanagustín, Kizilcec, Morales, & Munoz-Gama, 2018). The variability in the ways in which MOOC learners engage with the course content, makes it even more challenging to determine where to implement SRL support. We proposed to implement support at enrollment, since this would enable presentation of the SRL support to all learners. This is however only a suggestion; and where to implement an intervention should be studied further in the future.

The timing of SRL support

A final consideration when implementing an SRL intervention is the timing of the support. Cognitive load theory does not provide an unequivocal answer to the question when to offer support. Instructional design models based on cognitive load theory distinguish two types of information (Sweller et al., 2019; Van Merriënboer, Kirschner, & Kester, 2003). The first is procedural information. This information helps learners perform the recurrent aspects of learning tasks. The second type of information is supportive information. Supportive information consists of specific instructions for non-recurrent tasks. General SRL support resembles procedural information, for which cognitive load theory describes that it can best be offered to learners at the moment they should engage in the activity. However, prompting learners to engage in specific SRL activities shows more resemblance with supportive information than with procedural information. SRL support focused on specific SRL activities may therefore better be offered before the start of a task (Sweller et al., 2019; Van Merriënboer et al., 2003).

Research on productive failure provides an alternative framework for analyzing when to offer support to learners (Kapur, 2008). Productive failure implies that learners are more receptive to cognitive instruction after they failed to solve a problem on their own. When learners attempt, and fail, to solve a problem, they become aware of the gaps in their knowledge. Learners' awareness of knowledge gaps helps them focus on relevant parts of instruction that is offered later (Glogger-Frey, Gaus, & Renkl, 2017; Kapur, 2008). A similar mechanism may be in play for SRL support. It seems reasonable that learners would be more accepting of SRL support after struggling to self-regulate their learning and thereby failing to achieve their aims. Failure might make learners realize that they cannot sufficiently regulate their learning, and therefore make learners more receptive to SRL support. Sitzmann et al. (2009) studied the difference in effects of SRL prompts offered from the start of a 10-week course and SRL prompts offered from week five onwards. While the results did not indicate significant differences in achievement between learners who received immediate and delayed prompts, the authors did accentuate a question surrounding SRL support that has not yet been answered: when to offer SRL support. The analysis of differences in learners' SRL over time – both in sequentiality as well as in temporality – may be helpful to identify when learners need support (Molenaar & Järvelä, 2014; Sonnenberg & Bannert, 2016).

Personalized and adaptive support

The reflections described above indicate that what constitutes an effective SRL intervention design varies greatly between learners. The diversity in SRL interventions necessary to benefit all learners implicates the need for personalized and adaptive support. The automatic and real time collection of trace data might in the future enable offering learners in online education such individualized support (Azevedo & Aleven, 2013; Sonnenberg & Bannert, 2016). While we are aware of the challenges of using trace data to measure learners' SRL (see Chapter 6), trace data will likely be a proxy for at least some SRL activities in the future.

Based on our reflections on SRL support research, we identify three levels at which support could be personalized and adaptive. First, support could be personalized from the start of learning (e.g., Yeh et al., 2010). Learners could for instance be offered personalized support based on differences in their characteristics, such as prior knowledge and SRL skills. Second, support could be adapted based on learners' activities in the course environment (e.g., Azevedo, Cromley, Moos, Greene, & Winters, 2011; Davis et al., 2018; Puntambekar, Sullivan, & Hübscher, 2013). For instance, the kind of support offered may be adapted to stimulate engagement in activities the learner does not (yet) engage in. Finally, support could be adapted based on changes in learners' activities (e.g., Molenaar & Roda, 2008). Support may be offered in reaction to alterations in the temporal or sequential characteristics of learners' activities. Hereby, it might be possible to identify learners in need of support automatically and to adapt the offered support to their needs. In sum, the past decades of research on SRL have left us with an abundance of studies on the necessity of SRL for achievement and on the effects of SRL support. Nevertheless, there is also still much ground to cover, especially when considering the broad range of new opportunities offered by the digitalization of education. If better answers to the questions posed can be formulated, the impact of SRL research on educational practice will be improved.

Conclusion

The studies presented in this dissertation have, individually and altogether, improved our understanding of SRL in open online education. We have developed new research methods to study SRL in this online context. We have utilized these methods, analyzing questionnaire, trace, and interview data, to better understand learners' needs for SRL support. The results of our studies have (a) indicated how covert SRL and overt learner behavior are connected, (b) provided evidence for the importance of SRL support, and (c) shown that SRL support implemented in open online education is indeed effective in supporting learners' SRL and their course completion. Our studies have thereby provided valuable insights both for practice and for research. We have identified various interesting directions for future research, as we acknowledge that there is still much work to be conducted to fully understand the workings of SRL support in open online education. The research presented here indicates the value of this emerging field and provides a fruitful base for others to build upon.

R

References

List of supplementary materials

All references included in the meta-analyses presented in Chapter 2 are marked with an asterisk (*).

*Abd-El-Fattah, S. M. (2010). Garrison's model of self-directed learning: Preliminary validation and relationship to academic achievement. *The Spanish Journal of Psychology, 13,* 586–596. https://doi.org/10.1017/S1138741600002262

*Agustiani, H., Cahyad, S., & Musa, M. (2016). Self-efficacy and self-regulated learning as predictors of students academic performance. *The Open Psychology Journal, 9,* 1–6. https://doi.org/10.2174/1874350101609010001

Al-Imarah, A. A., & Shields, R. (2018). MOOCs, disruptive innovation and the future of higher education: A conceptual analysis. *Innovations in Education and Teaching International,* 1–12. https://doi.org/10.1080/14703297.2018.1443828

Allen, I. E., & Seaman, J. (2014). *Grade change: tracking online education in the United States.* Babson Survey Research Group.

Allen, I. E., & Seaman, J. (2016). *Online report card: Tracking online education in the United States.* Babson Survey Research Group.

Alshenqeeti, H. (2014). Interviewing as a data collection method: A critical review. *English Linguistics Research, 3*(1). https://doi.org/10.5430/elr.v3n1p39

*Anderton, B. (2006). Using the online course to promote self-regulated learning strategies in pre-service teachers. *Journal of Interactive Online Learning, 5,* 156–177.

*Aregu, B. B. (2013). Enhancing self-regulated learning in teaching spoken communication: Does it affect speaking efficacy and performance? *Electronic Journal of Foreign Language Teaching, 10,* 96–109.

Artino, A. (2007). Self-regulated learning in online education: A review of the empirical literature. *International Journal of Instructional Technology and Distance Learning, 4*(6), 3–18.

*Artino, Anthony R., Dong, T., DeZee, K. J., Gilliland, W. R., Waechter, D. M., Cruess, D., & Durning, S. J. (2012). Achievement goal structures and self-regulated learning: Relationships and changes in medical school. *Academic Medicine, 87,* 1375–1381. https://doi.org/10.1097/ACM.0b013e3182676b55

Artino, A. R. (2008). Motivational beliefs and perceptions of instructional quality: predicting satisfaction with online training: Predicting satisfaction with online training. *Journal of Computer Assisted Learning, 24*(3), 260–270. https://doi.org/10.1111/j.1365-2729.2007.00258.x

Artino, A. R., & Stephens, J. M. (2006). Learning online: Motivation to self-regulate? *Academic Exchange Quarterly, 10,* 176–182.

Azevedo, R. (2005). Using hypermedia as a metacognitive tool for enhancing student learning? The role of self-regulated learning. *Educational Psychologist, 40*(4), 199–209. https://doi.org/10.1207/s15326985ep4004_2

Azevedo, R., & Aleven, V. (2013). Metacognition and learning technologies: An overview of current interdisciplinary research. In R. Azevedo & V. Aleven (Eds.), *International Handbook of Metacognition and Learning Technologies* (pp. 1–16).

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

*Azevedo, R., Cromley, J. G., Moos, D. C., Greene, J. A., & Winters, F. I. (2011). Adaptive content and process scaffolding: A key to facilitating students' self-regulated learning with hypermedia. *Psychological Test and Assessment Modeling, 53,* 106–140.

*Azevedo, R., Cromley, J. G., & Seibert, D. (2004). Does adaptive scaffolding facilitate students' ability to regulate their learning with hypermedia? *Contemporary Educational Psychology, 29,* 344–370. https://doi.org/10.1016/j.cedpsych.2003.09.002

Azevedo, R., Harley, J., Trevors, G., Duffy, M., Feyzi-Behnagh, R., Bouchet, F., & Landis, R. S. (2013). Using trace data to examine the complex roles of cognitive, metacognitive, and emotional self-regulatory processes during learning with multi-agent systems. In R. Azevedo & V. Aleven (Eds.), *International handbook of metacognition and learning technologies* (pp. 427–449). New York: Springer.

*Backhaus, K., & Liff, J. P. (2007). Cognitive styles and approaches to studying in management education. *Journal of Management Education, 31,* 445–466. https://doi.org/10.1177/1052562905284674

*Bakracevic Vukman, K., & Licardo, M. (2010). How cognitive, metacognitive, motivational and emotional self-regulation influence school performance in adolescence and early adulthood. *Educational Studies, 36,* 259–268. https://doi.org/10.1080/03055690903180376

Bandura, A. (1994). Self-efficacy. In V. S. Ramachaudran (Ed.), *Encyclopedia of human behavior* (pp. 71–81). New York: Academic Press.

Bank, B. J., Slavings, R. L., & Biddle, B. J. (1990). Effects of peer, faculty, and parental influences on students' persistence. *Sociology of Education, 63*(3), 208. https://doi.org/10.2307/2112838

Banks, G. C., Kepes, S., & Banks, K. P. (2012). Publication bias: The antagonist of meta-analytic reviews and effective policymaking. *Educational Evaluation and Policy Analysis, 34,* 259–277. https://doi.org/10.3102/0162373712446144

*Bannert, M. (2006). Effects of reflection prompts when learning with hypermedia. *Journal of Educational Computing Research, 35,* 359–375. https://doi.org/10.2190/94V6-R58H-3367-G388

*Bannert, M., Hildebrand, M., & Mengelkamp, C. (2009). Effects of a metacognitive support device in learning environments. *Computers in Human Behavior, 25,* 829–835. https://doi.org/10.1016/j.chb.2008.07.002

*Bannert, M., & Reimann, P. (2012). Supporting self-regulated hypermedia learning through prompts. *Instructional Science, 40,* 193–211. https://doi.org/10.1007/s11251-011-9167-4

Bannert, M., Reimann, P., & Sonnenberg, C. (2014). Process mining techniques for analysing patterns and strategies in students' self-regulated learning. *Metacognition and Learning, 9,* 161–185. https://doi.org/10.1007/s11409-013-9107-6

*Bannert, M., Sonnenberg, C., Mengelkamp, C., & Pieger, E. (2015). Short- and long-term effects of students' self-directed metacognitive prompts on navigation behavior and learning performance. *Computers in Human Behavior, 52,* 293–306. https://doi.org/10.1016/j.chb.2015.05.038

Barnard, L., Lan, W. Y., To, Y. M., Paton, V. O., & Lai, S.-L. (2009). Measuring self-regulation in online and blended learning environments. *The Internet and Higher Education, 12*(1), 1–6. https://doi.org/10.1016/j.iheduc.2008.10.005

Barnard-Brak, L., Lan, W., & Paton, V. O. (2010). Profiles in self-regulated learning in the online learning environment. *International Review of Research in Open and Distance Learning, 11*(1), 61–79.

*Bartels, J. M., & Magun-Jackson, S. (2009). Approach–avoidance motivation and metacognitive self-regulation: The role of need for achievement and fear of failure. *Learning and Individual Differences, 19,* 459–463. https://doi.org/10.1016/j.lindif.2009.03.008

*Becker, L. L. (2013). Self-regulated learning interventions in the introductory accounting course: An empirical study. *Issues in Accounting Education, 28,* 435–460. https://doi.org/10.2308/iace-50444

Beishuizen, J., & Steffens, K. (2011). A conceptual framework for research on self-regulated learning. In R. Carneiro, P. Lefrere, K. Steffens, & J. Underwood (Eds.), *Self-Regulated Learning in Technology Enhanced Learning Environments* (pp. 3–19). Rotterdam, The Netherlands: Sense Publishers.

*Belski, R., & Belski, I. (2014). Cultivating student skills in self-regulated learning through evaluation of task complexity. *Teaching in Higher Education, 19,* 459–469. https://doi.org/10.1080/13562517.2014.880685

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

*Ben-Eliyahu, A., & Linnenbrink-Garcia, L. (2015). Integrating the regulation of affect, behavior, and cognition into self-regulated learning paradigms among secondary and post-secondary students. *Metacognition and Learning, 10,* 15–42. https://doi.org/10.1007/s11409-014-9129-8

*Bergin, S., Reilly, R., & Traynor, D. (2005). Examining the role of self-regulated learning on introductory programming performance. *Proceedings of the first international workshop on Computing Education Research,* 81–86. https://doi.org/10.1145/1089786.1089794

*Berthold, K., Nückles, M., & Renkl, A. (2007). Do learning protocols support learning strategies and outcomes? The role of cognitive and metacognitive prompts. *Learning and Instruction, 17*(5), 564–577. https://doi.org/10.1016/j.learninstruc.2007.09.007

Bertrams, A., & Schmeichel, B. J. (2014). Improving self-control by practicing logical reasoning. *Self and Identity, 13,* 419–431. https://doi.org/10.1080/15298868.2013.836562

Boekaerts, M. (1992). The adaptable learning process: Initiating and maintaining behavioural change. *Applied Psychology: An International Review, 41,* 377–397.

Boer, H. de, Donker-Bergstra, A. S., Kostons, D. D. N. M., & Korpershoek, H. (2013). *Effective strategies for self-regulated learning: a meta-analysis.* Groningen: GION/RUG.

*Bol, L., Campbell, K. D. Y., Perez, T., & Yen, C.-J. (2016). The effects of self-regulated learning training on community college students' metacognition and achievement in developmental math courses. *Community College Journal of Research and Practice, 40,* 480–495. https://doi.org/10.1080/10668926.2015.1068718

Bol, L., & Garner, J. K. (2011). Challenges in supporting self-regulation in distance education environments. *Journal of Computing in Higher Education, 23*(2–3), 104–123. https://doi.org/10.1007/s12528-011-9046-7

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (Eds.). (2009). *Introduction to meta-analysis.* Chichester, UK: Wiley.

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2014). *Comprehensive Meta Analysis Version 3.* Englewood, NJ, USA: Biostat.

Breslow, L., Pritchard, D. E., DeBoer, J., Stump, G. S., Ho, A. D., & Seaton, D. T. (2013). Studying learning in the worldwide classroom: research into edX's first MOOC. *Research & Practice in Assessment, 8,* 13–25.

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

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

Burke, L. A., & Hutchins, H. M. (2007). Training transfer: An integrative literature review. *Human Resource Development Review, 6,* 263–296. https://doi.org/10.1177/1534484307303035

*Carson, A. D. (2011). Predicting student success from the LASSI for Learning Online (LLO). *Journal of Educational Computing Research, 45,* 399–414. https://doi.org/10.2190/EC.45.4.b

*Chacko, S. B. (1989). *Cognitive abilities, affective characteristics and learning strategies as related to academic achievement among first year nursing students: test validation and causal modelling* (Doctoral dissertation). Retrieved from Retrospective Theses and Dissertations. (9113)

*Chang, M.-M. (2007). Enhancing web-based language learning through self-monitoring. *Journal of Computer Assisted Learning, 23,* 187–196. https://doi.org/10.1111/j.1365-2729.2006.00203.x

*Chen, A. (2010). Effects of listening strategy training for EFL adult listeners. *The Journal of ASIA TEFL, 7,* 135–169.

*Cheng, G., & Chau, J. (2013). Exploring the relationship between students' self-regulated learning ability and their ePortfolio achievement. *Internet and Higher Education, 17,* 9–15. https://doi.org/10.1016/j.iheduc.2012.09.005

Cheung, M. W.-L. (2014). Fixed- and random-effects meta-analytic structural equation modeling: Examples and analyses in R. *Behavior Research Methods, 46*, 29–40. https://doi.org/10.3758/s13428-013-0361-y

Cheung, M. W.-L. (2015). metaSEM: An R package for meta-analysis using structural equation modeling. *Frontiers in Psychology, 5*. https://doi.org/10.3389/fpsyg.2014.01521

Cho, M.-H., & Summers, J. (2012). Factor validity of the motivated strategies for learning questionnaire (MSLQ) in asynchronous online learning environments (AOLE). *Journal of Interactive Learning Research, 32*(1), 5–28.

Chung, L.-Y. (2015). Exploring the effectiveness of self-regulated learning in massive open online courses on non-native English speakers. *International Journal of Distance Education Technologies, 13*(3), 61–73. https://doi.org/10.4018/IJDET.2015070105

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

Clarebout, G., & Elen, J. (2006). Tool use in computer-based learning environments: towards a research framework. *Computers in Human Behavior, 22*, 389–411. https://doi.org/10.1016/j.chb.2004.09.007

Clarebout, G., Horz, H., Schnotz, W., & Elen, J. (2010). The relation between self-regulation and the embedding of support in learning environments. *Educational Technology Research and Development, 58*, 573–587. https://doi.org/10.1007/s11423-009-9147-4

*Cleary, T. J., Callan, G. L., Malatesta, J., & Adams, T. (2015). Examining the level of convergence among self-regulated learning microanalytic processes, achievement, and a self-report questionnaire. *Journal of Psychoeducational Assessment, 33*, 439–450. https://doi.org/10.1177/0734282915594739

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. New Jersey, NJ: Lawrence Erlbaum Associates.

*Coutinho, S. A., & Neuman, G. (2008). A model of metacognition, achievement goal orientation, learning style and self-efficacy. *Learning Environments Research, 11*, 131–151. https://doi.org/10.1007/s10984-008-9042-7

Credé, M., & Phillips, L. A. (2011). A meta-analytic review of the Motivated Strategies for Learning Questionnaire. *Learning and Individual Differences, 21*(4), 337–346. https://doi.org/10.1016/j.lindif.2011.03.002

Creswell, J. W. (2008). Mixed methods designs. In *Educational research: Planning, conducting, and evaluating quantitative and qualitative research* (pp. 551–595). New Jersey, NJ: Pearson Education International.

Davis, D., Chen, G., Van der Zee, T., Hauff, C., & Houben, G.-J. (2016). *Retrieval practice and study planning in MOOCs: Exploring classroom-based self-regulated learning strategies and scale*. 57–71.

Davis, D., Triglianos, V., Hauff, C., & Houben, G.-J. (2018). SRLx: A personalized learner interface for MOOCs. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong Technology-Enhanced Learning* (Vol. 11082, pp. 122–135). https://doi.org/10.1007/978-3-319-98572-5_10

De Bruijn-Smolders, M., Timmers, C. F., Gawke, J. C. L., Schoonman, W., & Born, M. Ph. (2016). Effective self-regulatory processes in higher education: research findings and future directions. A systematic review. *Studies in Higher Education, 41*, 139–158. https://doi.org/10.1080/03075079.2014.915302

De Bruin, A. B. H., & Van Merriënboer, J. J. G. (2017). Bridging cognitive load and self-regulated learning research: A complementary approach to contemporary issues in educational research. *Learning and Instruction, 51*, 1–9. https://doi.org/10.1016/j.learninstruc.2017.06.001

Deal III, W. F. (2002). Distance learning: Teaching technology online. *The Technology Teacher, 61*(8), 21–26.

DeBoer, J., Ho, A. D., Stump, G. S., & Breslow, L. (2014). Changing "course": Reconceptualizing educational variables for massive open online courses. *Educational Researcher, 43*(2), 74–84. https://doi.org/10.3102/0013189X14523038

*Delen, E., Liew, J., & Willson, V. (2014). Effects of interactivity and instructional scaffolding on learning: Self-regulation in online video-based environments. *Computers & Education, 78*, 312–320. https://doi.org/10.1016/j.compedu.2014.06.018

Deng, R., Benckendorff, P., & Gannaway, D. (2019). Progress and new directions for teaching and learning in MOOCs. *Computers & Education, 129*, 48–60. https://doi.org/10.1016/j.compedu.2018.10.019

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

Devolder, A., Van Braak, J., & Tondeur, J. (2012). Supporting self-regulated learning in computer-based learning environments: Systematic review of effects of scaffolding in the domain of science education. *Journal of Computer Assisted Learning, 28*, 557–573. https://doi.org/10.1111/j.1365-2729.2011.00476.x

DiCicco-Bloom, B., & Crabtree, B. F. (2006). The qualitative research interview. *Medical Education, 40*(4), 314–321. https://doi.org/10.1111/j.1365-2929.2006.02418.x

Dignath, C., Buettner, G., & Langfeldt, H.-P. (2008). How can primary school students learn self-regulated learning strategies most effectively? *Educational Research Review, 3*, 101–129. https://doi.org/10.1016/j.edurev.2008.02.003

Dignath, C., & Büttner, G. (2008). Components of fostering self-regulated learning among students. A meta-analysis on intervention studies at primary and secondary school level. *Metacognition and Learning, 3*, 231–264. https://doi.org/10.1007/s11409-008-9029-x

Dillon, C., & Greene, B. A. (2003). Learner differences in distance learning: Finding differences that matter. In M. G. Moore & W. G. Anderson (Eds.), *Handbook of distance education* (pp. 235–244). Mahwah, NJ, USA: Lawrence Erlbaum Associates.

Dirkx, K. J. H., Thoma, G.-B., Kester, L., & Kirschner, Paul. A. (2015). Answering questions after initial study guides attention during restudy. *Instructional Science, 43*(1), 59–71. https://doi.org/10.1007/s11251-014-9330-9

*Diseth, Å., & Kobbeltvedt, T. (2010). A mediation analysis of achievement motives, goals, learning strategies, and academic achievement. *British Journal of Educational Psychology, 80*, 671–687. https://doi.org/10.1348/000709910X492432

*Dörrenbächer, L., & Perels, F. (2016a). More is more? Evaluation of interventions to foster self-regulated learning in college. *International Journal of Educational Research, 78*, 50–65. https://doi.org/10.1016/j.ijer.2016.05.010

Dörrenbächer, L., & Perels, F. (2016b). Self-regulated learning profiles in college students: Their relationship to achievement, personality, and the effectiveness of an intervention to foster self-regulated learning. *Learning and Individual Differences, 51*, 229–241. https://doi.org/10.1016/j.lindif.2016.09.015

*Dousti, H., & Abolfathiasl, H. (2013). The effect of metacognitive listening strategy training on EFL learners' listening sub-skills performance. *International Journal of Applied Linguistics & English Literature, 2*(4), 50–55. https://doi.org/doi:10.7575/aiac.ijalel.v.2n.4p.50

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

Duncan, T. G., & McKeachie, W. J. (2005). The making of the motivated strategies for learning questionnaire. *Educational Psychologist, 40*(2), 117–128. https://doi.org/10.1207/s15326985ep4002_6

Dunlosky, J., & Lipko, A. R. (2007). Metacomprehension: A brief history and how to improve its accuracy. *Current Directions in Psychological Science, 16*(4), 228–232. https://doi.org/10.1111/j.1467-8721.2007.00509.x

Dunlosky, J., Rawson, K. A., Marsh, E. J., Nathan, M. J., & Willingham, D. T. (2013). Improving students' learning with effective learning techniques: Promising directions from cognitive and educational psychology. *Psychological Science in the Public Interest, 14*(1), 4–58. https://doi.org/10.1177/1529100612453266

Efklides, A. (2011). Interactions of metacognition with motivation and affect in self-regulated learning: The MASRL model. *Educational Psychologist, 46*, 6–25. https://doi.org/10.1080/00461520.2011.538645

*Elliot, A. J., McGregor, H. A., & Gable, S. (1999). Achievement goals, study strategies, and exam performance: A mediational analysis. *Journal of Educational Psychology, 91,* 549–563. https://doi.org/10.1037/0022-0663.91.3.549

Ericsson, K. A., & Simon, H. A. (1993). *Protocol analysis.* Cambridge, MA: MIT press.

Eriksson, T., Adawi, T., & Stöhr, C. (2017). "Time is the bottleneck": a qualitative study exploring why learners drop out of MOOCs. *Journal of Computing in Higher Education, 29*(1), 133–146. https://doi.org/10.1007/s12528-016-9127-8

*Fabriz, S., Dignath-Van Ewijk, C., Poarch, G., & Büttner, G. (2014). Fostering self-monitoring of university students by means of a standardized learning journal: A longitudinal study with process analyses. *European Journal of Psychology of Education, 29,* 239–255. https://doi.org/10.1007/s10212-013-0196-z

Feinstein, A. R., & Cicchetti, D. V. (1990). High agreement but low Kappa: I. the problems of two paradoxes. *Journal of Clinical Epidemiology, 43,* 543–549. https://doi.org/10.1016/0895-4356(90)90158-L

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th edition). Los Angeles London New Delhi Singapore Washington DC Melbourne: SAGE.

Fincham, O. E., Gasevic, D. V., Jovanovic, J. M., & Pardo, A. (2018). From study tactics to learning strategies: An analytical method for extracting interpretable representations. *IEEE Transactions on Learning Technologies, 12,* 59-72. https://doi.org/10.1109/TLT.2018.2823317

Fischer, G. (2014). Beyond hype and underestimation: identifying research challenges for the future of MOOCs. *Distance Education, 35*(2), 149–158. https://doi.org/10.1080/01587919.2014.920752

Fisher, Z., Tipton, E., & Zhipeng, H. (2017). robumeta: Robust Variance Meta-Regression (Version 2.0). Retrieved from https://CRAN.R-project.org/package=robumeta

*Ford, J. K., Smith, E. M., Weissbein, D. A., Gully, S. M., & Salas, E. (1998). Relationships of goal orientation, metacognitive activity, and practice strategies with learning outcomes and transfer. *Journal of Applied Psychology, 83,* 218–233.

Fox, A. (2013). From MOOCs to SPOCs. *Communications of the ACM, 56*(12), 38–40. https://doi.org/10.1145/2535918

Friedman, T. L. (2013, January 26). Revolution hits the universities. The New York Times. Retrieved from https://www.nytimes.com/2013/01/27/opinion/sunday/friedman-revolution-hits-the-universities.html

*Garavalia, L. S., & Gredler, M. E. (2002a). An exploratory study of academic goal setting, achievement calibration, and self-regulated learning. *Journal of Instructional Psychology, 29,* 221–230.

*Garavalia, L. S., & Gredler, M. E. (2002b). Prior achievement, aptitude, and use of learning strategies as predictors of college student achievement. *College Student Journal, 36,* 616–625.

Garrison, D. R. (2003). Self-directed learning and distance education. In M. G. Moore & W. G. Anderson (Eds.), *Handbook of distance education* (pp. 161–168). Mahwah, NJ, USA: Lawrence Erlbaum Associates.

Gatignon, H. (2010). Confirmatory factor analysis. In H. Gatignon (Ed.), *Statistical Analysis of Management Data* (pp. 59–122). New York, NY, USA: Springer Science+Business Media.

*Geddes, D. (2009). How am I doing? Exploring on-line gradebook monitoring as a self-regulated learning practice that impacts academic achievement. *Academy of Management Learning & Education, 8,* 494–510.

*Ghafournia, N., & Afghari, A. (2013). Relationship between reading proficiency, strategic competence, and reading comprehension test performance: A study of Iranian EFL learners. *International Education Studies, 6*(8), 21–30. https://doi.org/10.5539/ies.v6n8p21

Glogger-Frey, I., Gaus, K., & Renkl, A. (2017). Learning from direct instruction: Best prepared by several self-regulated or guided invention activities? *Learning and Instruction, 51,* 26–35. https://doi.org/10.1016/j.learninstruc.2016.11.002

Goda, Y., Yamada, M., Kato, H., Matsuda, T., Saito, Y., & Miyagawa, H. (2015). Procrastination and other learning behavioral types in e-learning and their relationship with learning outcomes. *Learning and Individual Differences, 37,* 72–80. https://doi.org/10.1016/j.lindif.2014.11.001

*González, A., & Paoloni, P.-V. (2015). Perceived autonomy-support, expectancy, value, metacognitive strategies and performance in chemistry: a structural equation model in undergraduates. *Chemistry Education Research and Practice, 16,* 640–653. https://doi.org/10.1039/C5RP00058K

*Greene, B. A., & Miller, R. B. (1996). Influences on achievement goals, perceived ability, and cognitive engagement. *Contemporary Educational Psychology, 21,* 181–192. https://doi.org/10.1006/ceps.1996.0015

*Greene, J. A., Hutchison, L. A., Costa, L.-J., & Crompton, H. (2012). Investigating how college students' task definitions and plans relate to self-regulated learning processing and understanding of a complex science topic. *Contemporary Educational Psychology, 37,* 307–320. https://doi.org/10.1016/j.cedpsych.2012.02.002

Greene, J. A., Oswald, C. A., & Pomerantz, J. (2015). Predictors of retention and achievement in a massive open online course. *American Educational Research Journal, 52*(5), 925–955. https://doi.org/10.3102/0002831215584621

Greene, J. A., & Azevedo, R. (2010). The measurement of learners' self-regulated cognitive and metacognitive processes while using computer-based learning environments. *Educational Psychologist, 45*(4), 203–209. https://doi.org/10.1080/00461520.2010.515935

*Guo, D. (2015). A study on promoting non-English major students' autonomous learning through metacognitive strategy training. *International Conference on Informatization in Education, Management and Business,* 307–311. Guangzhou, China.

*Gurung, R. A. R., Daniel, D. B., & Landrum, R. E. (2012). A multisite study of learning in introductory psychology courses. *Teaching of Psychology, 39,* 170–175. https://doi.org/10.1177/0098628312450428

*Hacker, D. J., Bol, L., & Bahbahani, K. (2008). Explaining calibration accuracy in classroom contexts: the effects of incentives, reflection, and explanatory style. *Metacognition and Learning, 3,* 101–121. https://doi.org/10.1007/s11409-008-9021-5

Hadwin, A. F., Nesbit, J. C., Jamieson-Noel, D., Code, J., & Winne, P. H. (2007). Examining trace data to explore self-regulated learning. *Metacognition and Learning, 2,* 107–124. https://doi.org/10.1007/s11409-007-9016-7

*Hall, C., Smith, K., & Chia, R. (2008). Cognitive and personality factors in relation to timely completion of a college degree. *College Student Journal, 42,* 1087–1098.

*Hardy, D. L. (2013). *Learning strategies and motivational patterns, as measured by the Motivated Strategies for Learning Questionnaire, among students pursuing nursing and allied health careers* (Doctoral dissertation). University of Akron, Akron, OH, USA.

Hartley, K., & Bendixen, L. D. (2001). Educational research in the internet age: Examining the role of individual characteristics. *Educational Researcher, 30*(9), 22–26. https://doi.org/10.3102/0013189X030009022

*Hartwig, M. K., Was, C. A., Isaacson, R. M., & Dunlosky, J. (2012). General knowledge monitoring as a predictor of in-class exam performance. *British Journal of Educational Psychology, 82,* 456–468. https://doi.org/10.1111/j.2044-8279.2011.02038.x

Hattie, J., Biggs, J., & Purdie, N. (1996). Effects of learning skills interventions on student learning: A meta-analysis. *Review of Educational Research, 66,* 99–136. https://doi.org/10.3102/00346543066002099

Hayton, J. C., Allen, D. G., & Scarpello, V. (2004). Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis. *Organizational Research Methods, 7*(2), 191–205. https://doi.org/10.1177/1094428104263675

Hedges, L. V., Tipton, E., & Johnson, M. C. (2010). Robust variance estimation in meta-regression with dependent effect size estimates. *Research Synthesis Methods, 1,* 39–65. https://doi.org/10.1002/jrsm.5

Henderikx, M. A., Kreijns, K., & Kalz, M. (2017). Refining success and dropout in massive open online courses based on the intention–behavior gap. *Distance Education, 38*(3), 353–368. https://doi.org/10.1080/01587919.2017.1369006

Hew, K. F., & Cheung, W. S. (2014). Students' and instructors' use of massive open online courses (MOOCs): Motivations and challenges. *Educational Research Review, 12,* 45–58. https://doi.org/10.1016/j.edurev.2014.05.001

Higgins, J. P. T., & Thompson, S. G. (2002). Quantifying heterogeneity in a meta-analysis. *Statistics in Medicine, 21,* 1539–1558. https://doi.org/10.1002/sim.1186

*Hodges, C. B., & Kim, C. (2010). Email, self-regulation, self-efficacy, and achievement in a college online mathematics course. *Journal of Educational Computing Research, 43,* 207–223. https://doi.org/10.2190/EC.43.2.d

*Hong, W. H., Vadivelu, J., Daniel, E. G. S., & Sim, J. H. (2015). Thinking about thinking: Changes in first-year medical students' metacognition and its relation to performance. *Medical Education Online, 20*(27561), 1–6. https://doi.org/10.3402/meo.v20.27561

Hooper, D., Coughlan, J., & Mullen, M. (2008). Structural equation modelling: Guidelines for determining model fit. *Electronic Journal of Business Research Methods, 6*(1), 53–60.

Howard-Rose, D., & Winne, P. H. (1993). Measuring component and sets of cognitive processes in self-regulated learning. *Journal of Educational Psychology, 85*(4), 591–604. https://doi.org/10.1037/0022-0663.85.4.591

Hox, J. J. (2010). The multilevel approach to meta-analysis. In *Quantitative Methodology Series. Multilevel analysis: techniques and applications* (2nd ed., pp. 205–232). New York, NY: Routledge.

*Hsu, L.-L., & Hsieh, S.-I. (2011). Factors associated with learning outcome of BSN in a blended learning environment. *Contemporary Nurse, 38,* 24–34. https://doi.org/10.5172/conu.2011.38.1-2.24

*Hu, H. (2007). *Effects of self-regulated learning strategy training on learners' achievement, motivation and strategy use in a web-enhanced instructional environment* (Doctoral dissertation). Retrieved from Florida State University Libraries. (3689)

*Ifenthaler, D. (2012). Determining the effectiveness of prompts for self-regulated learning in problem-solving scenarios. *Educational Technology & Society, 15,* 38–52.

Jak, S. (2015). *Meta-analytic structural equation modelling.* Springer International Publishing. https://doi.org/10.1007/978-3-319-27174-3

Jansen, R. S., Van Leeuwen, A., Janssen, J., & Kester, L. (2018). Validation of the revised self-regulated online learning questionnaire. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong Technology-Enhanced Learning* (Vol. 11082, pp. 116–121). https://doi.org/10.1007/978-3-319-98572-5_9

Jansen, R. S., Van Leeuwen, A., Janssen, J., Kester, L., & Kalz, M. (2017). Validation of the self-regulated online learning questionnaire. *Journal of Computing in Higher Education, 29,* 6–27. https://doi.org/10.1007/s12528-016-9125-x

Johnson, R. B., & Onwuegbuzie, A. J. (2004). Mixed methods research: A research paradigm whose time has come. *Educational Researcher, 33*(7), 14–26. https://doi.org/10.3102/0013189X033007014

Jordan, K. (2014). Initial trends in enrolment and completion of massive open online courses. *The International Review of Research in Open and Distributed Learning, 15*(1). https://doi.org/10.19173/irrodl.v15i1.1651

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

Kapur, M. (2008). Productive failure. *Cognition and Instruction, 26*(3), 379–424. https://doi.org/10.1080/07370000802212669

Karabenick, S. A., & Zusho, A. (2015). Examining approaches to research on self-regulated learning: conceptual and methodological considerations. *Metacognition and Learning, 10*(1), 151–163. https://doi.org/10.1007/s11409-015-9137-3

R

Kenny, D. A., Kaniskan, B., & McCoach, D. B. (2015). The performance of RMSEA in models with small degrees of freedom. *Sociological Methods & Research, 44*(3), 486–507. https://doi.org/10.1177/0049124114543236

*Khiat, H. (2015). Academic performance and the practice of self-directed learning: The adult student perspective. *Journal of Further and Higher Education, 41*, 44–59. https://doi.org/10.1080/0309877X.2015.1062849

Kim, T., Yang, M., Bae, J., Min, B., Lee, I., & Kim, J. (2017). Escape from infinite freedom: Effects of constraining user freedom on the prevention of dropout in an online learning context. *Computers in Human Behavior, 66*, 217–231. https://doi.org/10.1016/j.chb.2016.09.019

*Kim, Y. (2005). *Cultivating reflective thinking: The effects of a reflective thinking tool on learners' learning performance and metacognitive awareness in the context of on-line learning* (Doctoral dissertation). Pennsylvania State University, PA, USA.

Kizilcec, R. F., & Halawa, S. (2015). *Attrition and achievement gaps in online learning.* 57–66. https://doi.org/10.1145/2724660.2724680

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2016). Recommending self-regulated learning strategies does not improve performance in a MOOC. *Proceedings of the third ACM Conference on Learning @ Scale*, 101–104. https://doi.org/10.1145/2876034.2893378

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

Kizilcec, R. F., Piech, C., & Schneider, E. (2013). *Deconstructing disengagement: analyzing learner subpopulations in massive open online courses.* Presented at the LAK, Leuven, Belgium.

Kizilcec, R. F., Schneider, E., Cohen, G. L., & McFarland, D. A. (2014). Encouraging forum participation in online courses with collectivist, individualist and neutral motivational framings. *ELearning Papers, 37*, 13–22.

Kline, R. B. (2005). Details of path analysis. In D. A. Kenny (Ed.), *Principles and Practice of Structural Equation Modeling.* New York, NY: The Guilford Press.

Knight, S., & Friend Wise, A. (2017). Time for change: Why learning analytics needs temporal analysis. *Journal of Learning Analytics, 4*(3), 7–17. https://doi.org/10.18608/jla.2017.43.2

*Komarraju, M., & Nadler, D. (2013). Self-efficacy and academic achievement: Why do implicit beliefs, goals, and effort regulation matter? *Learning and Individual Differences, 25*, 67–72. https://doi.org/10.1016/j.lindif.2013.01.005

Kovanović, V., Gašević, D., Joksimović, S., Hatala, M., & Adesope, O. (2015). Analytics of communities of inquiry: Effects of learning technology use on cognitive presence in asynchronous online discussions. *The Internet and Higher Education, 27*, 74–89. https://doi.org/10.1016/j.iheduc.2015.06.002

Lamb, A., Smilack, J., Ho, A., & Reich, J. (2015). Addressing common analytic challenges to randomized experiments in MOOCs: Attrition and zero-inflation. *Proceedings of the second ACM Conference on Learning @ Scale*, 21-30. https://doi.org/10.1145/2724660.2724669

*Lan, W. Y. (1996). The effects of self-monitoring on students' course performance, use of learning strategies, attitude, self-judgment ability, and knowledge representation. *The Journal of Experimental Education, 64*, 101–115. https://doi.org/10.1080/00220973.1996.9943798

*Lee, H. W., Lim, K. Y., & Grabowski, B. L. (2010). Improving self-regulation, learning strategy use, and achievement with metacognitive feedback. *Educational Technology Research and Development, 58*, 629–648. https://doi.org/10.1007/s11423-010-9153-6

*Lee, T.-H., Shen, P.-D., & Tsai, C.-W. (2008). Applying web-enabled problem-based learning and self-regulated learning to add value to computing education in Taiwan's vocational schools. *Educational Technology & Society, 11*(3), 13–25.

*Leggett, H., Sandars, J., & Burns, P. (2012). Helping students to improve their academic performance: A pilot study of a workbook with self-monitoring exercises. *Medical Teacher, 34*(9), 751–753. https://doi.org/10.3109/0142159X.2012.691188

Lerche, T., & Kiel, E. (2018). Predicting student achievement in learning management systems by log data analysis. *Computers in Human Behavior, 89,* 367-372. https://doi.org/10.1016/j.chb.2018.06.015

Li, K. (2019). MOOC learners' demographics, self-regulated learning strategy, perceived learning and satisfaction: A structural equation modeling approach. *Computers & Education, 132,* 16–30. https://doi.org/10.1016/j.compedu.2019.01.003

Li, Q., & Baker, R. (2018). The different relationships between engagement and outcomes across participant subgroups in massive open online courses. *Computers & Education, 127,* 41–65. https://doi.org/10.1016/j.compedu.2018.08.005

*Lindsey, B. A., & Nagel, M. (2013). Assessing students' metacognitive calibration with knowledge surveys. *AIP Conference Proceedings, 1513,* 258–261. https://doi.org/10.1063/1.4789701

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

*Liu, H. K. (2016). Correlation research on the application of e-learning to students' self-regulated learning ability, motivational beliefs, and academic performance. *EURASIA Journal of Mathematics, Science & Technology Education, 12,* 1091–1100. https://doi.org/10.12973/eurasia.2016.1559a

Low, R., & Sweller, J. (2014). The modality principle in multimedia learning. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (2nd ed., pp. 227–246). Cambridge: Cambridge University Press.

*Lusk, A. (2016). Metacognitive strategies in the introduction to political science classroom. *Journal of Political Science Education, 12,* 141–150. https://doi.org/10.1080/15512169.2015.1060888

*Lynch, D. J. (2010). Motivational beliefs and learning strategies as predictors of academic performance in college physics. *College Student Journal, 44,* 920–927.

Mackness, J., Mak, S., & Williams, R. (2010). The ideals and reality of participating in a MOOC. In L. Dirckinck-Holmfeld, V. Hodgson, C. Jones, M. De Laat, D. McConnell, & T. Ryberg (Eds.), *Proceedings of the 7th International Conference on Networked Learning* (pp. 266–275).

*Maftoon, P., & Tasnimi, M. (2014). Using self-regulation to enhance EFL learners' reading comprehension. *Journal of Language Teaching and Research, 5,* 844–855. https://doi.org/10.4304/jltr.5.4.844-855

Maldonado-Mahauad, J., Pérez-Sanagustín, M., Kizilcec, R. F., Morales, N., & Munoz-Gama, J. (2018). Mining theory-based patterns from big data: Identifying self-regulated learning strategies in massive open online courses. *Computers in Human Behavior, 80,* 179–196. https://doi.org/10.1016/j.chb.2017.11.011

Margaryan, A., Bianco, M., & Littlejohn, A. (2015). Instructional quality of massive open online courses (MOOCs). *Computers & Education, 80,* 77–83. https://doi.org/10.1016/j.compedu.2014.08.005

*Marrs, H., Sigler, E., & Hayes, K. (2009). Study strategy predictors of performance in introductory psychology. *Journal of Instructional Psychology, 36,* 125–133.

*Masui, C., & De Corte, E. (2005). Learning to reflect and to attribute constructively as basic components of self-regulated learning. *British Journal of Educational Psychology, 75,* 351–372. https://doi.org/10.1348/000709905X25030

Mayer, R. E. (1998). Cognitive, metacognitive, and motivational aspects of problem solving. *Instructional Science, 26*(1–2), 49–63.

Mayer, R. E., & Chandler, P. (2001). When learning is just a click away: Does simple user interaction foster deeper understanding of multimedia messages? *Journal of Educational Psychology, 93*(2), 390–397. https://doi.org/10.1037//0022-0663.93.2.390

Mayer, R. E., & Moreno, R. (2003). Nine ways to reduce cognitive load in multimedia learning. *Educational Psychologist, 38*(1), 43–52. https://doi.org/10.1207/S15326985EP3801_6

McCardle, L., & Hadwin, A. F. (2015). Using multiple, contextualized data sources to measure learners' perceptions of their self-regulated learning. *Metacognition and Learning, 10*(1), 43–75. https://doi.org/10.1007/s11409-014-9132-0

McGrath, J. E., Martin, J., & Kulka, R. A. (1981). Some quasi-rules for making judgment calls in research. *American Behavioral Scientist, 25*(2), 211–224. https://doi.org/10.1177/000276428102500206

McIntosh, M. J., & Morse, J. M. (2015). Situating and constructing diversity in semi-structured interviews. *Global Qualitative Nursing Research, 2,* 1–12. https://doi.org/10.1177/2333393615597674

*McKeachie, W. J. (1990). Learning, thinking, and Thorndike. *Educational Psychologist, 25,* 127–141. https://doi.org/10.1207/s15326985ep2502_2

*McKenzie, K., Gow, K., & Schweitzer, R. (2004). Exploring first-year academic achievement through structural equation modelling. *Higher Education Research & Development, 23,* 95–112. https://doi.org/10.1080/0729436032000168513

*Meeus, W., Van Petegem, P., & Meijer, J. (2008). Portfolio as a means of promoting autonomous learning in teacher education: a quasi-experimental study. *Educational Research, 50,* 361–386. https://doi.org/10.1080/00131880802499837

Milligan, C., & Littlejohn, A. (2017). Why study on a MOOC? The motives of students and professionals. *International Review of Research in Open and Distance Learning, 18*(2), 92–102.

Milligan, G. W. (1980). An examination of the effect of six types of error perturbation on fifteen clustering algorithms. *Psychometrika, 45,* 325–342. https://doi.org/10.1007/BF02293907

Min, L., & Jingyan, L. (2017). Assessing the effectiveness of self-regulated learning in MOOCs using macro-level behavioural sequence data. *Proceedings of EMOOCs 2017,* 1-9.

Molenaar, I., & Järvelä, S. (2014). Sequential and temporal characteristics of self and socially regulated learning. *Metacognition and Learning, 9,* 75–85. https://doi.org/10.1007/s11409-014-9114-2

Molenaar, I., & Roda, C. (2008). Attention management for dynamic and adaptive scaffolding. *Pragmatics & Cognition, 16*(2), 224–271. https://doi.org/10.1075/pc.16.2.04mol

Mooi, E., & Sarstedt, M. (2010). Cluster analysis. In E. Mooi & M. Sarstedt, *A Concise Guide to Market Research* (pp. 237–284). https://doi.org/10.1007/978-3-642-12541-6_9

*Moos, D. C., & Bonde, C. (2016). Flipping the classroom: Embedding self-regulated learning prompts in videos. *Technology, Knowledge and Learning, 21,* 225–242. https://doi.org/10.1007/s10758-015-9269-1

Morse, J. M. (2010). Sampling in grounded theory. In A. Bryant & K. Charmaz (Eds.), *The SAGE handbook of grounded theory* (pp. 229–244). SAGE publications.

*Murray-Harvey, R. (1993). Identifying characteristics of successful tertiary students using path analysis. *The Australian Educational Researcher, 20*(3), 63–81. https://doi.org/10.1007/BF03219552

Narciss, S., Proske, A., & Koerndle, H. (2007). Promoting self-regulated learning in web-based learning environments. *Computers in Human Behavior, 23*(3), 1126–1144. https://doi.org/10.1016/j.chb.2006.10.006

Nelson, T. O., & Narens, L. (1990). Metamemory: A theoretical framework and new findings. In *Psychology of Learning and Motivation* (Vol. 26, pp. 125–173). Academic Press.

*Neuville, S., Frenay, M., & Bourgeois, E. (2007). Task value, self-efficacy and goal orientations: Impact on self-regulated learning, choice and performance among university students. *Psychologica Belgica, 47,* 95–117. https://doi.org/10.5334/pb-47-1-95

*Nguyen, L. T. C., & Gu, Y. (2013). Strategy-based instruction: A learner-focused approach to developing learner autonomy. *Language Teaching Research, 17*(1), 9–30. https://doi.org/10.1177/1362168812457528

Nicpon, M., Huser, L., Blanks, E., Sollenberger, S., Befort, C., & Robinson Kurpius, S. (2006). The relationship of loneliness and social support with college freshmen's academic performance and persistence. *Journal of College Student Retention: Research, Theory and Practice, 8*(3), 345–358. https://doi.org/10.2190/A465-356M-7652-783R

*Nietfeld, J. L., Cao, L., & Osborne, J. W. (2006). The effect of distributed monitoring exercises and feedback on performance, monitoring accuracy, and self-efficacy. *Metacognition and Learning, 1,* 159–179. https://doi.org/10.1007/s10409-006-9595-6

*Ning, H. K., & Downing, K. (2012). Influence of student learning experience on academic performance: the mediator and moderator effects of self-regulation and motivation. *British Educational Research Journal, 38,* 219–237. https://doi.org/10.1080/01411926.2010.538468

Ning, H. K., & Downing, K. (2015). A latent profile analysis of university students' self-regulated learning strategies. *Studies in Higher Education, 40*(7), 1328–1346. https://doi.org/10.1080/03075079.2014.880832

*Nückles, M., Hübner, S., & Renkl, A. (2009). Enhancing self-regulated learning by writing learning protocols. *Learning and Instruction, 19,* 259–271. https://doi.org/10.1016/j.learninstruc.2008.05.002

O'Connor, B. P. (2000). SPSS and SAS programs for determining the number of components using parallel analysis and Velicer's MAP test. Behavior Research Methods, Instrumentation, and Computers, 396–402.

Orwin, R. G. (1983). A fail-safe N for effect size in meta-analysis. *Journal of Educational and Behavioral Statistics, 8,* 157–159. https://doi.org/10.3102/10769986008002157

Owston, R. D. (1997). The world wide web: A technology to enhance teaching and learning? *Educational Researcher, 26*(2), 27–33. https://doi.org/10.3102/0013189X026002027

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology, 8,* 1–28. https://doi.org/10.3389/fpsyg.2017.00422

Panadero, E., Klug, J., & Järvelä, S. (2016). Third wave of measurement in the self-regulated learning field: When measurement and intervention come hand in hand. *Scandinavian Journal of Educational Research, 60*(6), 723–735. https://doi.org/10.1080/00313831.2015.1066436

Pappano, L. (2012, February 11). The year of the MOOC. The New York Times. Retrieved from https://www.nytimes.com/2012/11/04/education/edlife/massive-open-online-courses-are-multiplying-at-a-rapid-pace.html

*Pardo, A., Han, F., & Ellis, R. A. (2016). Exploring the relation between self-regulation, online activities, and academic performance: a case study. *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge,* 422–429. https://doi.org/10.1145/2883851.2883883

Paris, S. G., & Paris, A. H. (2001). Classroom applications of research on self-regulated learning. *Educational Psychologist, 36*(2), 89–101. https://doi.org/10.1207/S15326985EP3602_4

Perels, F., Gürtler, T., & Schmitz, B. (2005). Training of self-regulatory and problem-solving competence. *Learning and Instruction, 15,* 123–139. https://doi.org/10.1016/j.learninstruc.2005.04.010

Pérez-Álvarez, R., Maldonado-Mahauad, J., & Pérez-Sanagustín, M. (2018). Tools to support self-regulated learning in online environments: Literature review. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong Technology-Enhanced Learning* (Vol. 11082, pp. 16–30). https://doi.org/10.1007/978-3-319-98572-5_2

Peverly, S. T., Brobst, K. E., Graham, M., & Shaw, R. (2003). College adults are not good at self-regulation: A study on the relationship of self-regulation, note taking, and test taking. *Journal of Educational Psychology, 95*(2), 335–346. https://doi.org/10.1037/0022-0663.95.2.335

*Phan, H. P. (2009a). Amalgamation of future time orientation, epistemological beliefs, achievement goals and study strategies: Empirical evidence established. *British Journal of Educational Psychology, 79,* 155–173. https://doi.org/10.1348/000709908X306864

*Phan, H. P. (2009b). Exploring students' reflective thinking practice, deep processing strategies, effort, and achievement goal orientations. *Educational Psychology, 29,* 297–313. https://doi.org/10.1080/01443410902877988

Phillips, R., Maor, D., Cumming-Potvin, W., Roberts, P., Herrington, J., Preston, G., ... Perry, L. (2011). *Learning analytics and study behaviour: A pilot study.* Presented at the Australasian Society for Computers in Learning in Tertiary Education, Hobart, Tasmania, Australia.

R

Pieger, E., & Bannert, M. (2018). Differential effects of students' self-directed metacognitive prompts. *Computers in Human Behavior, 86*, 165–173. https://doi.org/10.1016/j.chb.2018.04.022

Pilli, O., Admiraal, W., & Salli, A. (2018). MOOCs: Innovation or stagnation? *Turkish Online Journal of Distance Education, 19*(3), 169–181.

Pintrich, P. R. (1999). The role of motivation in promoting and sustaining self-regulated learning. *International Journal of Educational Research, 31*, 459–470. https://doi.org/10.1016/S0883-0355(99)00015-4

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451–502). San Diego, CA, USA: Academic Press.

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

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology, 82*, 33–40. https://doi.org/10.1037/0022-0663.82.1.33

Pintrich, P. R., Smith, D. A., Garcia, T., & McKeachie, W. J. (1991). *A manual for the use of the Motivated Strategies for Learning Questionnaire*. Ann Arbor, MI: The Regents of the University of Michigan.

*Pishghadam, R., & Khajavy, G. H. (2013). Intelligence and metacognition as predictors of foreign language achievement: A structural equation modeling approach. *Learning and Individual Differences, 24*, 176–181. https://doi.org/10.1016/j.lindif.2012.12.004

*Pizzimenti, M. A., & Axelson, R. D. (2015). Assessing student engagement and self-regulated learning in a medical cross anatomy course. *Anatomical Sciences Education, 8*, 104–110. https://doi.org/10.1002/ase.1463

Puntambekar, S., Sullivan, S. A., & Hübscher, R. (2013). Analyzing navigation patterns to scaffold metacognition in hypertext systems. In R. Azevedo & V. Aleven (Eds.), *International Handbook of Metacognition and Learning Technologies* (pp. 261–275). New York, NY: Springer New York.

*Puspitasari, K. (2012). *The effects of learning strategy intervention and study time management intervention on students' self-regulated learning, achievement, and course completion in a distance education learning environment* (Doctoral Dissertation). Retrieved from Florida State University Libraries. (5124)

Puustinen, M., & Pulkkinen, L. (2001). Models of self-regulated learning: A review. *Scandinavian Journal of Educational Research, 45*, 269–286. https://doi.org/10.1080/00313830120074206

Qayyum, A., & Zawacki-Richter, O. (2018). Distance education in Australia, Europe and the Americas. In A. Qayyum & O. Zawacki-Richter (Eds.), *Open and Distance Education in Australia, Europe and the Americas: National Perspectives in a Digital Age* (pp. 121–131). https://doi.org/10.1007/978-981-13-0298-5

R Core Team. (2016). R: A language and environment for statistical computing. Retrieved from https://www.R-project.org/

*Rahimirad, M., & Moini, M. R. (2015). The challenges of listening to academic lectures for EAP learners and the impact of metacognition on academic lecture listening comprehension. *SAGE Open, 5*(2), 1–9. https://doi.org/10.1177/2158244015590609

*Ravenscroft, S. P., Waymire, T. R., & West, T. D. (2012). Accounting students' metacognition: The association of performance, calibration error, and mindset. *Issues in Accounting Education, 27*, 707–732. https://doi.org/10.2308/iace-50148

*Rawson, K. A., O'Neil, R., & Dunlosky, J. (2011). Accurate monitoring leads to effective control and greater learning of patient education materials. *Journal of Experimental Psychology: Applied, 17*, 288–302. https://doi.org/10.1037/a0024749

Reich, J., & Ruipérez-Valiente, J. A. (2019). The MOOC pivot. *Science, 363*(6423), 130–131. https://doi.org/10.1126/science.aav7958

*Reid, A. J., & Morrison, G. R. (2014). Generative learning strategy use and self-regulatory prompting in digital text. *Journal of Information Technology Education: Research, 13*, 49–72.

*Reid, A. J., Morrison, G. R., & Bol, L. (2017). Knowing what you know: improving metacomprehension and calibration accuracy in digital text. *Educational Technology Research and Development, 65,* 29–45. https://doi.org/10.1007/s11423-016-9454-5

Reimann, P. (2009). Time is precious: Variable- and event-centred approaches to process analysis in CSCL research. *International Journal of Computer-Supported Collaborative Learning, 4*(3), 239–257. https://doi.org/10.1007/s11412-009-9070-z

Reimann, P., Markauskaite, L., & Bannert, M. (2014). e-Research and learning theory: What do sequence and process mining methods contribute?: e-Research and learning theory. *British Journal of Educational Technology, 45*(3), 528–540. https://doi.org/10.1111/bjet.12146

Robinson, O. C. (2014). Sampling in interview-based qualitative research: A theoretical and practical guide. *Qualitative Research in Psychology, 11*(1), 25–41. https://doi.org/10.1080/14780887.2013.801543

*Rosário, P., Núñez, J. C., González-Pienda, J., Valle, A., Trigo, L., & Guimarães, C. (2010). Enhancing self-regulation and approaches to learning in first-year college students: a narrative-based programme assessed in the Iberian Peninsula. *European Journal of Psychology of Education, 25,* 411–428. https://doi.org/10.1007/s10212-010-0020-y

*Rosário, P., Núñez, J. C., Trigo, L., Guimarães, C., Fernández, E., Cerezo, R., ... Figueiredo, M. (2015). Transcultural analysis of the effectiveness of a program to promote self-regulated learning in Mozambique, Chile, Portugal, and Spain. H*igher Education Research & Development, 34,* 173–187. https://doi.org/10.1080/07294360.2014.935932

Roth, A., Ogrin, S., & Schmitz, B. (2016). Assessing self-regulated learning in higher education: a systematic literature review of self-report instruments. *Educational Assessment, Evaluation and Accountability, 28*(3), 225–250. https://doi.org/10.1007/s11092-015-9229-2

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

Russo, J. E., Johnson, E. J., & Stephens, D. L. (1989). The validity of verbal protocols. *Memory & Cognition, 17*(6), 759–769. https://doi.org/10.3758/BF03202637

Saint, J., Gašević, D., & Pardo, A. (2018). Detecting learning strategies through process mining. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong Technology-Enhanced Learning* (Vol. 11082, pp. 385–398). https://doi.org/10.1007/978-3-319-98572-5_29

*Schleifer, L. L. F., & Dull, R. B. (2009). Metacognition and performance in the accounting classroom. *Issues in Accounting Education, 24,* 339–367. https://doi.org/10.2308/iace.2009.24.3.339

*Schmidt, A. M., & Ford, J. K. (2003). Learning within a learner control training environment: The interactive effects of goal orientation and metacognitive instruction on learning outcomes. *Personnel Psychology, 56,* 405–429. https://doi.org/10.1111/j.1744-6570.2003.tb00156.x

Schmitt, T. A. (2011). Current methodological considerations in exploratory and confirmatory factor analysis. *Journal of Psychoeducational Assessment, 29*(4), 304–321. https://doi.org/10.1177/0734282911406653

Schmitz, B., & Wiese, B. S. (2006). New perspectives for the evaluation of training sessions in self-regulated learning: Time-series analyses of diary data. *Contemporary Educational Psychology, 31*(1), 64–96. https://doi.org/10.1016/j.cedpsych.2005.02.002

Schnotz, W. (2010). Reanalyzing the expertise reversal effect. *Instructional Science, 38*(3), 315–323. https://doi.org/10.1007/s11251-009-9104-y

Schraw, G. (2010). Measuring self-regulation in computer-based learning environments. *Educational Psychologist, 45*(4), 258–266. https://doi.org/10.1080/00461520.2010.515936

Schraw, G., & Dennison, R. S. (1994). Assessing metacognitive awareness. *Contemporary Educational Psychology, 19*(4), 460–475. https://doi.org/10.1006/ceps.1994.1033

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of Educational Research, 99*(6), 323–338. https://doi.org/10.3200/JOER.99.6.323-338

Schunk, D. H. (2005). Self-regulated learning: The educational legacy of Paul R. Pintrich. *Educational Psychologist, 40*(2), 85–94. https://doi.org/10.1207/s15326985ep4002_3

*Seabi, J. (2011). Relating learning strategies, self-esteem, intellectual functioning with academic achievement among first-year engineering students. *South African Journal of Psychology, 41,* 239–249. https://doi.org/10.1177/008124631104100212

Seaman, J. E., Allen, I. E., & Seaman, J. (2018). *Grade increase: tracking distance education in the United States*. Babson Survey Research Group.

*Senler, B., & Sungur-Vural, S. (2014). Pre-service science teachers' use of self-regulation strategies. *Procedia - Social and Behavioral Sciences, 152,* 551–556. https://doi.org/10.1016/j.sbspro.2014.09.242

Shah, D. (2015, December 30). Less experimentation, more iteration: A review of MOOC stats and trends in 2015. Retrieved from Class Central: MOOC report website: https://www.class-central.com/report/moocs-stats-and-trends-2015/

*Shawer, S. F. (2016). Four language skills performance, academic achievement, and learning strategy use in preservice teacher training programs. *TESOL Journal, 7,* 262–303. https://doi.org/10.1002/tesj.202

*Shell, D. F., Hazley, M. P., Soh, L.-K., Ingraham, E., & Ramsay, S. (2013). Associations of students' creativity, motivation, and self-regulation with learning and achievement in college computer science courses. *Proceedings of the IEEE Frontiers in Education Conference*. https://doi.org/10.1109/FIE.2013.6685116

*Shen, C.-Y., & Liu, H.-C. (2011). Metacognitive skills development: A web-based approach in higher education. *The Turkish Online Journal of Educational Technology, 10,* 140–150.

*Sinkavich, F. J. (1994). Metamemory, attributional style, and study strategies: predicting classroom performance in graduate students. *Journal of Instructional Psychology, 21,* 172–182.

*Sitzmann, T., Bell, B. S., Kraiger, K., & Kanar, A. M. (2009). A multilevel analysis of the effect of prompting self-regulation in technology-delivered instruction. *Personnel Psychology, 62,* 697–734. https://doi.org/10.1111/j.1744-6570.2009.01155.x

Sitzmann, T., & Ely, K. (2011). A meta-analysis of self-regulated learning in work-related training and educational attainment: What we know and where we need to go. *Psychological Bulletin, 137,* 421–442. https://doi.org/10.1037/a0022777

Snow, R. E. (1991). Aptitude-treatment interaction as a framework for research on individual differences in psychotherapy. *Journal of Consulting and Clinical Psychology, 59*(2), 205–216. https://doi.org/10.1037//0022-006X.59.2.205

*Soares, A. P., Guisande, A. M., Almeida, L. S., & Páramo, F. M. (2009). Academic achievement in first year Portuguese college students: The role of academic preparation and learning strategies. *International Journal of Psychology, 44,* 204–212. https://doi.org/10.1080/00207590701700545

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

Sonnenberg, C., & Bannert, M. (2016). Evaluating the impact of instructional support using data mining and process mining: a micro-level analysis of the effectiveness of metacognitive prompts. *Journal of Educational Data Mining, 8*(2), 51–83.

Sonnenberg, C., & Bannert, M. (2019). Using process mining to examine the sustainability of instructional support: How stable are the effects of metacognitive prompting on self-regulatory behavior? *Computers in Human Behavior, 96,* 259–272. https://doi.org/10.1016/j.chb.2018.06.003

Staker, H., & Horn, M. B. (2012). *Classifying K-12 blended learning* (pp. 1–22). Innosight Institute, Inc.

*Stark, R., & Krause, U.-M. (2009). Effects of reflection prompts on learning outcomes and learning behaviour in statistics education. *Learning Environments Research, 12*, 209–223. https://doi.org/10.1007/s10984-009-9063-x

Strauss, A., & Corbin, J. (1994). Grounded theory methodology: an overview. In N. K. Denzin & Y. S. Lincoln (Eds.), *Handbook of qualitative research* (pp. 273-285). Thousand Oaks, CA, USA: SAGE Publications.

*Su, J. M. (2014). A self-regulated learning system to support adaptive scaffolding in hypermedia-based learning environments. *Proceedings of the 7th International Conference on Ubi-Media Computing and Workshops*, 326–331. https://doi.org/10.1109/U-MEDIA.2014.13

*Sungur, S. (2007). Contribution of motivational beliefs and metacognition to students' performance under consequential and nonconsequential test conditions. *Educational Research and Evaluation, 13*, 127–142. https://doi.org/10.1080/13803610701234898

Sweller, J., Van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review, 31*, 261–292. https://doi.org/10.1007/s10648-019-09465-5

*Taasoobshirazi, G., & Farley, J. (2013). A multivariate model of physics problem solving. *Learning and Individual Differences, 24*, 53–62. https://doi.org/10.1016/j.lindif.2012.05.001

Tabachnick, B. G., & Fidell, L. S. (2001). *Using Multivariate Statistics*. Boston: Allyn and Bacon.

Tallent-Runnels, M. K., Thomas, J. A., Lan, W. Y., Cooper, S., Ahern, T. C., Shaw, S. M., & Liu, X. (2006). Teaching courses online: A review of the research. *Review of Educational Research, 76*(1), 93–135. https://doi.org/10.3102/00346543076001093

*Tangworakitthaworn, P., Gilbert, L., & Wills, G. B. (2015). A conceptualization of intended learning outcomes supporting self-regulated learners in indicating learning paths: A conceptualization of ILOs. *Journal of Computer Assisted Learning, 31*, 393–404. https://doi.org/10.1111/jcal.12068

*Tanriseven, I. (2014). A tool that can be effective in the self-regulated learning of pre-service teachers: The mind map. *Australian Journal of Teacher Education, 39*, 65–80. https://doi.org/10.14221/ajte.2014v39n1.1

Theobald, M., Bellhäuser, H., & Imhof, M. (2018). Identifying individual differences using log-file analysis: Distributed learning as mediator between conscientiousness and exam grades. *Learning and Individual Differences, 65*, 112–122. https://doi.org/10.1016/j.lindif.2018.05.019

*Tong, Y., & Tong, D. (2010). An empirical study on web-based English listening autonomous learning model. *Proceedings of the 3rd International Conference on Computer Science and Information Technology*, 524–527. https://doi.org/10.1109/ICCSIT.2010.5564999

Toven-Lindsey, B., Rhoads, R. A., & Lozano, J. B. (2015). Virtually unlimited classrooms: Pedagogical practices in massive open online courses. *The Internet and Higher Education, 24*, 1–12. https://doi.org/10.1016/j.iheduc.2014.07.001

*Tuysuzoglu, B. B., & Greene, J. A. (2015). An investigation of the role of contingent metacognitive behavior in self-regulated learning. *Metacognition and Learning, 10*, 77–98. https://doi.org/10.1007/s11409-014-9126-y

UNESCO Institute for Information Technologies in Education. (2013, June). *Introduction to MOOCs: Avalance, illusion or augmentation?*

*Uzun, A. M., Unal, E., & Yamac, A. (2013). Service teachers' academic achievements in online distance education: The roles of online self-regulation and attitudes. *Turkish Online Journal of Distance Education, 14*(2), 131–140.

*Vadhan, V., & Stander, P. (1994). Metacognitive ability and test performance among college students. *The Journal of Psychology, 128*, 307–309. https://doi.org/10.1080/00223980.1994.9712733

*Valle, A., Cabanach, R. G., Núñez, J. C., González-Pienda, J., Rodríguez, S., & Piñeiro, I. (2003). Cognitive, motivational, and volitional dimensions of learning: An empirical test of a hypothetical model. *Research in Higher Education, 44*, 557–580. https://doi.org/10.1023/A:1025443325499

*Van den Boom, G., Paas, F., & Van Merriënboer, J. J. G. (2007). Effects of elicited reflections combined with tutor or peer feedback on self-regulated learning and learning outcomes. *Learning and Instruction, 17,* 532–548. https://doi.org/10.1016/j.learninstruc.2007.09.003

Van Gog, T., Paas, F., Van Merriënboer, J. J. G., & Witte, P. (2005). Uncovering the problem-solving process: Cued retrospecitve reporting versus concurrent and retrospective reporting. *Journal of Experimental Psychology: Applied, 11*(4), 237–244. https://doi.org/10.1037/1076-898X.11.4.237

Van Laer, S., & Elen, J. (2017). In search of attributes that support self-regulation in blended learning environments. *Education and Information Technologies, 22,* 1395–1454. https://doi.org/10.1007/s10639-016-9505-x

Van Laer, S., & Elen, J. (2018). Towards a methodological framework for sequence analysis in the field of self-regulated learning. *Frontline Learning Research, 6*(3), 228–249.

Van Leeuwen, A. (2015). T*eacher regulation of CSCL: Exploring the complexity of teacher regulation and the supporting role of learning analytics* (Doctoral dissertation). Utrecht University, Utrecht, NL.

Van Merriënboer, J. J. G., & Kester, L. (2014). The four-component instructional design model: multimedia principles in environments for complex learning. In R. E. Mayer (Ed.), *The Cambridge Handbook of Multimedia Learning* (pp. 71-93). Cambridge University Press.

Van Merriënboer, J. J. G., Kirschner, P. A., & Kester, L. (2003). Taking the load off a learner's mind: Instructional design for complex learning. *Educational Psychologist, 38*(1), 5–13. https://doi.org/10.1207/S15326985EP3801_2

Veenman, M. V. J. (2005). The assessment of metacognitive skills: What can be learned from multi-method design? In C. Artelt & B. Moschner (Eds.), *Lernstrategien und Metakognition: Implikationen für Forschung und Praxis* (pp. 75–97). Berlin: Waxmann.

Veenman, M. V. J. (2007). The assessment and instruction of self-regulation in computer-based environments: A discussion. *Metacognition and Learning, 2*(2–3), 177–183. https://doi.org/10.1007/s11409-007-9017-6

Veenman, M. V. J. (2016). Learning to self-monitor and self-regulate. In R. E. Mayer & P. A. Alexander (Eds.), *Handbook of Research on Learning and Instruction* (pp. 233–257). New York, NY: Routledge.

Veenman, M. V. J., Van Hout-Wolters, B. H. A. M., & Afflerbach, P. (2006). Metacognition and learning: conceptual and methodological considerations. *Metacognition and Learning, 1*(1), 3–14. https://doi.org/10.1007/s11409-006-6893-0

Veletsianos, G., Reich, J., & Pasquini, L. A. (2016). The life between big data log events: Learners strategies to overcome challenges in MOOCs. *AERA Open, 2*(3). https://doi.org/10.1177/2332858416657002

Vermunt, J. D., & Verloop, N. (1999). Congruence and friction between learning and teaching. *Learning and Instruction, 9*(3), 257–280. https://doi.org/10.1016/S0959-4752(98)00028-0

*Villavicencio, F. T., & Bernardo, A. B. I. (2013). Positive academic emotions moderate the relationship between self-regulation and academic achievement. *British Journal of Educational Psychology, 83,* 329–340. https://doi.org/10.1111/j.2044-8279.2012.02064.x

*Volet, S. E. (1991). Modelling and coaching of relevant metacognitive strategies for enhancing university students' learning. *Learning and Instruction, 1,* 319–336. https://doi.org/10.1016/0959-4752(91)90012-W

*Volet, S. E., & Lund, C. P. (1994). Metacognitive instruction in introductory Computer Programming: A better explanatory construct for performance than traditional factors. *Journal of Educational Computing Research, 10,* 297–328. https://doi.org/10.2190/9A08-Y2Q0-6AER-6KLQ

Walsh, P. (2009). *Global trends in higher education, adult and distance learning.* International Council for Open and Distance Education.

*Wang, C., Hu, J., Zhang, G., Chang, Y., & Xu, Y. (2012). Chinese college students' self-regulated learning strategies and self-efficacy beliefs in learning English as a foreign language. *Journal of Research in Education, 22,* 103–135.

Wang, C.-H., Shannon, D. M., & Ross, M. E. (2013). Students' characteristics, self-regulated learning, technology self-efficacy, and course outcomes in online learning. *Distance Education, 34,* 302–323. https://doi.org/10.1080/01587919.2013.835779

*Wang, C.-Y. (2015). Exploring general versus task-specific assessments of metacognition in university chemistry students: A multitrait-multimethod analsyis. *Research in Science Education, 45,* 555–579. https://doi.org/10.1007/s11165-014-9436-8

*Warr, P., & Downing, J. (2000). Learning strategies, learning anxiety and knowledge acquisition. *British Journal of Psychology, 91,* 311–333. https://doi.org/10.1348/000712600161853

Waschull, S. B. (2001). The online delivery of psychology courses: Attrition, performance, and evaluation. *Teaching of Psychology, 28,* 143–147.

*Wellmann, G. S. (2005). Comparing learning style to performance in on-line teaching: Impact of proctored v. un-proctored testing. *Journal of Interactive Online Learning, 4,* 20–39.

*West, C., & Sadoski, M. (2011). Do study strategies predict academic performance in medical school? *Medical Education, 45,* 696–703. https://doi.org/10.1111/j.1365-2923.2011.03929.x

Whipp, J. L., & Chiarelli, S. (2004). Self-regulation in a web-based course: A case study. *Educational Technology Research and Development, 52*(4), 5–21. https://doi.org/10.1007/BF02504714

White, S., Davis, H., Dickens, K., León, M., & Sánchez-Vera, M. M. (2015). MOOCs: What motivates the producers and participants? In S. Zvacek, M. T. Restivo, J. Uhomoibhi, & M. Helfert (Eds.), *Computer Supported Education* (Vol. 510, pp. 99–114). https://doi.org/10.1007/978-3-319-25768-6_7

Williams, P. E., & Hellman, C. M. (2004). Differences in self-regulation for online learning between first- and second-generation college students. *Research in Higher Education, 45*(1), 71–82. https://doi.org/10.1023/B:RIHE.0000010047.46814.78

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

Winne, P. H. (2014). Issues in researching self-regulated learning as patterns of events. *Metacognition and Learning, 9*(2), 229–237. https://doi.org/10.1007/s11409-014-9113-3

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

Winne, P. H., & Jamieson-Noel, D. (2002). Exploring students' calibration of self reports about study tactics and achievement. *Contemporary Educational Psychology, 27*(4), 551–572. https://doi.org/10.1016/S0361-476X(02)00006-1

Winne, P. H., Jamieson-Noel, D., & Muis, K. R. (2002). Methodological issues and advances in researching tactics, strategies, and self-regulated learning. In P. R. Pintrich & M. L. Maehr (Eds.), *New directions in measures and methods* (1. ed, pp. 121–155). Amsterdam: JAI, An Imprint of Elsevier Science.

Winne, P. H., & Perry, N. E. (2000). Measuring self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 531–566). Elsevier.

Winters, F. I., Greene, J. A., & Costich, C. M. (2008). Self-regulation of learning within computer-based learning environments: A critical analysis. *Educational Psychology Review, 20,* 429–444. https://doi.org/10.1007/s10648-008-9080-9

*Wischgoll, A. (2016). Combined training of one cognitive and one metacognitive strategy improves academic writing skills. *Frontiers in Psychology, 7,* 1–13. https://doi.org/10.3389/fpsyg.2016.00187

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

Woods, C. M. (2006). Careless responding to reverse-worded items: Implications for confirmatory factor analysis. *Journal of Psychopathology and Behavioral Assessment, 28*(3), 186–191. https://doi.org/10.1007/s10862-005-9004-7

Yeh, Y.-F., Chen, M.-C., Hung, P.-H., & Hwang, G.-J. (2010). Optimal self-explanation prompt design in dynamic multi-representational learning environments. *Computers & Education, 54*(4), 1089–1100. https://doi.org/10.1016/j.compedu.2009.10.013

Yeomans, M., & Reich, J. (2017). Planning prompts increase and forecast course completion in massive open online courses. P*roceedings of the Seventh International Learning Analytics & Knowledge Conference*, 464-473. https://doi.org/10.1145/3027385.3027416

You, J. W. (2016). Identifying significant indicators using LMS data to predict course achievement in online learning. *The Internet and Higher Education, 29,* 23–30. https://doi.org/10.1016/j.iheduc.2015.11.003

*Yukselturk, E., & Bulut, S. (2007). Predictors for student success in an online course. *Educational Technology & Society, 10*(2), 71–83.

*Zabrucky, K. M., Agler, L. L., & Moore, D. (2009). Metacognition in Taiwan: Students' calibration of comprehension and performance. *International Journal of Psychology, 44,* 305–312. https://doi.org/10.1080/00207590802315409

*Zhang, H., & Huang, R. (2010). Learning in CALL environments: An exploration of the effects of self-regulated learning constructs on Chinese students' academic performance. In P. Tsang, S. K. S. Cheung, V. S. K. Lee, & R. Huang (Eds.), *Hybrid Learning* (pp. 370–382). https://doi.org/10.1007/978-3-642-14657-2_34

Zheng, S., Rosson, M. B., Shih, P. C., & Carroll, J. M. (2015). Understanding student motivation, behaviors and perceptions in MOOCs. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing,* 1882-1895. https://doi.org/10.1145/2675133.2675217

Zimmerman, B. J. (1986). Becoming a self-regulated learner: Which are the key subprocesses? *Contemporary Educational Psychology, 11*(4), 307–313. https://doi.org/10.1016/0361-476X(86)90027-5

Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist, 25,* 3–17. https://doi.org/10.1207/s15326985ep2501_2

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory into Practice, 41,* 64–70. https://doi.org/10.1207/s15430421tip4102_2

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

Zimmerman, B. J. (2015). Self-regulated learning: Theories, measures, and outcomes. *International Encyclopedia of the Social & Behavioral Sciences, 21,* 541–546. https://doi.org/10.1016/B978-0-08-097086-8.26060-1

Zimmerman, B. J., & Martinez-Pons, M. (1986). Development of a structured interview for assessing student use of self-regulated learning strategies. *American Educational Research Journal, 23*(4), 614–628. https://doi.org/10.3102/00028312023004614

Zimmerman, B. J., & Martinez-Pons, M. (1990). Student differences in self-regulated learning: Relating grade, sex, and giftedness to self-efficacy and strategy use. *Journal of Educational Psychology, 82*(1), 51–59. https://doi.org/10.1037/0022-0663.82.1.51

*Zou, X., & Zhang, X. (2013). Effect of different score reports of web-based formative test on students' self-regulated learning. *Computers & Education, 66,* 54–63. https://doi.org/10.1016/j.compedu.2013.02.016

*Zvacek, S. M., De Fátima Chouzal, M., & Restivo, M. T. (2015). Accuracy of self-assessment among graduate students in mechanical engineering. *Proceedings of the International Conference on Interactive Collaborative Learning,* 1130-1133. https://doi.org/10.1109/ICL.2015.7318192

Zwick, W. R., & Velicer, W. F. (1986). Comparison of five rules for determining the number of components to retain. *Psychological Bulletin, 99*(3), 432–442.

List of supplementary materials

All supplementary materials are available online at www.bit.ly/dealingwithautonomy.

Chapter 2

- Coding scheme with interrater agreement
- Data and syntax for MASEM analysis
- Data and syntax for univariate meta-analyses
- Overview of included studies
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Chapter 5

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Chapter 6

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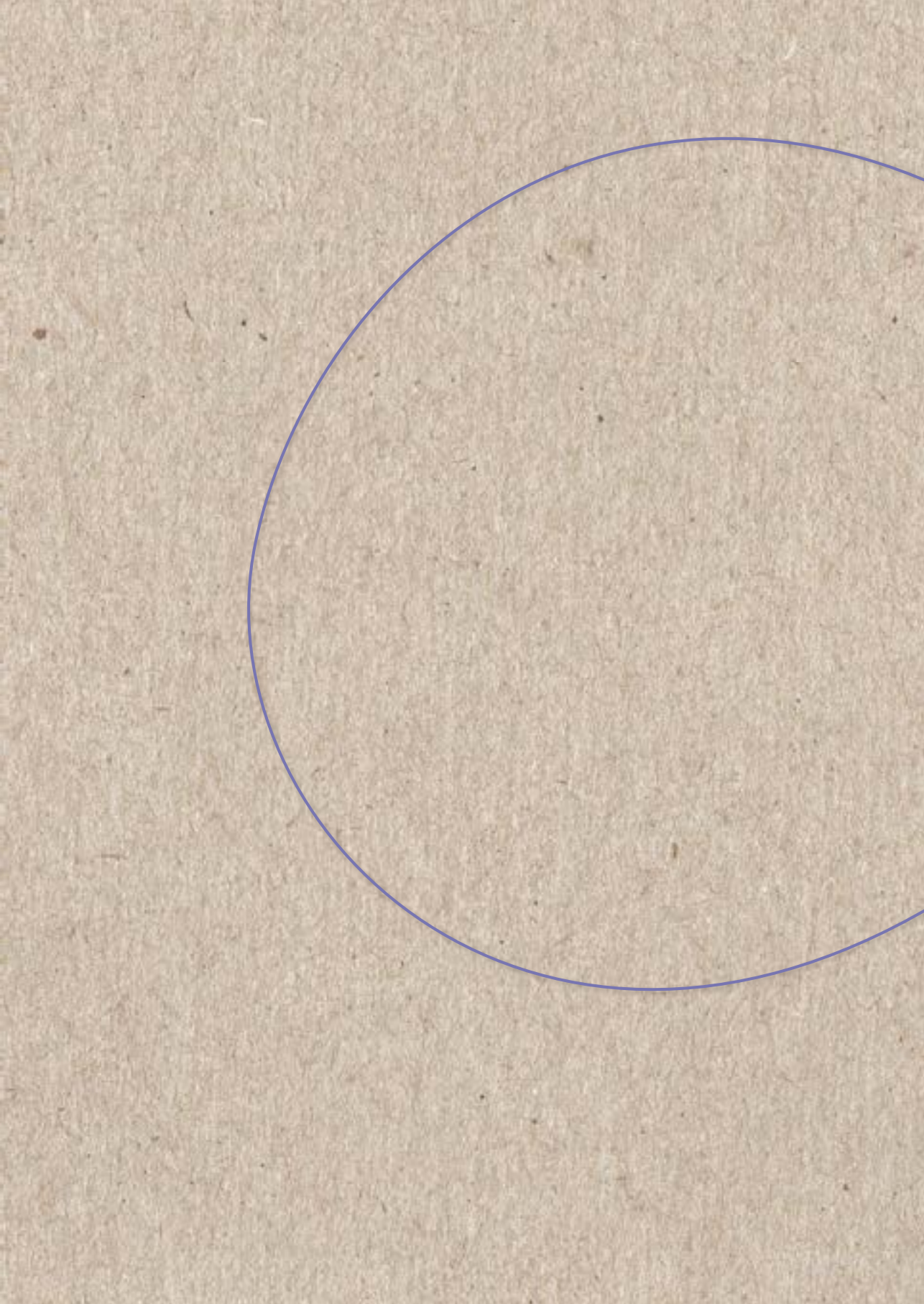

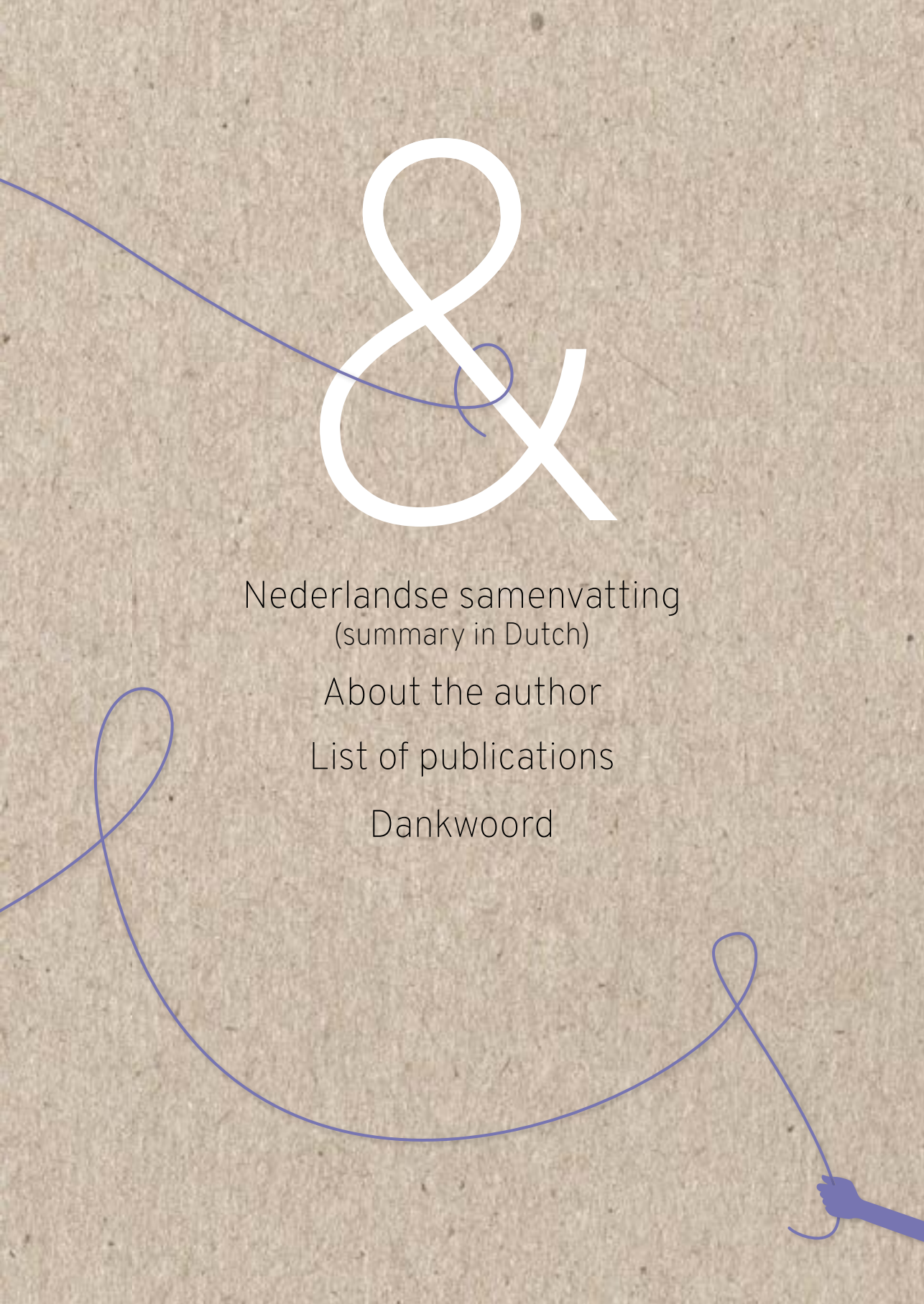

Nederlandse samenvatting
(summary in Dutch)

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Dankwoord

Nederlandse samenvatting

Steeds meer onderwijs wordt online aangeboden (Allen & Seaman, 2016; Qayyum & Zawacki-Richter, 2018; Seaman, Allen, & Seaman, 2018). Open online cursussen (massive open online courses; MOOCs) zijn een snelgroeiende vorm van online onderwijs. Deze cursussen zijn meestal gratis toegankelijk voor iedereen met een internetverbinding. Door deze vrije toegankelijkheid biedt open online onderwijs een scala aan mogelijkheden (Pappano, 2012). Zo kunnen volwassenen middels deze cursussen hun (werkgerelateerde) kennis verbreden. In open online onderwijs kunnen studenten zelf bepalen welk deel van een cursus ze afronden, waar en wanneer ze studeren en in welk tempo ze studeren. Studenten in een open online cursus hebben hierdoor veel zelfstandigheid: ze zijn autonoom in het vormgeven van hun leerproces (Beishuizen & Steffens, 2011; Wang, Shannon, & Ross, 2013). Om succesvol te zijn in open online onderwijs, moeten studenten goed om kunnen gaan met deze autonomie. Studenten moeten zelf hun eigen leerproces reguleren (e.g., Azevedo, 2005; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Wang et al., 2013) en studenten die niet in staat zijn tot zelfregulatie van hun leerproces (vanaf hier: zelfregulatie) vallen mogelijk vervroegd uit (Eriksson, Adawi, & Stöhr, 2017; Hew & Cheung, 2014; Zheng, Rosson, Shih, & Carroll, 2015).

Het belang van zelfregulatie voor succesvol leren in open online onderwijs is vaker beschreven (e.g., Azevedo & Aleven, 2013; Kizilcec et al., 2017; Wang et al., 2013). Er is echter nog weinig bekend over hoe studenten hun leerproces reguleren in open online onderwijs. En hoewel bekend is dat veel studenten moeite hebben met het adequaat reguleren van hun leerproces (e.g., Azevedo & Cromley, 2004; Bol & Garner, 2011), is de wetenschappelijke kennis over het ondersteunen van zelfregulerend leren van studenten in open online onderwijs beperkt. Meer onderzoek naar zelfregulerend leren, en meer specifiek naar het ondersteunen van zelfregulatie in open online onderwijs, is daarom noodzakelijk. Een voorwaarde voor succesvolle ondersteuning van zelfregulatie is het accuraat meten van het zelfregulerend leren van studenten. De onderzoeksvraag die in dit proefschrift centraal staat is daarom: "Hoe kan het zelfregulerend leren van studenten in open online onderwijs worden gemeten en ondersteund?". In deze Nederlandstalige samenvatting wordt eerst kort de achtergrond van deze vraag beschreven (zie voor meer informatie **Hoofdstuk 1**). Vervolgens worden de individuele studies in dit proefschrift gepresenteerd. Deze Nederlandse samenvatting wordt afgesloten met een discussie van de onderzoeksresultaten.

Achtergrond onderzoeksvraag

Het ondersteunen van zelfregulerend leren

Studenten die zelfregulerend leren zijn actief betrokken bij hun leerproces (Panadero, 2017). Dit betekent dat studenten hun leerproces monitoren en hun leeractiviteiten (e.g., lezen, het maken van aantekeningen) controleren. Zelfregulatieactiviteiten zijn zowel metacognitief, gedragsmatig en motivationeel van aard en vinden plaats in drie fasen: voor, tijdens en na het leren (Zimmerman, 1986, 2002). Studenten die zelfregulerend leren stellen, voorafgaand aan het leren, doelen en maken een planning. Tijdens het leren ondernemen studenten leeractiviteiten. Studenten monitoren hun voortgang en passen hun leeractiviteiten indien nodig aan. Daarnaast verdelen ze hun tijd, denken ze na over een geschikte plek om te studeren, zoeken ze hulp wanneer nodig en zetten ze door als

hun motivatie afneemt. Na afloop van het leren reflecteren studenten op hun voortgang en de effectiviteit van de ondernomen leeractiviteiten. Studenten die hun leren succesvol reguleren zijn in alle drie deze fasen actief.

Veel studenten hebben moeite om hun leren adequaat te reguleren (e.g., Azevedo & Cromley, 2004; Bol & Garner, 2011). Verschillende literatuurstudies hebben aangetoond dat het bieden van zelfregulatieondersteuning het zelfregulerend leren en de leerprestaties van studenten verbetert (e.g., Boer, Donker-Bergstra, Kostons, & Korpershoek, 2013; De Bruijn-Smolders, Timmers, Gawke, Schoonman, & Born, 2016; Devolder, Van Braak, & Tondeur, 2012; Dignath & Büttner, 2008). De positieve effecten van zelfregulatieondersteuning gevonden in het primair, voortgezet en hoger onderwijs maken het relevant om te bestuderen of zelfregulatieondersteuning ook in open online onderwijs kan bijdragen aan de prestaties van studenten. De resultaten van het kleine aantal studies dat is uitgevoerd naar zelfregulatieondersteuning in open online onderwijs zijn gematigd positief: Studenten die gebruik maakten van de aangeboden ondersteuning waren actiever in de cursussen (e.g., keken meer video's) en maakten meer van de gevolgde cursus af dan studenten die geen gebruik maakten van de aangeboden ondersteuning (Davis, Triglianos, Hauff, & Houben, 2018; Kizilcec, Pérez-Sanagustín, & Maldonado, 2016; Yeomans & Reich, 2017). Desalniettemin is er nog veel verbetering mogelijk, met name omdat veel studenten geen gebruik maakten van de geboden ondersteuning. Gezien de grote autonomie die studenten in open online onderwijs wordt geboden, is het belang van zelfregulatie in open online onderwijs groot. Daarom doen we in dit proefschrift verder onderzoek naar de mogelijkheden om zelfregulerend leren in open online onderwijs te ondersteunen.

Het meten van zelfregulerend leren

Het accuraat meten van zelfregulerend leren is een voorwaarde voor adequate, effectieve ondersteuning van zelfregulatie. Het meten van zelfregulerend leren is echter niet zonder problemen (McCardle & Hadwin, 2015; Winne, 2010). Wij achten de volgende twee aspecten van belang voor accurate meting van zelfregulatie: (1) het meten van de beweegredenen van de student en (2) het meten zelfregulerend leren over tijd (e.g., Molenaar & Järvelä, 2014; Sonnenberg & Bannert, 2016; Veenman, 2007; Winne, 2010).

Leergedrag kan gemeten worden door middel van observatie, maar de achterliggende reden of motivatie voor dit gedrag kan zo niet gemeten worden. Men kan bijvoorbeeld zien waar een student leert, maar of deze locatie het resultaat is van een bewuste keuze en welke redenen de student heeft voor deze keuze, blijft onduidelijk. Zelfregulatie is daardoor vaak onzichtbaar. Voor een accurate meting van zelfregulatie is het noodzakelijk het onzichtbare zelfregulerend leren in kaart te brengen (Winne, 2010). Zelfregulerend leren betekent immers dat de student actief zijn leerproces monitort en zijn leeractiviteiten bewust reguleert (Nelson & Narens, 1990).

Daarnaast is het belangrijk om zelfregulatie te meten over tijd (McCardle & Hadwin, 2015). Studenten die zelfregulerend leren passen hun leren continu aan de context waarin ze zich bevinden. Het is hierom belangrijk om veranderingen in het leergedrag en de zelfregulatie van studenten in kaart te brengen. Dit kan door zelfregulatie te meten over tijd, met zogenoemde procesmaten (Winne, 2010). Hiervoor is temporele informatie nodig over de leeractiviteiten van studenten. Dit type informatie is beschikbaar middels *trace data*. In trace data worden de leeractiviteiten van studenten opgeslagen met een studentcode en een tijdsmarkering. Voorbeelden van leeractiviteiten die opgeslagen worden zijn het

bekijken van video's en het beantwoorden van quizvragen. Trace data vormen daarmee een zeer gedetailleerd overzicht van het gedrag van studenten in een online leeromgeving. Aangezien trace data door de tijdsmarkering temporele informatie bevatten, kunnen trace data gebruikt worden voor het analyseren van de zelfregulatie en het leergedrag van studenten over tijd. De beschikbaarheid van trace data, samen met het belang van het accuraat meten van zelfregulerend leren voor succesvolle ondersteuning van zelfregulatie, heeft ertoe geleid dat we in dit proefschrift ook enkele methodologische vraagstukken behandelen.

Overzicht van de studies in dit proefschrift

Literatuuronderzoek

Het is bekend dat zelfregulatie-interventies positieve effecten hebben op de leerprestaties van studenten (e.g., Boer et al., 2013; De Bruijn-Smolders et al., 2016; Dignath & Büttner, 2008). Vaak wordt aangenomen dat deze positieve effecten komen doordat de zelfregulatie-interventies zorgen voor een verbetering in de zelfregulatie van studenten en dat de verbeterde zelfregulatie op haar beurt zorgt voor verbeterde leerprestaties. Met andere woorden: er wordt verwacht dat zelfregulerend leren het effect van zelfregulatie-interventies op prestatie medieert. De mate waarin zelfregulatie de effecten van zelfregulatie-interventies op leerprestaties in het hoger onderwijs daadwerkelijk medieert, is echter nog nooit onderzocht. In **Hoofdstuk 2** hebben we daarom een literatuuronderzoek uitgevoerd naar zelfregulatie-interventies in het hoger onderwijs. In dit literatuuronderzoek hebben we gekeken naar de effecten van zelfregulatie-interventies op de leerprestatie van studenten, de effecten van zelfregulatie-interventies op het zelfregulerend leren van studenten, alsmede naar de relatie tussen zelfregulerend leren en leerprestatie.

In totaal zijn 142 studies, gepubliceerd in 126 artikelen, geïncludeerd in de meta-analyse. We hebben gebruik gemaakt van meta-analyse padmodellen (*meta-analytic structural equation modeling*; MASEM; Jak, 2015) om te onderzoeken of de positieve effecten van zelfregulatie-interventies op leerprestatie werden gemedieerd door zelfregulatie. Hoewel de gevonden mediatie significant was, was het mediërende effect klein ($\beta = .05$, $p < .05$). We concludeerden daarom dat, hoewel zelfregulatie-interventies effectief zijn in het verbeteren van zowel zelfregulerend leren ($\beta = .22$, $p < .05$) als prestatie ($\beta = .18$, $p < .05$), de effecten van zelfregulatie-interventies op prestatie voornamelijk door andere factoren worden veroorzaakt. Eén van de factoren die de gevonden partiële mediatie mogelijk verklaart, is de tijd die studenten besteden aan de leertaak. Zelfregulatie-interventies verhogen mogelijk de tijd die studenten besteden aan de leertaak, waardoor studenten beter gaan presteren zonder dat dit veroorzaakt wordt door veranderingen in hun zelfregulatie. Doordat de leertijd in geen enkele van de geïncludeerde studies werd gerapporteerd, kon deze mogelijke verklaring niet worden getoetst.

In de literatuurstudie hebben we verder afzonderlijke meta-analyses uitgevoerd voor elk van de drie onderzochte relaties. De gevonden effect groottes waren $d = .49$ voor het effect van zelfregulatie-interventies op leerprestatie, $d = .50$ voor het effect van zelfregulatie-interventies op zelfregulerend leren en $r = .28$ voor de relatie tussen zelfregulerend leren en leerprestatie. Aangezien er sprake was van significante heterogeniteit in de effectgroottes, hebben we vervolgens een reeks studie-, metings- en interventiekenmerken getest als potentiële moderatoren van de effectgroottes. Online of offline onderwijs

en de kwaliteit van de studie waren enkele van de geïncludeerde studiekenmerken. Het gemeten type zelfregulatieactiviteit (e.g., metacognitief, tijdsmanagement) en het gebruikte meetinstrument waren enkele van de geïncludeerde metingskenmerken. Het format van de interventie (e.g., instructie, toepassing of prompten) en de ondersteunde zelfregulatieactiviteit waren enkele van de geïncludeerde interventiekenmerken. Op basis van de resultaten van de moderatoranalyses konden geen specifieke richtlijnen voor het ontwerp van zelfregulatie-interventies worden bepaald. Wel kon worden vastgesteld dat zelfregulatie-interventies effectief zijn in het verbeteren van het zelfregulerend leren van studenten, alsmede in het verbeteren van de leerprestaties van studenten. De resultaten van het literatuuronderzoek onderstrepen daarom het belang van het implementeren van zelfregulatie-interventies in het hoger onderwijs.

Vragenlijstontwikkeling

In open online onderwijs moeten studenten hun leren meer en anders reguleren dan in traditioneel hoger onderwijs op een universiteit (e.g., Azevedo, 2005; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Wang et al., 2013). Doordat al het studiemateriaal online wordt aangeboden zijn studenten bijvoorbeeld vrij om te studeren waar en wanneer ze willen. Hoewel er verschillende vragenlijsten bestaan voor het meten van zelfregulatie, is er geen vragenlijst beschikbaar om de verschillende aspecten van zelfregulerend leren (e.g., planning, tijdsmanagement) in open online onderwijs te meten. In **Hoofdstuk 3** hebben we daarom een vragenlijst ontwikkeld om het zelfregulerend leren van studenten in open online onderwijs te meten. De studie bevat een vergelijking van de aspecten van zelfregulerend leren die gemeten kunnen worden met bestaande, veel gebruikte vragenlijsten. Vervolgens is op basis van de items in deze bestaande vragenlijsten een nieuwe vragenlijst samengesteld. Hiervoor zijn relevante items uit de bestaande vragenlijsten gebruikt. Aan ieder item is de tekst "in deze online cursus" toegevoegd om de context waarover de vraag beantwoord diende te worden te benadrukken. De vragenlijst is getest door middel van exploratieve ($n = 162$) en confirmatieve ($n = 159$) factor analyse. Dit proces heeft geleid tot de *Self-regulated Online Learning Questionnaire* (SOL-Q). De SOL-Q bestaat uit 36 items verdeeld over vijf schalen: metacognitieve vaardigheden, tijdsmanagement, omgevingsregulering, doorzettingsvermogen en hulp zoeken.

De schaal metacognitieve vaardigheden was naar verhouding groot (18 items) en de items waren conceptueel verschillend. Daarom is in een tweede studie een gereviseerde versie van de vragenlijst ontwikkeld en getest (SOL-Q-R). De SOL-Q-R bestaat uit 42 items verdeeld over zeven schalen: metacognitieve activiteiten voorafgaand aan het leren, metacognitieve activiteiten tijdens het leren, metacognitieve activiteiten na het leren, tijdsmanagement, omgevingsregulering, doorzettingsvermogen en hulp zoeken. Deze gereviseerde vragenlijst is valide en betrouwbaar bevonden ($n = 222$). Wat betreft het meten van de metacognitieve activiteiten van studenten biedt de SOL-Q-R meer inzicht voor onderzoekers dan de SOL-Q. Metacognitieve activiteiten voor, tijdens en na het leren kunnen nu apart worden gemeten. De SOL-Q-R is daarom een verbetering ten opzichte van de SOL-Q en geschikt voor het meten van het zelfregulerend leren van studenten in open online onderwijs.

De invloed van zelfregulerend leren op leergedrag

De zelfregulatie van studenten beïnvloedt hun leerprestaties (Broadbent & Poon, 2015; Dent & Koenka, 2016; Sitzmann & Ely, 2011). Dit verband tussen zelfregulatie en prestatie komt zeer waarschijnlijk doordat studenten die hun leren meer of beter reguleren, andere

leeractiviteiten ondernemen en daardoor beter presteren. Het onzichtbare zelfregulerend leren van studenten beïnvloedt immers hun observeerbare leeractiviteiten (Nelson & Narens, 1990). In **Hoofdstuk 4** onderzochten we hoe de zelfregulatie van studenten hun leergedrag in open online onderwijs beïnvloedt. Studenten in een MOOC werden in de eerste week van de cursus gevraagd om de SOL-Q in te vullen. De studenten ($n = 69$) werden vervolgens geclusterd in vier groepen op basis van hun zelf-gerapporteerde zelfregulatie: gemiddelde zelfregulatie, zwakke zelfregulatie, hulp zoekenden en *zelf*-reguleerders. Om de invloed van zelfregulerend leren op het leerproces van de verschillende groepen studenten te onderzoeken is gebruik gemaakt van *process mining* (Sonnenberg & Bannert, 2015, 2018). Met process mining werden de typerende transities van studenten tussen de belangrijkste activiteiten in de MOOC (e.g., kijken van video's, goed/fout beantwoorden van vragen) gevisualiseerd, terwijl weinig voorkomende transities werden weggelaten om ruis te minimaliseren. De procesmodellen lieten zien dat studenten in alle vier de clusters zich in grote lijnen hielden aan de structuur die door de cursusontwikkelaars was ingebouwd in de leeromgeving. Er waren echter ook duidelijke verschillen in de procesmodellen van de verschillende clusters. Zo hielden studenten in het cluster "zwakke zelfregulatie" veel sterker vast aan de geboden structuur dan studenten in de andere drie clusters.

Op basis van dit onderzoek trokken we twee conclusies. Ten eerste liet het onderzoek zien dat zelfregulatieondersteuning het beste ingebouwd kan worden in de cursusstructuur om studenten met zwakke zelfregulatie te ondersteunen. Het is bekend dat studenten die moeite hebben om hun leren te reguleren vaak niet zelf op zoek gaan naar ondersteuning (Clarebout & Elen, 2006). De procesmodellen lieten zien dat studenten met zwakke zelfregulatie vanzelf in aanraking komen met ondersteuning als deze wordt ingebouwd in de cursusstructuur. Daarnaast waren er duidelijke verschillen in de procesmodellen en deze verschillen konden worden gerelateerd aan het zelfregulerend leren dat door de studenten werd gerapporteerd. Zo gingen studenten in het cluster "hulp zoekenden" enkel door van de ene module naar de volgende module via het forum. Deze verschillen in de procesmodellen leiden tot de conclusie dat onzichtbare zelfregulatie activiteiten de zichtbare leeractiviteiten beïnvloeden.

Effecten van zelfregulatieondersteuning in MOOCs

Zoals beschreven in Hoofdstuk 2 is het ondersteunen van zelfregulatie effectief voor het verbeteren van het zelfregulerend leren en de leerprestaties van studenten in het hoger onderwijs. Doordat zelfregulatie van het leren in open online onderwijs zo mogelijk nog belangrijker is dan in traditioneel, face-to-face, hoger onderwijs, hebben we in **Hoofdstuk 5** de effecten van een zelfregulatie-interventie in drie MOOCs onderzocht. We hebben gekeken naar de effecten van de zelfregulatie-interventie op de mate waarin studenten de MOOC afmaakten, alsmede naar de effecten op het zelfregulerend leren van de studenten.

Bij aanmelding voor de MOOC ($n = 2.426$) werden studenten willekeurig verdeeld over een interventie- en controlegroep. De toevoeging van de zelfregulatie-interventie in de interventieconditie was het enige verschil tussen de twee groepen. De interventie bestond uit drie korte zelfregulatie instructievideo's (max. 4 minuten). In alle video's werden de drie fasen van zelfregulerend leren benoemd en kort uitgelegd. Verder werden in video 1 suggesties gegeven voor het verbeteren van zelfregulatie *voor* het leren, in video 2 suggesties voor zelfregulatie *tijdens* het leren en in video 3 suggesties voor zelfregulatie *na* het leren. De video's waren geïntegreerd in de cursusinhoud van respectievelijk week 1, 2 en 3 van de MOOCs. Om de effecten van de interventie op het zelfregulerend leren en de

mate waarin studenten de MOOCs afrondden te meten, hebben we gebruik gemaakt van de automatisch opgeslagen trace data. Hiermee kon voor elke student berekend worden welk deel van de cursus hij of zij succesvol had afgerond en konden variabelen berekend worden die een indicator vormden van de zelfregulatie van studenten. Enkele van deze vooraf gedefinieerde variabelen waren het raadplegen van het cursusforum (indicator van hulp zoeken) en het succesvol afronden van quizvragen vóór de deadline (indicator van tijdsmanagement). De analyses werden enkel uitgevoerd voor studenten die op enige manier actief waren geweest in de MOOC, dat wil zeggen: minimaal eenmaal inloggen in de MOOC en niet enkel registreren (n = 1.471).

De resultaten lieten zien dat studenten in de interventieconditie een groter gedeelte van de cursus afmaakten dan studenten in de controleconditie. Daarnaast lieten studenten in de interventieconditie die ten minste één interventievideo hadden bekeken, meer gedrag zien dat een indicator was van zelfregulerend leren. Echter, slechts een klein deel van de studenten in de interventieconditie had ten minste één van de interventievideo's bekeken (n = 76). Aanvullende analyses lieten zien dat het merendeel van de studenten al uit de MOOCs was gestapt voordat ze in aanraking kwamen met de zelfregulatie-interventie. Aangezien het ondersteunen van zelfregulatie dus positieve effecten had op de mate waarin de MOOC werd afgerond en het zelfregulerend leren van de studenten, dient in de toekomst gekeken te worden naar manieren om ervoor te zorgen dat meer studenten aangeboden ondersteuning opvolgen.

Mixed methods onderzoek naar zelfregulerend leren

Trace data worden automatisch verzameld en bevatten gedetailleerde informatie over de activiteiten van studenten. Daarom worden trace data gezien als een waardevolle bron van informatie voor het meten van zelfregulatie. In **Hoofdstuk 6** identificeerden we desalniettemin twee problemen met het meten van zelfregulerend leren met trace data. Ten eerste wordt in trace data opgeslagen *wat* studenten doen, maar niet *waarom* ze dat doen. Zonder informatie over de beweegredenen van de student is het moeilijk om trace data correct te interpreteren. Ten tweede wordt het zelfregulerend leren van studenten buiten de online leeromgeving niet opgeslagen in trace data.

We presenteerden het combineren van trace data met interview data, in een mixed methods onderzoek, als mogelijke oplossing voor deze twee problemen. We hebben vier studenten uitgebreid geïnterviewd over hun leerproces in MOOCs. Ieder interview bestond uit twee delen. In het eerste deel van het interview kreeg de student een visualisatie te zien van zijn of haar trace data. De student werd gevraagd uit te leggen waarom hij of zij op deze manier in de MOOC actief was geweest. In het tweede deel van het interview werd met de student gesproken over het zelfregulerend leren buiten de online leeromgeving. Met de interviews kon ambiguïteit in de interpretatie van de trace data worden weggenomen. Met de kennis vergaard in de interviews konden we begrijpen waarom de studenten in grote lijnen lineair door de MOOCs heen gingen, ze weinig op het forum kwamen en hoe ze omgingen met de video's en de quizvragen. Daarnaast werd met de interviews inzicht verkregen in de zelfregulatie van de studenten buiten de online leeromgeving. De interviews hielpen begrijpen hoe studenten hun leren reguleerden voorafgaand, tijdens en na het leren in de MOOCs, alsmede hoe de studenten hun tijd verdeelden, hoe ze zochten naar hulp en hoe ze een geschikte studielocatie kozen.

Het combineren van trace data met interview data vormde dus een succesvolle oplossing voor de twee beschreven problemen. Het interviewen van studenten is echter tijdrovend. De voordelen van de automatische, grootschalige dataverzameling van trace data worden teniet gedaan als trace data altijd gecombineerd dienen te worden met interview data. Door trace data vaker te combineren met interview data, kunnen sommige onderdelen van trace data wellicht betrouwbaar worden geïnterpreteerd zonder aanvullende informatie. Voor het meten van zelfregulatie buiten de online leeromgeving zou, op basis van wat studenten rapporteren over hun zelfregulerend leren, een valide vragenlijst kunnen worden opgesteld. Daarmee zou het in de toekomst mogelijk zijn om het zelfregulerend leren van studenten betrouwbaar en valide te meten met trace data voor zelfregulatie in de leeromgeving en een vragenlijst voor zelfregulatie buiten de leeromgeving.

Discussie

Beantwoording onderzoeksvraag

Overkoepelend laten de resultaten van de studies in dit proefschrift zien dat het ondersteunen van zelfregulatie succesvol is voor het verbeteren van het zelfregulerend leren en de prestaties van studenten (H2 en H5). Het inbouwen van zelfregulatieondersteuning om studenten te helpen omgaan met de geboden autonomie in open online onderwijs is daarom belangrijk. Daarnaast is het van belang dat de effecten van zelfregulatieondersteuning op zowel zelfregulatie als leerprestaties worden onderzocht, aangezien we hebben laten zien dat zelfregulatie-interventies verschillende resultaten kunnen hebben voor deze uitkomstmaten (H2 en H5). Door de effecten van een zelfregulatie-interventie op beide uitkomstmaten te onderzoeken kan meer inzicht worden verkregen in de effecten van deze interventies en kan beter worden begrepen waarom zelfregulatie-interventies succesvol zijn in het verbeteren van zelfregulerend leren en leerprestaties.

Wat betreft het meten van zelfregulerend leren laten de studies in dit proefschrift zien dat voor het meten van de zelfregulatie van studenten in online onderwijs andere meetmethoden nodig zijn vergeleken met het meten van de zelfregulatie van studenten in traditioneel, face-to-face onderwijs (H3 en H6). Studenten dienen hun leren meer te reguleren in open online onderwijs. Meetinstrumenten die daarbij passen zijn noodzakelijk om het zelfregulerend leren van studenten in open online onderwijs accuraat te meten. Verder hebben we laten zien dat trace data gebruikt kunnen worden voor het meten van zelfregulerend leren in open online onderwijs, zowel door inzicht te geven in het verband tussen zelfregulatie en leergedrag (H4), als door de effecten van de zelfregulatie-interventie te onderzoeken met trace data (H5). De studies in dit proefschrift hebben daarmee onze kennis over het gebruik van trace data voor het meten van zelfregulerend leren in open online onderwijs vergroot.

Het gebruik van trace data voor het meten van zelfregulatie is echter niet zonder problemen. Als zelfregulatie enkel gemeten wordt met trace data zijn er twee duidelijke barrières te identificeren: trace data biedt geen inzicht in de beweegredenen van de student en zelfregulatie buiten de online leeromgeving wordt niet opgeslagen in trace data. Daarom adviseren we om trace data te combineren met een andere meetmethode. Daarnaast beïnvloeden alle keuzes die gemaakt worden bij het filteren en analyseren van trace data de gevonden resultaten. We hebben in dit proefschrift voornamelijk gekeken naar de volgorde van de leeractiviteiten van studenten, de zogenoemde *sequentiality*.

Echter bevatten trace data ook informatie over de tijdsduur van leeractiviteiten en de tijd tussen activiteiten (de zogenoemde *temporality*; Van Laer & Elen, 2018). Deze temporele informatie is in dit proefschrift grotendeels buiten beschouwing gelaten. In **Hoofdstuk 7** hebben we deze limitatie verder beschreven, samen met verschillende mogelijkheden die het bestuderen van temporality biedt voor vervolgonderzoek.

Vervolgonderzoek zou zich ook kunnen richten op het onderzoeken van de invloed van taakmotivatie op het zelfregulerend leren van studenten in open online onderwijs. Taakmotivatie en zelfregulatie zijn sterk verbonden (Panadero, 2017). Taakmotivatie wordt gezien als een voorbode van zelfregulatie: zij die meer gemotiveerd zijn voor het uitvoeren van een taak, zijn ook meer geneigd tot (adequate) zelfregulatie (Efklides, 2011; Pintrich, 1999). Het is denkbaar dat taakmotivatie ook van invloed is op de effecten van zelfregulatieondersteuning, zo zouden studenten met een hogere taakmotivatie meer geneigd kunnen zijn tot het opvolgen van een zelfregulatie-interventie en zouden studenten met een hogere taakmotivatie meer baat kunnen hebben bij een zelfregulatie-interventie. Aanwijzingen voor de invloed van taakmotivatie op de effectiviteit van zelfregulatieondersteuning zijn gevonden in eerder onderzoek (Duffy & Azevedo, 2015; Sitzmann, Bell, Kraiger, & Kanar, 2009) en vervolgonderzoek naar de invloed van taakmotivatie op zelfregulatie(ondersteuning) in open online onderwijs zou onze kennis over deze relatie vergroten.

De toekomst van MOOCs en zelfregulatieondersteuning

Tot slot reflecteren we aan het eind van dit onderzoek naar zelfregulerend leren in open online onderwijs op de toekomst van MOOCs en op mogelijk toekomstig onderzoek naar zelfregulatieondersteuning. Nu de hype rondom MOOCs voorbij is, het aantal inschrijvingen in MOOCs daalt en er meer onderzoek naar MOOCs is uitgevoerd, is het belangrijk om te kijken naar de toekomst van MOOCs (Reich & Ruipérez-Valiente, 2019). Tot op heden bestaat er nog geen winstgevend bedrijfsmodel voor het ontwikkelen van MOOCs. Het is daarom aannemelijk dat er in de komende jaren iets moet - en zal – veranderen. Op dit moment worden MOOCs al in toenemende mate geïntegreerd in het traditioneel onderwijs, bijvoorbeeld als een online keuzevak. Deze ontwikkeling zal zich waarschijnlijk doorzetten (Fox, 2013; Reich & Ruipérez-Valiente, 2019). Door MOOCs te integreren in traditionele curricula wordt het belang voor studenten om de online cursus af te ronden in veel gevallen vergroot. Studenten kunnen dan immers studiepunten behalen door de cursus succesvol af te ronden. De autonomie die studenten wordt geboden blijft echter onverminderd hoog. Ook in de toekomst van open online onderwijs zal zelfregulerend leren dus een belangrijke voorwaarde blijven voor het succes van studenten.

Daarom zal zelfregulatieondersteuning ook in de toekomst van open online onderwijs van belang blijven. In de discussie identificeerden we verschillende vraagstukken rondom zelfregulatieondersteuning waar meer onderzoek naar nodig is. Zo is in slechts een klein aantal studies gekeken naar de invloed van studentkenmerken op de effectiviteit van zelfregulatie-interventies. Deze studies lieten zien dat studentkenmerken zoals taak motivatie, voorkennis en cognitieve capaciteiten van invloed waren op de effecten van zelfregulatie-interventies (Duffy & Azevedo, 2015; Sitzmann et al., 2009; Yeh, Chen, Hung, & Hwang, 2010). Meer onderzoek naar welke interventie, wanneer, voor welke student effectief is, is nodig voor het ontwikkelen en implementeren van adequate ondersteuning op maat.

Conclusie

De studies in dit proefschrift hebben ons inzicht in zelfregulerend leren in open online onderwijs vergroot. Ze laten zien dat zelfregulatieondersteuning effectief is voor het verbeteren van zelfregulerend leren en leerprestaties en ze bieden nieuwe methoden voor het meten van zelfregulatie in open online onderwijs. Dit proefschrift biedt daarmee handvatten voor het ondersteunen en meten van zelfregulerend leren in open online onderwijs. Om zelfregulerend leren in open online onderwijs volledig te begrijpen is nog veel onderzoek nodig. Het onderzoek in dit proefschrift biedt een solide basis om met toekomstig onderzoek op voort te bouwen.

About the author

Renée Jansen was born on April 12 1992 in Wijchen, The Netherlands. In 2009 she started studying at Eindhoven University of Technology. She obtained her Bachelor's degree in Industrial Engineering in 2012. Renée continued her education at Eindhoven University of Technology in the master's program Human Technology Interaction. During this time, she developed an interest in the use of technology in education, writing her thesis on the differences between longhand and digital note-taking. After obtaining her Master's degree in 2015 *(cum laude)*, she pursued this interest further when she started her PhD research on self-regulated learning in open online education at Utrecht University. Next to her work as a PhD candidate, Renée taught courses, was a board member of VPO (VOR Promovendi Overleg; a Dutch/Flemish association for PhD students in the field of Education), and a member of the PhD Council of the Faculty of Social and Behavioral Sciences of Utrecht University.

List of publications

Peer-reviewed publications

Jansen, R.S., Van Leeuwen, A., Janssen, J., Kester, L., & Kalz, M. (2017). Validation of the self-regulated online learning questionnaire. *Journal of Computing in Higher Education, 29*, 6–27.

Jansen, R.S., Lakens, D., & IJsselsteijn, W. A. (2017). An integrative review of the cognitive costs and benefits of note-taking. *Educational Research Review, 22*, 223–233.

Submitted for publication

Jansen, R.S., Van Leeuwen, A., Janssen, J., & Kester, L. (2019). *A mixed methods approach to studying self-regulated learning in MOOCs: Combining trace data with interviews*. Manuscript submitted for publication.

Jansen, R.S., Van Leeuwen, A., Janssen, J., Conijn, R., & Kester, L. (2019). *Supporting learners' self-regulated learning in Massive Open Online Courses*. Manuscript submitted for publication.

Jansen, R.S., Van Leeuwen, A., Janssen, J., & Kester, L. (2019). *Exploring the link between self-regulated learning and learner behavior in a MOOC*. Manuscript submitted for publication.

Jansen, R.S., Van Leeuwen, A., Janssen, J., Jak, S., & Kester, L. (2018). *Self-regulated learning partially mediates the effect of self-regulated learning interventions on achievement in higher education: A meta-analysis*. Manuscript submitted for publication.

Conference presentations and proceedings

Jansen, R.S., Van Leeuwen, A., Janssen, J., & Kester, L. (2019, August). *The effect of self-regulated learning interventions on achievement: A meta-analysis*. Paper presented at the meeting of the European Association for Research on Learning and Instruction (EARLI), Aachen, Germany.

Jansen, R.S., Van Leeuwen, A., Janssen, J., Conijn, R., & Kester, L. (2019, August). *Supporting learners' self-regulated learning in Massive Open Online Courses*. Poster session presented at the meeting of the European Association for Research on Learning and Instruction (EARLI), Aachen, Germany.

Jansen, R.S., Van Leeuwen, A., Janssen, J., Conijn, R., & Kester, L. (2019, June). Ondersteunen van zelfregulatie in MOOCs. In P. Van Rosmalen (Chair), *SOONER: uitdagingen van open online onderwijs in het Nederlandse hoger onderwijs*. Symposium conducted at the Onderwijs Research Dagen (ORD), Heerlen, The Netherlands.

Jansen, R.S., Van Leeuwen, A., Janssen, J., Jak, S., & Kester, L. (2019, April). *Self-regulated learning partially mediates the effect of self-regulated learning interventions on achievement: A meta-analysis*. Paper presented at the meeting of the American Educational Research Association (AERA), Toronto, Canada.

Jansen, R.S., Van Leeuwen, A., Janssen, J., & Kester, L. (2018, August). *Barriers in self-regulated learning in online education: A qualitative study*. Paper presented at the EARLI SIG 6-7: Instructional Design/Technology-Enhanced Learning and Instruction, Bonn, Germany.

Jansen, R.S., Van Leeuwen, A., Janssen, J., & Kester, L. (2018). Validation of the revised self-regulated online learning questionnaire. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong Technology-Enhanced Learning* (Vol. 11082, pp. 116–121).

Jansen, R.S., Van Leeuwen, A., Janssen, J., & Kester, L. (2017, September). *Motivation, SRL and learner behaviour in MOOCs*. Paper presented at the meeting of the European Association for Research on Learning and Instruction (EARLI), Tampere, Finland.

Jansen, R.S., Van Leeuwen, A., Janssen, J. & Kester, L. (2017, August). *Meta-analyses of the relationships between SRL interventions, SRL and learning outcomes*. Poster session presented at the meeting of the Junior Researchers of EARLI (JURE), Tampere, Finland. *(Awarded best poster.)*

Jansen, R.S., Van Leeuwen, A., Janssen, J., & Kester, L. (2017, June). De relatie tussen motivatie, zelfregulatie en leergedrag in MOOCs. In M. Kalz (Chair), *De uitdagingen van open online onderwijs/MOOCs*. Symposium conducted at the Onderwijs Research Dagen (ORD), Antwerpen, Belgium.

Jansen, R.S., Van Leeuwen, A., Janssen, J., & Kester, L. (2017, June). Onderwijskundige interventies om zelfregulatie en prestatie te bevorderen: Een meta-analyse in drie delen. In J. Janssen (Chair), *Onderwijskundige meta-analyses met een twist*. Symposium conducted at the Onderwijs Research Dagen (ORD), Antwerpen, Belgium.

Jansen, R.S., Van Leeuwen, A., Janssen, J., & Kester, L. (2016, May). *Validatie van een vragenlijst voor zelfregulerend leren in MOOCs*. Paper presented at the Onderwijs Research Dagen (ORD), Rotterdam, The Netherlands.

Jansen, R.S., Van Leeuwen, A., Janssen, J., & Kester, L. (2016, May). De invloed van motivatie op zelfregulatie in open online onderwijs. In M. Kalz (Chair), *De uitdagingen van open online onderwijs/MOOCs*. Symposium conducted at the Onderwijs Research Dagen (ORD), Rotterdam, The Netherlands.

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droge humor steeds verbaasd en altijd laat lachen. Lieve HTI vriendjes, ik ben blij dat we elkaar steeds weer vinden. Al was het maar omdat we anders als heersend vrouwenteam niemand meer zouden hebben om te verslaan met Party & Co ;-).

Familie

Laatst hoorde ik broers en zussen omschreven worden als "ongevraagde cadeaus". Treffender zou een omschrijving niet kunnen zijn. Lieve Ellen en Peter, bedankt dat jullie elke overwinning, hoe klein ook, met mij vierden. Het voelt vanzelfsprekend dat we er voor elkaar zijn, en het is juist die vanzelfsprekendheid waar ik zo gelukkig mee ben. Ik ben trots op wie jullie zijn. Op jou Peter, mijn grote kleine broertje. Op hoe je steeds weer bewijst dat (bijna) alles kan, als je maar durft te vragen. En op jou Ellen, op je wilskracht en op hoe je kunt genieten van de kleine dingen. Jullie zijn cadeautjes! Ik geniet van de tijd die we samen doorbrengen. Van de vertrouwdheid en onze – soms iets luidruchtige – gezelligheid. Van de gele kaart grappen, samen eten, spelletjes spelen en onze (tot op heden zeer succesvolle) escape rooms. Lieve Niek en Anneloes, jullie zijn de perfecte aanvulling van ons ESCAPE team. Met jullie is het nóg gezelliger!

Lieve mama, bedankt dat papa en jij me altijd de ruimte hebben gegeven om mijn eigen keuzes te maken. Jullie hebben me geleerd kansen te grijpen, door te zetten als het lastig is en verantwoordelijkheid te nemen. Dingen die me iedere dag van pas komen en die er zeker aan hebben bijgedragen dat hier nu een proefschrift ligt waar ik trots op mag zijn. Ik prijs me gelukkig dit te hebben kunnen leren wetende dat ik altijd op jullie terug kon vallen. Mama, hoewel de dingen die ik vertel soms net geheimtaal voor je zijn, zeker als het gaat over allerlei ingewikkelde analyses, blijf je naar me luisteren en probeer je het te begrijpen. Ik weet dat ik altijd thuis kan komen.

Lieve papa, je keek me altijd lachend aan, je hield zo van het leven. Ik heb zo veel van je geleerd en zo veel met je gelachen. Ik had zo graag meer tijd gehad. Ik mis je.

Tot slot

Waar ik heen wil en wat ik wil worden weet ik nog steeds niet. Ik weet niet wat de toekomst brengt, maar dat het goed komt weet ik zeker. Voor nu ben ik blij met dit proefschrift en alle mensen om me heen. Samen met jullie is de wereld een nog mooiere plek. Ik mag trots zijn.

Nachtenlang kun je wakker liggen,

Dagen half in slaap.

Ergens staat "er is een tijd voor alles"

En het maakt niet uit hoe de sterren staan,

Er komt altijd weer vanzelf een nieuwe maan.

Uit: Nieuwe maan – Stephanie Struijk