Associations between self-reported self-regulatory learning activities and behavioural traces left by vocational trainees in an online learning environment

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Course Code: 201500173

Master thesis MSc Program of Psychology

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Abstract

A significant body of research from psychology and educational sciences emphasizes the essential role of the ability to continuously regulate ongoing learning progress by strategical planning, monitoring, and evaluating one's learning progress to be successful in online education. However, previous research identified a gap between learners' desirable usage of self-regulatory learning strategies and the regulatory practice by learners of all ages. One potential explanation may lie in the inadequate application of self-regulated learning strategies. This hypothesis firstly suggests the need for valid instruments that capture self-regulatory activities in online learning behaviours. To this end, the presented study examined the association between self-reported online self-regulated learning competencies and behavioural logs captured in an online learning environment. Due to technical difficulties in log data collection, the concept of engagement was partially used as a vehicle to reason about the associations between log data and self-reported self-regulation skills. The sample consisted of 47 German vocational education students. The results suggest that the total session count measured as the number of logins, the regular reviewing of one's learning tasks, and the percentage of correct responses to questions during an assessment were positively associated with self-reported regulatory abilities. Unexpectedly, the SRL score was not associated with a higher engagement quality with the learning content, measured as the completion rate of learning phases.

With the emergence of the COVID-19 pandemic and the resulting shutdown of many public areas, many companies were challenged to reform their previous face-to-face educational approach and find appropriate distance-learning solutions (Cedefop, 2020). Learning and development departments began to seek opportunities to include computer-supported learning in the company's workplace learning regime. Due to the week-long shutdown of vocational schools, learning and development departments began to seek opportunities to include computer-supported learning in their vocational training program. As a result, online learning experience platforms specialized in vocational training gained great popularity as they promised to cushion the potential learning gap that threatened to evolve during the closure of the schools (Cedefop, 2020).

Vocational trainees usually learn within a teacher-controlled learning environment where the educational authorities and work demands mostly predetermine the curriculum and lesson delivery (Fürstenau et al., 2014). Hence, compared to a learning experience platform, the mode, context, and pace of education are usually controlled by the teachers or trainers at the workplace. Nevertheless, when interacting with an online learning environment, without direct teacher support, learners must organize their learning more autonomously than in face-to-face education (McMahon & Oliver, 2001). Most of a student's learning progress in asynchronous distance learning does not occur during structured and time-bound lessons within a classroom but during an open-ended, self-paced online learning session. This presses vocational students to study in a self-directed manner, a skill their previous educational setting did not demand extensively.

In the context of self-directed learning, a skillset termed self-regulated learning (SRL) has received considerable attention in learning sciences research. In the literature, it is referred to as the ability to deliberately regulate one's cognitive and metacognitive processes (Cleary & Zimmerman, 2012). Research linked an individual’s ability for SRL with improved academic success, especially in online learning environments (Wang et al., 2013). Due to the growth of online learning environments and the disruption of regular face-to-face instruction, communication between learners and instructors has shifted to virtual spaces. Consequently, important indicators of a student's deficiencies in planning and performing learning tasks that the teacher may use to diagnose SRL difficulties through classroom interaction (Callan & Shim, 2019) (e.g., a student having difficulty managing their time throughout class assignments) ceased. However, scientific evidence illuminates teachers' crucial role in supporting their students when applying metacognitive learning strategies for SRL (Kramarski, 2017). Most online learning environments are characterized by limited student-teacher interaction, potentially preventing the detection of SRL deficits and, consequently, the necessary support in developing SRL abilities. Indeed, research shows that many learners need to gain these skills and be sufficiently prepared to continue learning after shifting to online learning environments (Anthonysamy et al., 2020), highlighting the need for effective SRL support in digital learning environments tailored to the learners' needs.

Online learning platforms register a steadily increasing number of users with differing prior knowledge and variating self-regulatory learning abilities. Consistently assessing the learner's online SRL abilities is necessary to provide support that considers the learner's SRL profile and helps improve SRL skills effectively. However, established measurements of SRL, such as self-report questionnaires (Rovers et al., 2019) and thinking-aloud protocols (Greene et al., 2011), are time-consuming and expensive to obtain and cannot capture an individual's progress dynamically due to time delays (Wolters & Won, 2017).

With the emergence of technology-enhanced learning environments, new information about learners' behaviour is readily available and stored in behavioural log files (Brooks & Thompson, 2017). Researchers identified behavioural logs that automatically capture the interaction with an online learning environment before storing them as comprehensive events as a promising alternative to self-report measurement (Bernacki, 2017). They permit the constant gathering of dynamic self-regulatory learning processes by collecting behavioural learner data throughout the learning process (Bernacki, 2017). As Wang et al. (2013) identified, collecting data within the field of learning analytics may be the missing puzzle piece to provide adaptive SRL support. Effective adaptive support requires an unobtrusive yet valid and reliable measurement instrument of online SRL (R. Jansen et al., 2020). However, evidence regarding the effectiveness of behavioural logs in capturing online SRL activities is scarce. Kizilcec (2017) showed that more self-reported engagement in SRL activities was associated with higher likelihood of revisiting a video lecture. Applying process mining Maldonado-Mahauad (2018) identified usage patterns and provided an explanation how each pattern of learning activities relate to SRL. Recently Jansen et al., (2022) triangulated self-reported SRL with behavioural activity data from a massive open online learning course using process mining. Jansen et al. (R. S. Jansen et al., 2022) identified four different models of a learning process and interpreted the patterns in the light of SRL theory. They reported that the different process model of learning may be linked to participants differences in SRL scores.

This research aims to fill this gap by creating an attempt to align an aptitude and a conceivable event-based measurement of online SRL. The study investigates the relationship between self-reported online self-regulatory learning activities and behavioural traces. The sample consists of vocational trainees that learn in an online learning environment. Learners' self-reported SRL activities are correlated with their behavioural log files aggregated during their engagement with the learning content.

The Social Cognitive Model of Self-Regulated Learning

Pintrich (2000, p. 453) defined self-regulated learning (SRL) as "an active and constructive process whereby learners set goals for their learning and then attempt to monitor, regulate and control their cognition, motivation and behaviour, guided and constrained by their goals and the contextual features in the environment". Zimmerman (2000) developed a three-phase cyclical model of SRL called the social cognitive model for SRL. For this, Zimmerman proposed that SRL involves metacognitive, motivational, and behavioural processes that improve learning outcomes through SRL processes such as goal setting, planning and application of learning strategies and self-reinforcement (Cleary & Zimmerman, 2012). Congruent with this definition, the three-phase model by Zimmerman (2000) contained a forethought, a performance and an evaluation phase and has frequently been applied as a framework to guide SRL research in different learning domains. The following section briefly describes the social-cognitive model of SRL as it acted as the foundational theoretical structure for the presented study.

Zimmerman (2000) claimed that learners analyze the task during the *forethought phase* before learning begins under the influence of self-motivational beliefs. Goal setting and strategic planning are the subprocesses of task analysis and are impacted by previous experience, the individual's motivation, outcome expectations, and self-efficacy regarding the upcoming task (Panadero & Alonso-Tapia, 2014; Winne, 2013). Strategic planning is one of the strongest predictors of successful learning, but its implementation depends on individual motivation and beliefs (Panadero & Alonso-Tapia, 2014; Zimmerman, 2012). Effective goal setting and strategic planning is associated with an appropriate degree of goal orientation (Pintrich, 2000) and the use of effective learning strategies, resulting in deep learning (Grant & Dweck, 2003).

During the *performance phase,* the learner engages with the learning material (Zimmerman, 2000). A skilled self-regulator monitors their cognition, emotions and environmental settings and audits the learning strategies' effectiveness. The performance phase consists of two distinct processes. First, self-control refers to the individual's ability to use cognitive and behavioural strategies to enhance task performance and optimize effort regulation. Second, self-monitoring entails ongoing metacognitive progress that assesses learning performance and progress throughout the task (Panadero & Jonsson, 2013). These processes' effectiveness is partially facilitated by the quality of the set goals, as more specific processes related to proximal events promote more effective self-observations. Thus, the proposed phases are interdependent.

Finally, during the *reflection phase,* the learner self-assesses their use of learning strategies and adapts their approach based on the self-reflection results. This phase is also divided into two sub-processes. When engaging in self-judgment, the learner evaluates their performance and attributes learning outcomes to external and internal causes. This self-judgment process is closely related to the self-reaction process. The self-reaction process involves an affective component regarding the learner's experienced intrinsic value or importance of the learning task. After completing the self-judgement process, the learner concludes with possible alterations concerning their learning behaviour. Ideally, the learner makes adaptive inferences directing themselves to more effective self-regulatory processes, enhanced learning strategies and improved goal setting.

Noteworthily, when self-regulated learning theory emerged, technologically enhanced learning environments were not available. However, these original theories, especially the Zimmerman cyclical model, were tested in new educational environments with technological progress. Until now, Zimmerman's model has acted as the most prominent model for the increasing number of studies that examine the role of self-regulated learning in technology-enhanced learning environments (Urbina et al., 2021).

Usher and Schunk (2017) described all these phases as cyclical intertwined, and one phase's quality may impact the following phase's quality. For example, students who struggle to monitor their use of learning strategies effectively may have difficulties adequately reviewing their strategies and adapting their behaviour accordingly. Thus, adequate assessment instruments and support of SRL, targeting all subphases of Zimmerman's (R. Baker et al., 2019; Michinov et al., 2011) model are needed.

SRL and Time Management

An essential aspect of successful learning besides SRL skills are time management skills (R. Baker et al., 2019; Michinov et al., 2011). Research also indicated that time management skills depend on strategy use and self-reported use of metacognitive and self-regulatory strategies (Credé & Phillips, 2011; Wolters et al., 2017). In fact, a recent review by

Wolters and Brady (2021) identified strong conceptual ties between SRL phases and time management. Concludingly the authors suggested considering "time management as part of SRL for students at all academic levels" (Wolters & Brady, 2021, p. 1343). Therefore, the presented study also included a measure of time management and investigated whether self-reported measures would correlate with time-management indicators from the log data (Jo et al., 2016).

SRL in Online Learning Environments

According to a meta-analysis conducted by Broadbent and Poon (2015), effective SRL strategies and time management skills have been positively associated with academic success in online learning environments. Research suggests that students with well-developed self-regulatory learning skills understand and use specific learning strategies to secure their success in learning (Winne & Marzouk, 2019), buttressing the significance for learners to possess sufficient regulatory competencies to continuously follow a successful learning path after transitioning into a technologically enhanced learning environment.

Behavioural activity logs recently raised interest as a potential indicator for a varied range of learning processes, and activity levels have been found to correlate with academic performance in online courses (Cerezo et al., 2016; Pardo et al., 2017). You (2016) modelled self-regulated learning by integrating viewing time, the number of logins, and late submissions in a hierarchical regression model that explained more than half of the variance in academic performance. Research by Zacharis (2015) identified that the number of quizzes and content files viewed predicted learning outcomes in a web-based learning environment. Kizilec et al. (2017) found that higher SRL skills were associated with a greater frequency of checking assessments and course materials. However, recent investigations by Quick et al. (2020) attempted to identify correlations between behavioural logs in online learning environments and self-regulatory measures with little success. Thus, this study attempts to associate the frequency with which students interact with a particular feature of the learning environment with their self-report SRL abilities.

SRL in Vocational Training

Generally, SRL is considered one of the essential skills to master workplace learning (Littlejohn et al., 2016; Sitzmann & Ely, 2011). Research confirmed the vital role of SRL skills in vocational training as it empowers young learners with the relevant knowledge to become autonomously working employees (de Bruijn et al., 2017; Jossberger et al., 2010, 2018). In the currently available literature on self-regulated learning in higher education, most studies have relied on university students as their sample (Urbina et al., 2021), and research regarding self-regulatory learning processes in online vocational training is scarce (Quesada-Pallarès et al., (2019). Quesada-Pallarès et al. (2019) recognized this issue leading to research among vocational education and training (VET) students comparing motivational and self-regulated learning strategies in online and classroom environments. They found that VET students enrolled in online classes perceived their effort regulation and metacognitive self-regulation levels as higher than those learning in a traditional classroom setting. Research by Jossberger et al. (2020) found that during workplace learning, VET students performed well at planning their time and monitoring their work process but experienced difficulties planning their learning behaviours effectively. While the literature in the field of SRL during vocational training is scarce, the evidence indicates that for vocational trainees to be successful online learners, they need self-regulatory learning skills.

Engagement

A standard metric in academic and industrial research to measure the success of an online learning environment is the learner engagement it generates (Lee et al., 2021; Martin & Borup, 2022; Noe et al., 2010). An engaged learner participates actively and remains involved during achievement-related activities. The literature differentiates between cognitive, emotional, and behavioural engagement (Fredricks et al., 2004). Behavioural engagement can broadly be defined as the extent of involvement, effort, and intensity of persistence with which one works on a task (Sinatra et al., 2015). Cognitive engagement may be conceptualized as the extent to which an individual thinks strategically during the learning process (Cleary & Zimmerman, 2012; Li & Lajoie, 2021). Emotional engagement refers to the extent that learners react to academic tasks and subjects (Pekrun & Linnenbrink-Garcia, 2012). While the relationship between them is considered complex behavioural engagement is viewed as the overt representation of cognitive and emotional engagement (Hu & Li, 2017). Across different learning environments, populations, and academic fields, increased engagement positively predicts academic performance (Lei et al., 2018). Research indicated that activity logs of learners in online learning environments, such as the average number of page views, may act as a valid and scalable approach to capture engagement (Motz et al., 2019; Paquette & Bosch, 2020). Nevertheless, researchers also mention the difficulty of identifying a learner activity, saved as log data that reliably proxies behaviour engagement in online learning environments (Gray & Bergner, 2022).

SRL and Engagement

Engagement and SRL share many characteristics and were positively correlated across different studies (Cleary et al., 2021). Both constructs are considered multidimensional and studied as mediators between learners' personal factors and academic performance (Wolters & Taylor, 2012). Besides, SRL and engagement theories stress the role of cognitive and metacognitive processes as crucial indicators for observable student behaviour, representing student academic functioning, e.g., the exertion of effort or, instead, its omission (Skinner et al., 2009). In their book chapter, Wolters and Taylor summarized the relationship between self-regulated learning and engagement: "students who are characterized as self-regulated learners will exhibit the types of cognitive activities, emotional experiences, and overt behaviour that reflect increased student engagement." (2012, S. 647). Further, researchers have argued for greater integration of SRL theories and engagement theories (Wolters & Taylor, 2012). For the presented study, learner engagement was broadly defined as learners' enactment of different activities (see table 2 for an overview). Research showed that the positive relationship between self-regulation and behavioural intention in online learning is mediated by engagement (Xu & Qiu, 2021). Hence engagement in learning activities may be the link between self-reported self-regulatory skills and behavioural intention, e.g., the use of effective strategies and positive learning outcomes.

The Current Study

Two challenges accompany behavioural logs as indicators of SRL activities in online learning environments. First, research validating the association between log data and SRL processes is limited (R. S. Jansen et al., 2022; Kizilcec et al., 2017; Maldonado-Mahauad et al., 2018). Second, developing effective SRL data-driven support, e.g., comprehensive digital dashboards, is still in its infancy. Nevertheless, effective support elements are demanded, as research points towards deficiencies in planning and management processes during learning, particularly in vocational educational trainees (Jossberger et al., 2020). This highlights the need to understand better how different constructs of the self-regulated learning framework can be assessed with data obtained in an online learning environment that vocational trainees use.

The presented study investigated the link between the learner's perception of their engagement in self-regulated learning and time-management activities and their activity logs from an online learning environment. To this end, the usage of SRL was assessed with a self-report questionnaire. This questionnaire focused on the metacognitive activities that are integral to self-regulated learning (Zimmerman, 2000). Specific learner behaviour and learning events assumed to be related to self-regulatory subprocesses and engagement were collected from the online learning environment as log files.

Since SRL is a cyclical process that unfolds over timestamp data, sequential mining techniques would be desirable. Unfortunately, no reliable time stamp data were available after data collection due to technical difficulties. However, research showed that SRL scores could be related to online learner activity captured in log files (R. S. Jansen et al., 2022; Maldonado-Mahauad et al., 2018), a relationship between SRL and a variety of engagement facets. Since event-based behavioural log data were available and proposed to be proxies of engagement (Carrillo et al., 2019), event measures were considered for the analysis. The log data captured the frequency of different learning-related user activities within

the span of 6 months. Different measures were calculated for each trainee to capture the quality of behavioural engagement (see below for details). The goal of this study is to link the results of the self-regulated learning questionnaire with theoretically related learner activities.

Research Questions and Hypotheses

RQ1: How is the behavioural learning engagement of vocational trainees associated with their SRL score?

H1 a) Trainees with a higher metacognitive ability (SRL) are expected to show greater behavioural engagement measured as the total number of logins.

H1 b) SRL are expected to correlate positively with the mean number of started learning activities.

RQ2: How do the scores of specific SRL subprocesses relate to particular learners' actions in the learning environment?

H2 a) The inspection of the study list as task analysis (Usher & Schunk, 2018) belonging to the forethought phase of the SRL model is positively associated with self-reported metacognitive ability before learning.

H2 b) Requesting case solutions to compare one's solution to the sample solution is a monitoring behaviour (Usher & Schunk, 2018) belonging to the performance phase and thus correlates positively with metacognitive ability during learning.

H2 c) Selecting the option to "watch later" after stopping a presentation instead of deciding to complete a presentation prematurely entails monitoring one's learning progress (Usher & Schunk, 2018) before deliberately choosing to resume the learning process at a later point in time. Thus, the "watch later" event is expected to be positively associated with metacognitive ability during learning.

RQ3: How do self-reported SRL abilities relate to the use of effective online learning strategies and learning outcomes?

H3 a): The self-reported usage of effective learning strategies are associated with cognitive engagement, thus the strategic application of learning strategies (Cleary & Zimmerman, 2012; Li & Lajoie, 2021). For this study, improved strategic problem-solving is expected to be reflected in an increased completion rate of each learning phase. Thus, a positive association between the SRL score and the rate of completed presentations, investigations, and assessments is expected.

H3 b) It is expected that increased self-regulation scores positively correlate with the study engagement during assessments, measured as the submission ratio of responses per assessment.

H3 c) Due to their stronger cognitive engagements, students with greater SRL scores are more likely to think "strategically across the learning" (Li & Lajoie, 2021, p. 2), which may be reflected as intentionally seeking an overview of the learning tasks they are commissioned to do when they begin a learning session. Thus, a positive correlation is expected between a trainee's SRL score and the ratio of the study list viewed per login.

H3 d) Previous research findings emphasizing the crucial role SRL abilities play in online learning environments for university students can be replicated and transferred to VET students learning online (Broadbent & Poon, 2015). This relation is positively associated with the trainee's SRL score and the percentage of correctly responded items during an assessment.

RQ4: How do self-reported time management abilities relate to the use of effective online learning strategies and learning outcomes?

H4 a) For successful learning time management, an accurate awareness of the to-be-completed learning tasks is critical (Wolters & Brady, 2021). Thus, time management is hypothesized to be positively associated with the absolute sum of the event "study list viewed" and the ratio of study list viewed per login.

H4 b) Research shows that self-reported time management abilities positively correlated with the login frequency in an online learning platform (Jo et al., 2016). The authors finding are expected to be replicated in this study.

H4 c) Since time management ability correlates positively with academic performance in online courses (e.g., Michinov et al., 2011), the percentage correct during an assessment is expected to correlate positively with time-management skills.

Methods

Participants

All participants of this study were users of Cornelsen eCademy®, a web-based learning application for vocational trainees in the German-speaking region. In total, 48 participants gave consent to participate in this study, of which 47 (40 males) completed the online questionnaire. A tree donation for each completed questionnaire was offered as an incentive. The participants reported a mean training year of 1.44 (SD = .66), and a total of eight different vocational training programs were completed in three different companies.

Material

The learning environment can be defined as a learning experience platform (Weller, 2007). The platform enhances occupational training by providing additional learning opportunities for vocational trainees. The desired learning mode is blended learning (e.g., as a form of a flipped-classroom approach). Meaning, that eCademy® does not attempt to replace vocational education at school or the workplace but instead acts as a supplementary learning environment that the trainers can use to guide their trainees' theoretical learning before linking the fundamental knowledge gained on the learning platform with real-life examples from the professional context. The instructional goal is to free up resources for hands-on learning, which is critical for vocational training (Jossberger et al., 2020) and focus on individual strengths and weaknesses during learning time at work.

The didactical concept of the learning units pursues three goals. First, introducing new knowledge is represented as the presentation mode on the eCademy® app. Each learning module begins with a short presentation containing text, visual representations, and auditorial explanations. Second, learners receive instructions on the practical application of the given learning content. During the investigation phase, the trainees gain insights into the practical utilization of the learning content using constructed model assignments. For this purpose, eCademy® provides interactive simulators and scenario-based training assignments that aid the trainee by providing a realistic problem and an opportunity to explore the practical application of the newly acquired knowledge. Third, trainees can autonomously evaluate their learning progress. For this, trainees take an assessment consisting of single-choice and enter-value questions. The trainee receives instant feedback on the correctness of their responses, containing an explanation or a solution. Finally, learners evaluate their performance through a feedback report on their percentage of correctly responded items. Usually, trainees cannot deviate from the instructional order of presentation, investigation and test but can prematurely close presentations or investigation to skip straight to the test. The trainees can interrupt a learning session and continue later.

To support the timely delivery of the correct content, eCademy® has developed a study list feature. The trainers can select and share a list of relevant learning content for their trainees. The trainers can review the trainees' progress on their study list using the reporting function. The trainees can open their study list to view an up-to-date list of learning units recommended by their trainer. The study list helps trainees to plan and monitor their learning. The trainees receive a list with which they can ensure that they work on all learning content relevant to their work context. For example, the trainer can help the learners prepare for their exam by adding the exam training and the critical content to the study list.

Measurements

The Online Self-regulated Learning Questionnaire

As an aptitude measure of SRL, the online self-regulated learning questionnaire's revised version was used (Jansen et al., 2018). This questionnaire was initially designed to measure SRL activities in the context of Massive Open Online Courses (MOOCs), including all phases of Zimmerman's (2000) cognitive processing model and additional scales targeting time management, environmental structuring, persistence, and help-seeking. The present study only included the scales on metacognitive activities before (MAB), during (MAD) and after (MAA) learning, as well as the specific subscale for time management (TM). The reasons for this are two-folded, either the eCademy® app did not provide any specific event that usage could be traced and correlated to the corresponding scales (help-seeking and persistence), or the items referred to behavioural activities that did not describe online activities and thus were unapplicable for online trace data (environmental structuring). In total, 23 seven-point Likert-scale items, phrased as statements, were presented to the participants, asking them to indicate to what degree these statements apply to them. A one indicated "not at all true for me", and a seven meant "very true for me". Two independent translators translated the questionnaire into German, adapted it to the learning context (the eCademy® app) and shortened it. The final MAB subscale included six items targeting preparatory metacognitive activities, e.g., "I think about what I really need to learn before I begin a task in the eCademy® app". The final MAD subscale consisted of seven items, e.g., "I periodically review to help me understand important relationships in learning content in the eCademy app". The final MAD scale contained six items, e.g., "After studying with the eCademy app, I reflect on what I have learned". Five items targeted time management, e.g., "I allocate studying time to learn with the eCademy app." An overview of the original and adapted phrasing of all the items used for this study is presented in Appendix A.

Two negatively phrased time management items, asking for possible difficulties with handling the learning list and the presence of possible distractors, were rescored inversely after response collection. Scores for each subscale were computed by calculating the mean of each subscale and computing a grand mean SRL score by creating a mean of all subscale means. The item questioning the start of the traineeship was recoded by subtracting the current year (2021) from the indicated starting year of the vocational training to receive a number between 1 and 3. Data regarding the profession were recoded as nominal data to be included in further analysis. Inter-Item correlations between the items of each subscale were obtained (see Table 1). Two items of the time management scale were removed to improve Cronbach's alpha to an acceptable value of .715 (Streiner, 2003).

Table 1

Internal Reliabilities of the Contextualized SRL-Q-R Subscales.

	Number of Items	α
MAB	6	.858
MAD	7	.867
MAA	6	.878
TM	3	.715

Note: MAB = Metacognitive ability before learning. MAD = Metacognitive ability during learning. MAA = Metacognitive ability after learning. TM = Time Management.

Behavioural Logs

When learning with the eCademy® app, the learner's measurable behaviours as specific actions are stored in behavioural logs. The retrieved log data were aggregated over six months across multiple learning units. The events expected to be related to specific self-regulated learning processes were retrieved using the commercially available Mixpanel® software. In total, twenty events were considered potentially relevant for the present study. The selected events are listed and described in Table 2. Additional to the events, the average percentage of correct responses when assessing the eCademy® app was obtained. The logs and their corresponding User IDs were matched with those collected during the SRL questionnaire's completion.

To enable a more profound analysis and gain deeper insights into user behaviour, ratio scores that were considered conceivably suited as indicators of specific self-regulatory sub-processes were calculated. First, the completion rate of presentations was calculated by dividing the number of presentations stopped by the number of presentations started. Second, the completion rate of investigations and assessments were calculated uniformly to the completion rate of presentations. Third, the rate of repeated assessments was computed by dividing the number of assessments repeated by the number of assessments ended. Fourth, to gain insight into the engagement when performing assessments, the submission rate of answers was computed by dividing the total number of submitted answers by the sum of assessments. Finally, the number of study lists viewed was divided by the number of logins detected in the past six months. The results of these were saved as new variables. Further, the mean number of presentations, investigations and assessments started was computed to include a measure of learning phases started.

Table 2

Event Names and Corresponding Definitions of Each Event

Event name	Definition of the traced event
Presentation started	Fires whenever a presentation is started
Presentation stopped sum	Fires whenever a presentation is stopped
Presentation "watch later" selected	Fires whenever a presentation is stopped, and the option to continue to watch it later is selected
Investigation started	Fires whenever an investigation is started
Investigation closed	Fires whenever an investigation is closed
Investigation case solution toggled	Fires whenever the solution of an investigation is requested
Assessment started	Fires whenever an assessment is started
Assessment ended	Fires whenever an assessment is completed
Assessment stopped	Fires whenever an assessment is stopped before it is completed

Assessment repeated	Fires whenever an assessment that was completed before is opened again
Study list viewed	Fires whenever a study list is opened
Exam simulation started	Fires whenever an exam simulation is started
Exam simulation ended	Fires whenever an exam simulation is completed
Exam simulation answer submitted	Fires whenever an answer for an exam simulation question is submitted
Exam training started	Fires whenever an exam training is started
Exam training stopped	Fires whenever an exam training is stopped before it is completed
Exam training continued	Fires whenever an exam training that was stopped before is continued
Logged in	Fires whenever a user logs in to the webpage

Procedure

The self-regulated learning questionnaire was distributed through the conversational relationship platform intercom®, and typeform® aided the collection process. After logging in to the platform, all trainees employed by companies who agreed to participate in this study were prompted to complete the designed questionnaire. When the responses were collected, information about the study year and the participants' gender indicated their gender, profession, and employment company manually. User IDs were traced in the background. The average completion time for the questionnaire was 4 min 49 seconds. The participants completed the translated and adapted version of the online-self-regulated learning questionnaire between April 2021 and May 2021. The questionnaire was withdrawn from the platform on the same day the accumulated trace data was retrieved.

Results

Computation of mean scores

The means and standard deviations for the items corresponding to metacognitive activities before, during, and after learning and time management were computed. Finally, a grand SRL mean score of the collected items was computed. Table 3 displays the relevant descriptive statistics of the self-regulated learning questionnaire.

Table 3

Descriptive Statistics of the SRL-Q-R Subscales and Grand Mean

	MAB	MAD	MAA	TM	Grand SRL Mean
Mean	4.01	4.34	4.35	4.44	4.28
Std. Deviation	1.39	1.39	1.26	.98	1.08

Note: MAB = Metacognitive ability before learning. MAD = Metacognitive ability during learning. MAA = Metacognitive ability after learning. TM = Time Management.

Correlational Analysis

The normality assumption critical for applying Pearson's correlation coefficient was frequently violated for several events stored in behavioural logs. Hence it was decided to continue the correlational analysis with the non-parametric correlation coefficient spearman's rho. Table 4 contains the results of the correlational analysis.

RQ1: SRL Score and Behavioural Learner Engagement

Research question one investigated the association between the number of logins, the start of learning activities and a participant's grand mean SRL score. As predicted, a trainee's grand SRL mean score was positively associated with the number of detected logins (r (45) =.349, p =.016). The hypothesis that trainees with higher SRL scores start more learning processes could not be supported (r (45) = .189, p = .203).

RQ2: Behavioural Logs and SRL Subprocesses

Contrary to the first hypothesis, the number of study lists viewed was not significantly correlated with self-reported metacognitive abilities before learning (r (45) = .269, p = .068). Noticeably the students with greater metacognitive ability during learning (r (45) = .337, p = .021), after learning (r (45) = .457, p = .001) and a greater SRL grand mean score (r (45) = .401, p = .005) were more likely to check their study lists regularly. Neither the expected association between the frequency of monitoring one's learning process through requesting a sample solution and metacognitive ability during learning

(r (45) = .097, p = .515) nor the association between intending to resume a presentation at a later point in time and the self-reported ability to make use of metacognitive activities during learning (r (45) = .225, p = .128) were found.

RQ3: SRL Scores and Enhanced Learning Activity Quality

The first hypothesis that students with greater self-reported SRL abilities are more likely to complete the learning phases could not be validated. No significant association between the grand SRL mean and the completion ratio of any of the three learning phases was found significant (presentation (r (45) = -.138, p = .353)), (investigation

(r (45) = -.111, p = .457)), (assessments (r (45) = -.058, p = .697)). However, the results show that SRL scores positively correlate with the ratio of assessments submitted (r (45) = 326, p = .26), as was expected in the second hypothesis of this research question. The results also suggest that contrary to the third hypothesis, SRL scores were not significantly associated with the ratio of study list viewed per login (r (45) = .148, p = .214). The final hypothesis of this research question was supported as SRL scores were significantly positively associated with the percentage of correctly responded items (r (45) = .302, p = .39).

RQ4: Behavioural Logs and Time Management Scores

In support of the first proposed hypothesis, the trainee's self-reported ability to manage their learning time positively correlates with the frequency of viewing their study list (r (45) = .457, p = .001). However, this association was insignificant for the ratio of the study list viewed per login (r (45) = .204, p = .169). As predicted, the number of logins was positively correlated with self-reported time-management abilities (r (45) =.464, p < .01). In support of the final hypothesis, the average percentage correct during an exam positively correlated with self-reported time-management skills (r (45) =.570, p < .01).

Table 4

Spearman-rank Correlations Between Behavioural Log Data and SRL-Q-R Means

	MAB	MAD	MAA	TM	Grand SRL Mean
Logins	.214	.279	.349*	.464**	.349*
Learning phases started	.098	.103	.189	.414**	.189
Study List viewed	.269	.337*	.401**	.457**	.401**
Presentation "watch later" selected	.096	.225	.215	.336*	.215
Case solution requested	-.062	.097	.042	.106	.042
Ratio of Presentations completed	-.110	-.250	-.138	-.037	-.138
Ratio of Investigations completed	.030	-.185	-.111	-.017	-.111
Ratio of Assessments completed	.035	.070	-.058	-.238	-.058
Ratio of Assessments submitted	.276	.334*	.326*	.308*	.326*
Ratio of Study List viewed per Login	.175	.180	.214	.204	.214
Percentage Correct	.192	.246	.302*	.570**	.302*
Assessment Repeated	.229	.275	.374**	.461**	.374**
Ratio of Assessments repeated	.302*	.358*	.442**	.512**	.442**
Exam simulations started	.001	.187	.099	.015	.099

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Discussion

This study aimed to find behavioural activities stored in log files associated with self-reported SRL scores, reflected as the use of metacognitive strategies, and hence could potentially be used to unobtrusively assess self-regulatory activities of learners in a highly frequented online learning environment without disrupting the learning process. A self-report questionnaire that measured online self-regulated learning activities and individual behavioural data in the form of online activity data were aligned, and correlations between these two measurements were applied to investigate the research questions.

Generally, self-reported SRL activities were expected to be positively associated with the frequency of engagement in behavioural activities because greater metacognitive ability and cognitive engagement lead to using more effective learning strategies that are reflected as specific behaviours when learning online. As expected, a positive relationship between SRL scores and the frequency of usage of the platform was confirmed. This means learners with enhanced metacognitive abilities use the platform more frequently, conceivably because they have understood the importance of regular learning progress. In contradiction with the first hypothesis, the SRL score was neither correlated with the engagement measured as learning activities that were started nor with the completion rate of these. These findings may be explained by the research of Bodily et al. (2017), which illustrated the difficulty of measuring learners' engagement using instruments used in the field of learning analytics. They partially explained this by the mismatch of the currently available granularity of online trace data stored in behavioural logs and the degree of granularity that a distinct pedagogical theory on engagement would require to confirm predictions of an engagement model.

Neither this research found a significant association between subphases of Zimmerman’s (2000) social cognitive model of self-regulated learning and intention to return to a presentation later and the number of study lists and sample solutions views. Interestingly, the results suggest that the learners may use this feature to monitor and evaluate their learning, as the correlation with these measures was significant. The expected association between the frequency of requesting sample solutions as comparisons to own solutions as an indicator for monitoring behaviour during the performance phase could not be supported. The same is true for the hypothesis: the frequency of indicating an intention to resume a presentation later represents an evaluation process of the current learning progress. This could be because learners use a feature such as requesting a case solution differently depending on context. When learners are certain about the answer, they may request a sample solution to monitor their response's correctness. However, if they do not know the answer, they use this button to seek external help showing the technical limitations of this study. The analysis purely relied on frequency data obtained over a certain period. However, SRL is a cyclical process that is context and time-dependent. By exclusively relying on frequency data, crucial contextual information to explain behaviours may be lost. Temporal data properties were not readily available for this research, and therefore the temporal context in which events occurred was not considered, and engagement was used as a substitute concept. For example, only limited data were available that helped to explain how requesting a sample solution button was used. When requested at the beginning of a task, it could be a form of gaming the system in that the learner is trying to shorten the learning path and be presented with the correct solution (Baker et al., 2013). However, later in the learning process, it could be interpreted as help-seeking or monitoring behaviour. Therefore, gaining insights into the temporal pattern of the behavioural logs may be valuable to link Zimmerman's cyclical model of self-regulated learning to real-world behaviours stored in digital logs.

It was expected that self-reported SRL activities would also be positively associated with measures of academic performance. This hypothesis found support in the data, despite the small sample size of 47. Higher SRL scores were associated with greater academic success measured as the percentage correct on an assessment. Therefore, this study underlines the strong positive relationship between SRL activities and academic performance and extend former finding from studies that drew samples from university students to the vocational trainee population (e.g., Broadbent & Poon, 2015; Cazan, 2014). Forthcoming studies may extend the finding of this study towards looking at the association between online SRL behaviours and workplace performance outcomes.

The results of this study highlight the role of time management abilities in becoming a successful online learner. Interestingly, trainees who reported good time-management ability performed better in assessments and were more likely to log in frequently and review their study list more often. This finding indicates that students aware of time constraints during learning purposefully monitor their to-be-completed modules, which helps them achieve success during online learning. Hence, a monitoring dashboard that visualizes their time resources may help trainees with less developed management capabilities to allocate their learning time better and achieve better results (Matcha et al., 2020).

According to the results of the correlational analysis, the two activities most frequently significantly associated with self-reported engagement in metacognitive strategies were viewing the study list and the likelihood of repeating an assessment. Translating these results into actionable implications could raise awareness in trainees and trainers to use the study list feature whenever possible and for trainers to encourage their students to repeat assessments if they have not received a satisfying result.

Strengths of this study

The presented study uniquely contributes to the broader research body on online self-regulated learning by focussing on the underrepresented population of vocational educational trainees that learn with a commercially available learning experience platform. The study provides first insights into the learning behaviour of vocational trainees studying in an online learning environment. The educational background and learning style of trainees in the company's dual system between theoretical learning and practical application is quite different from university students, making specific insights into their self-regulated learning behaviour interesting. The presented research attempted to illuminate this research gap by collecting data in an authentic online learning environment exclusively used by vocational trainees.

Suggestions for Future Research

Greater sample sizes and contextual (sequential) fine-grained behavioural log data would allow more insightful analyses. Work by Bannert et al. (2014), Sabourin, Mott and Lester (2013), Maldonado-Mahauad et al. (2018) and Jansen et al. (2022) showed that process mining algorithms, as well as sequential pattern mining techniques, suitable instruments detect SRL processes through patterns in behavioural logs. For the context of the eCademy® app, sequential pattern analysis may, for example, be used to investigate if a trainee's SRL score is associated with whether the learners use the study list function before looking at content.

This study predominantly focused on the association between behavioural measures and self-reported SRL scores, but measures of success in learning were only marginally appraised. This was due to the low availability of this kind of data. Additionally, no external measures of work performance or grades at the final examination could be integrated into the analysis of this study. Additional sources should be considered to understand the relationship between online self-regulation skills and academic performance.

Practical Implications

Two broad practical implications can be drawn from this study. First, when trying to improve the effectiveness of the learning platform, SRL processes should be considered and investigated how the development of new features can support vocational trainees in becoming more self-regulated learners. For this, capturing the learner's actions in log files that carry a timestamp would be important to open the opportunity to measure dynamic, time-bound learning processes. Applied research can help continuously improve existing learning experience platforms to identify indicators of regulatory activity, visualize them for teachers and trainers, and finally create adaptive learning products that support self-regulating learning through interventions tailored to the learners' needs. In the long term, developing a virtual dashboard that represents events associated with different SRL processes could be a valuable tool to constantly aggregate information about the trainee's self-regulation behaviours when interacting with the platform and identify trainees who would benefit from tailored interventions. For instance, eCademy® integrated a glossary tool for students to receive factorial information about a technical term. Recording its usage as an indicator for help-seeking could be a potential addition to the monitoring dashboard. Second, the study list function should be further enhanced and communicated to the trainers to help learners organize their learning on the platform. Research from Van der Kleij et al. (2015) suggests that students' learning traces captured during their interaction with an online learning environment prove valuable to prompt students to reflect on their learning strategies and adapt their self-regulatory activities. Cornelsen eCademy® could, for example, enact the positive association between the number of times the trainee viewed their study list and self-regulation scores by incorporating this event in a monitoring dashboard for trainers.

Conclusion

As previously mentioned, one of the most significant challenges to online SRL research is to find valid and reliable yet non-disruptive measurements of self-regulatory online learning activities and metacognitive strategy use. The presented study targeted triangulating a well-established aptitude and promising event-based measure of online self-regulatory learning. The results of the presented study allow three broad conclusions. First, research findings on the critical role of SRL skills for academic success are replicable in online learning environments. Second, self-reported self-regulatory activities are at least partially reflected through online learning activities. Third, analyzing behavioural logs as indicators for metacognitive activities remains a promising field of research. However, the associations between processes defined in Zimmerman's social-cognitive model of self-regulated learning and behavioural logs are more complex than first anticipated. Nevertheless, as research insights progress in this field of study and online behavioural data is more readily accessible, they may guide the design of effective and adaptive SRL support.

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Appendix A

Target Self-regulatory Phase, Original Wording, and Adapted Wording for Each Question

Targeted phase	Original item wording as proposed by Jansen et al. (2018)	Adapted item word to eCademy context
Metacognitive activities before learning	I think about what I really need to learn before I begin a task in this online course.	I think about what I really need to learn before I begin a task in the eCademy app.
Metacognitive activities before learning	I ask myself questions about what I am to study before I begin to learn for this online course.	I ask myself questions about what I am to study before I begin to learn with the eCademy app.
Metacognitive activities before learning	I set short-term (daily or weekly) goals as well as long-term goals (monthly or for the whole online course).	I set short-term (daily or weekly) as well as long-term goals (monthly or for learning in the eCademy app).
Metacognitive activities before learning	I set goals to help me manage my studying time for this online course.	I set goals to help me manage my studying time in the eCademy app.
Metacognitive activities before learning	I set specific goals before I begin a task in this online course	I set specific goals before I begin a task in the eCademy app.
Metacognitive activities before learning	At the start of a task, I think about the study strategies I will use	At the start of a task, I think about the study strategies I will use.
Metacognitive activities during learning	I have a specific purpose for each strategy I use in this online course.	I have a specific purpose for each strategy I use in the eCademy app.
Metacognitive activities during learning	When I study for this online course, I try to use strategies that have worked in the past.	When I study with the eCademy app, I try to use strategies that have worked in the past.

Targeted phase	Original item wording as proposed by Jansen et al. (2018)	Adapted item word to eCademy context
Metacognitive activities during learning	I am aware of what strategies I use when I study for this online course.	I am aware of what strategies I use when I study with the eCademy app.
Metacognitive activities during learning	I change strategies when I do not make progress while learning for this online course.	I change strategies when I do not make progress while learning with the eCademy app.
Metacognitive activities during learning	I periodically review to help me understand important relationships in this online course.	I periodically review to help me understand important relationships in the learning content in the eCademy app.
Metacognitive activities during learning	I find myself pausing regularly to check my comprehension of this online course	I find myself pausing regularly to check my comprehension of the learning content in the eCademy app.
Metacognitive activities during learning	I ask myself questions about how well I am doing while learning something in this online course.	I ask myself questions about how well I am doing while learning something with the eCademy app.
Metacognitive activities after learning	I think about what I have learned after I finish working on this online course.	I think about what I have learned after I finish working with the eCademy app.
Metacognitive activities after learning	I ask myself how well I accomplished my goals once I'm finished working on this online course.	I ask myself how well I accomplished my goals once I'm finished working with the eCademy app.
Metacognitive activities after learning	After studying for this online course, I reflect on what I have learned.	After studying with the eCademy app, I reflect on what I have learned.

Targeted phase	Original item wording as proposed by Jansen et al. (2018)	Adapted item word to eCademy context
Metacognitive activities after learning	I find myself analyzing the usefulness of strategies after I studied for this online course.	I find myself analyzing the usefulness of strategies after I studied with the eCademy app.
Metacognitive activities after learning	I ask myself if there were other ways to do things after I finish learning for this online course	I ask myself if there were other ways to do things after I finish learning with the eCademy app.
Metacognitive activities after learning	After learning for this online course, I think about the study strategies I used.	After learning with the eCademy app, I think about the study strategies I used.
Time Management	I make good use of my study time for this online course.	I make good use of my study time when learning with the eCademy app.
Time Management	I find it hard to stick to a study schedule for this online course.	I find it hard to follow the study list when learning with the eCademy app.
Time Management	I make sure I keep up with the weekly readings and assignments for this online course.	I make sure I keep up with the study list when learning with the eCademy app.
Time Management	I often find that I don't spend very much time on this online course because of other activities.	I often find that I don't spend very much time with the eCademy app because of other activities.
Time Management	I allocate studying time for this online course.	I allocate studying time to learn with the eCademy app.
Time Management	I allocate studying time for this online course.	I allocate studying time to learn with the eCademy app.