Accepted Manuscript

Relations between Students' Perceived Levels of Self-Regulation and their Corresponding Learning Behavior and Outcomes in a Virtual Experiment Environment

Sjors Verstege, Héctor J. Pijeira-Díaz, Omid Noroozi, Harm Biemans, Julia Diederen

PII: S0747-5632(19)30072-X

DOI: 10.1016/j.chb.2019.02.020

Reference: CHB 5924

To appear in: *Computers in Human Behavior*

Received Date: 05 September 2018

Accepted Date: 17 February 2019

Please cite this article as: Sjors Verstege, Héctor J. Pijeira-Díaz, Omid Noroozi, Harm Biemans, Julia Diederen, Relations between Students' Perceived Levels of Self-Regulation and their Corresponding Learning Behavior and Outcomes in a Virtual Experiment Environment, *Computers in Human Behavior* (2019), doi: 10.1016/j.chb.2019.02.020

Relations between Students' Perceived Levels of Self-Regulation and their Corresponding Learning Behavior and Outcomes in a Virtual Experiment Environment

Sjors Verstege [a], Héctor J. Pijeira-Díaz [b], Omid Noroozi [c], Harm Biemans [c], Julia Diederen [a,*]

[a] Laboratory of Food Chemistry, Wageningen University & Research, the Netherlands
[b] Faculty of Education, University of Oulu, Finland
[c] Chair group of Education and Learning Sciences, Wageningen University & Research, the Netherlands

* Corresponding author at:

Laboratory of Food Chemistry, Wageningen University & Research, the Netherlands
E-mail address: julia.diederen@wur.nl

Relations between Students' Perceived Levels of Self-Regulation and their Corresponding Learning Behavior and Outcomes in a Virtual Experiment Environment

Abstract

Virtual Experiment Environments (VEEs) have been shown as effective preparation steps for laboratory classes in natural science education. Given the self-directed nature of VEEs, students need adequate Self-Regulated Learning (SRL) skills. This study explores the relation between students' perceived SRL level and their behavior and outcomes in a VEE in the field of enzymology. Ninety-seven higher education students were divided into three groups of perceived SRL level (high, medium, and low). The VEE learning behavior (e.g., number of attempts and hints accessed) and VEE outcomes of these groups were compared while keeping prior knowledge as a covariate. While low self-regulated learners showed the least level of engagement with the VEE, high self-regulated learners showed the most optimum learning activity. Medium self-regulated learners engaged more in gaming the system behavior, and consequently learned the least. These results suggest that there is a nonlinear relationship between perceived SRL level and outcomes, since the intermediate level seems to be detrimental to learning, as explained through behavior. The intermediate level was characterized by an increase in agency, but a lack of goal-directed and planning behavior. Implications for self-regulated learning theory and the design of VEEs in the best interest of students are discussed.

Keywords: self-regulated learning, virtual experiment environment, learning behavior, learning outcomes, higher education

1 Introduction and theoretical framework

1.1 Laboratory education

Laboratory education is a commonly used practice in natural science education and is generally regarded as a vital component of a chemistry curriculum (Bruck & Towns, 2013). Teachers have several goals for laboratory classes, including hands-on research experience, group work, broader communication skills, data collection and (error) analysis, planning, and laboratory report writing (Bruck & Towns, 2013; Kirschner & Meester, 1988; Verstege, Van der Kolk, Diederen, Hartog, & Gruppen, 2016). However, many of these goals have been argued to be better accomplished outside the cognitively demanding learning environment of the laboratory (Hartog, Van der Schaaf, Beulens, & Tramper, 2009).

While it is acknowledged that laboratory practicals play an indispensable role in the conveyance of tacit knowledge, concerns have been raised that not all intended learning outcomes may be achieved by the students, and that some laboratory practicals may even confuse or demotivate students (Kirschner & Huisman, 1998). Doubts on the quality of knowledge construction and learning gains from laboratory classes (Abdulwahed & Nagy, 2009; Hawkes, 2004; Hawkins & Phelps, 2013; Kirschner & Huisman, 1998; Kirschner & Meester, 1988) have been explained by their cognitively demanding nature (Buntine et al., 2007). During laboratory classes students need to plan their time, use (unfamiliar) equipment, find their way around the lab, remember all the safety rules, translate a protocol into action, etc. When performing experiments, students use most of their cognitive abilities

for the act itself, the motor skills and the planning skills, acquiring mainly tacit knowledge about the experiments, while underexposing higher cognitive levels of scientific inquiry (Domin, 1999).
In addition, a number of practical challenges in laboratory education have been reported, including, but not limited to, ill-prepared students, difficulties with teaching assistants, high enrollments, diverse majors, a decline in resources and an increase in responsibilities (Bruck & Towns, 2013). The use of laboratories is increasingly costly (Hawkins & Phelps, 2013), and the effective and efficient use of time spent in the laboratory is a necessity for all educational institutions (Kirschner & Meester, 1988).
Careful preparation for laboratory classes, such as practicing with the chemical concepts and data analysis skills, has proven to increase the quality of knowledge construction during laboratory classes (Bannert, 2002; Crandall et al., 2015; Winberg & Berg, 2007). Virtual and simulated laboratories are valuable assets to prepare students for laboratory classes (Abdulwahed & Nagy, 2009), and are also a convenient and effective replacement of laboratory classes, especially in contexts where the laboratory is not an option such as distance education (Hawkins & Phelps, 2013).

1.2 Simulations and virtual experiment environments
In order to prepare students for laboratory classes, many different learning activities have been developed over the past decades, including pre-laboratory videos (Spagnoli, Wong, Maisey, & Clemons, 2017), animations (Limniou & Whitehead, 2010), pre-laboratory quizzes, tutorials, (digital) assignments (Diederen, Gruppen, Hartog, & Voragen, 2006; Koehler & Orvis, 2003; Spagnoli et al., 2017; Van der Kolk, Beldman, Hartog, Moerland, & Gruppen, 2013), and simulations (Crandall et al., 2015; Limniou & Whitehead, 2010). Simulations, virtual laboratories, online laboratories or remote laboratories, have been referred to as non-traditional labs. An extensive review (Brinson, 2015, p.218) on the difference in achieved learning outcomes between students in a non-traditional lab compared to traditional labs reported that “learning outcome achievement is equal or higher in a non-traditional lab versus traditional labs across all learning outcome categories (knowledge and understanding, inquiry skills, practical skills, perception, analytical skills, and social and scientific communication)”. Another review of 17 studies on the effects of computer simulations as a supplement or alternative to traditional laboratory activities in science education concluded that traditional instruction can be successfully enhanced by using computer simulations (Rutten, van Joolingen, & van der Veen, 2012). In most of the 17 reviewed studies, improved learning outcomes were shown. Also, when simulations were used as a preparatory activity, positive effects were found for the comprehension of the lab task as well as for practical laboratory skills during the real lab activity (Rutten et al., 2012).
A simulation environment that can be used to prepare students for laboratory classes, or even (partly) replace them, is referred to as a Virtual Experiment Environment (VEE). A VEE is “any educational resource that enables students to design and/or carry out virtual experiments and/or to process data, and to analyze and interpret results” (Hartog et al., 2009, p.376). A VEE can be a rich interactive learning environment in which students work on self-directed learning tasks. Students can, for example, design the experiments themselves, answer closed questions, ask for feedback or hints, seek additional information about the chemical methods including visual information such as videos, photos and animations, and process and make sense of data. In order to complete a VEE, students must adopt an active learning attitude and, accordingly, students need self-regulated learning skills.

1.3 Self-regulated learning

As educational psychology transitioned from behaviorism to cognitivism and constructivism, learners were no longer considered as passive, receptive subjects, but rather as subjects with agency (Bandura, 1986) responsible for their learning (Hoadley, 2018). The behavioral, motivational, and metacognitive active participation of students in their own learning processes is referred to as self-regulated learning (SRL) (Zimmerman, 1989). As students set their own learning goals, plan learning activities, execute tasks, adopt, enact, develop and refine strategies, monitor and control their learning process, and adapt it to meet their goals, they engage in SRL (Hadwin, Järvelä, & Miller, 2011). SRL is inherent in goal-directed activity (Winne, 1997) and essentially a cyclical process (Zimmerman, 2015). Given SRL's wide scope, different models of SRL have been proposed in literature (for reviews, see Panadero (2017); Winne (2015)). Although there is overlap between them, the models focus on different aspects of SRL. This article adopts Zimmerman's cyclical phases model, for its balance in cognition, emotion and motivation as facets of learning, and because it has been the most widely adopted according to its number of citations (Panadero, 2017). Zimmerman's model has been predominant as it offers a robust and complete vision of different types of subprocesses that articulate the interaction of students' personal and behavioral characteristics (Moos & Ringdal, 2012).

The cyclical phases model (Zimmerman, 2000; Zimmerman & Moylan, 2009) consists of three phases, namely forethought, performance and self-reflection. Each phase, in turn, is divided in two categories. The forethought phase comprises the categories of task analysis and self-motivation beliefs. During the task analysis, the students set their goals and strategically do their planning, which depends on motivational beliefs in relation to the task, such as self-efficacy (i.e., to what extent they feel capable of accomplishing the task), expectations, interest, and value. The categories of self-control and self-observation determine the performance phase. As part of self-control, students choose the strategies to approach the task, gather information, seek help, and manage the available time, among other activities. Meanwhile, self-observation essentially refers to monitoring their performance. Monitoring is central to the third phase, self-reflection, where students evaluate their performance and react to the evaluation by making adaptations to the forethought phase (e.g., adjusting the goals and modifying the plan), thus initiating another cycle of SRL. In sum, SRL is a cyclical process through which students take command of their own learning, stemming from task identification, planning learning activities, monitoring progress, diagnosing problems, testing their learning outcomes, adjusting, and reflecting (Schunk & Zimmerman, 2011; Zimmerman, 2000). SRL is thus expected to increase efficiency when the learner addresses analogous tasks in the future (Winne & Perry, 1994).

According to Vermunt and Donche (2017), the way students approach a learning activity such as a VEE depends, among others, on their learning patterns. A learning pattern is an interrelationship between the conception of learning, learning motivation, processing strategies, and regulation strategies. These learning patterns influence the learning outcomes of the students and are in turn influenced by contextual factors and personal factors. Regulation strategies are a central element of the learning patterns. For example, students who have a meaning-directed learning pattern, learn in a self-regulated way, not limiting themselves to prescribed materials through consulting literature and other sources.

1.4 SRL in relation to outcomes and behavior

Students who set superior goals proactively, monitor their learning intentionally, use strategies effectively, and respond to personal feedback adaptively not only attain mastery more quickly, but also are more motivated to sustain their efforts to learn (Zimmerman, 2013). Students' beliefs about their efficacy to regulate their academic learning activities have been found to be highly predictive of their academic achievement (Zimmerman & Schunk, 2003). The personal capabilities that enable students to develop as independent, self-regulated learners are highly related to their achievement (Chen, 2002; Zimmerman & Pons, 1986).

Several SRL strategies have been listed, of which metacognition, time management, effort regulation, and critical thinking were found to have higher associations with academic achievement (Broadbent & Poon, 2015; Richardson, Abraham, & Bond, 2012; Zimmerman & Pons, 1986). Most prior research has focused on the relation between regulation and academic achievement in traditional classrooms (Boekaerts & Corno, 2005; Moos & Ringdal, 2012; Vermunt & Donche, 2017).

More recently, the increasing availability and use of online learning environments (e.g., massive open online courses (Kay, Reimann, Diebold, & Kummerfeld, 2013) and learning management systems (Coates, James, & Baldwin, 2005)) are leading to a growing interest in the exploration of the interrelation among students' SRL level and behavior and outcomes in these environments, given the increased autonomy they confer upon students (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Tempelaar, Rienties, & Giesbers, 2015). Students' behavior in online learning environments has been measured through a variety of indicators based on trace data, seamlessly recorded by these environments. The behaviors chosen for analysis have customarily been determined by the characteristics and features of the environments (Lowes, Lin, & Kinghorn, 2015). Commonly explored students' behaviors in online learning environments include number of logins, time on task, number of discussion forum posts viewed and authored, number of assignments completed, and number of accesses to different course pages (Gašević, Dawson, Rogers, & Gasevic, 2016; Kovanović et al., 2015; Tempelaar et al., 2015). Although, in general, higher levels of engagement in online learning environments have been associated with better learning outcomes (Lowes et al., 2015), the findings in terms of the predictive power of such behavioral variables on students' learning outcomes have been mixed, spanning all the spectrum from weak to strong (Gašević et al., 2016; Tempelaar et al., 2015). The study of these relations using massive open online courses has enabled big sample sizes, in the order of hundreds (e.g., Tempelaar et al., 2015) or even thousands (e.g., Gašević et al., 2016) of participants. However, other types of online learning environments have different characteristics than massive open online courses and require specific research, since the characteristics and purpose of the environment strongly determine the students' behavior (Gašević et al., 2016; Winne & Hadwin, 1998). This paper focuses on a particular type of online learning environment (a VEE) designed to enhance students' learning outcomes from their laboratory practices. To date, little is known about the relation between students' SRL skills with their learning behavior and outcomes in the context of a VEE, which is precisely what this research addresses.

1.5 Aim of the study

The aim of this study was to explore differences in learning behavior, in terms of how often students access multiple forms of information included in a VEE, and learning outcomes between groups of students with different perceived (i.e. self-reported) levels of self-regulation. The following research questions were formulated:

1. What is the relationship between students' perceived SRL level and their VEE behavior?

2. What is the relationship between students' perceived SRL level and their VEE learning outcomes?
3. What is the relationship between students' VEE behavior and VEE learning outcomes according to their perceived SRL level?

2 Method

2.1 Participants

This study was conducted at a university in the Netherlands. All participants (*N* = 97), a group of students with heterogeneous educational backgrounds, were enrolled in a 168-h MSc level course related to enzymology. All students had previously obtained a BSc degree in natural sciences: 39% from the Netherlands, 56% from a university outside the Netherlands, and 5% was unknown. All students were enrolled in an MSc study program, being Food technology (60%), Biotechnology (33%), or other (7%). Each MSc study program is subdivided in several specializations. The prior knowledge of students was diverse because of the aforementioned differences in prior education, MSc study program, and specialization. The students were 23.3 years old (*SD* = 2.4) on average. About 63% of the students was female and the rest were males.

2.2 Independent and dependent variables

The independent variable in this study was the self-reported or, in other words, perceived level of SRL. The dependent variables were students' VEE behavior (i.e., attempts to complete preparation questions, number of clicks, feedback on experimental design, background information, attempts for simulation questions, answers requested, and hints accessed) and VEE learning outcomes in terms of content-specific knowledge. Students' prior knowledge was included as a covariate in the data analyses to be able to control for differences in this regard.

2.3 The LabBuddy VEE

The VEE was purposefully developed for the course as a preparation for the laboratory classes. The VEE is an extended version of a previously developed web-based experiment designer and web laboratory manual (Van der Kolk, Beldman, Hartog, & Gruppen, 2012), nowadays known as LabBuddy® (Kryt b.v., Wageningen, the Netherlands) (Van der Kolk et al., 2013). Figure 1 depicts four screenshots of the LabBuddy® VEE, including some annotated functionality.

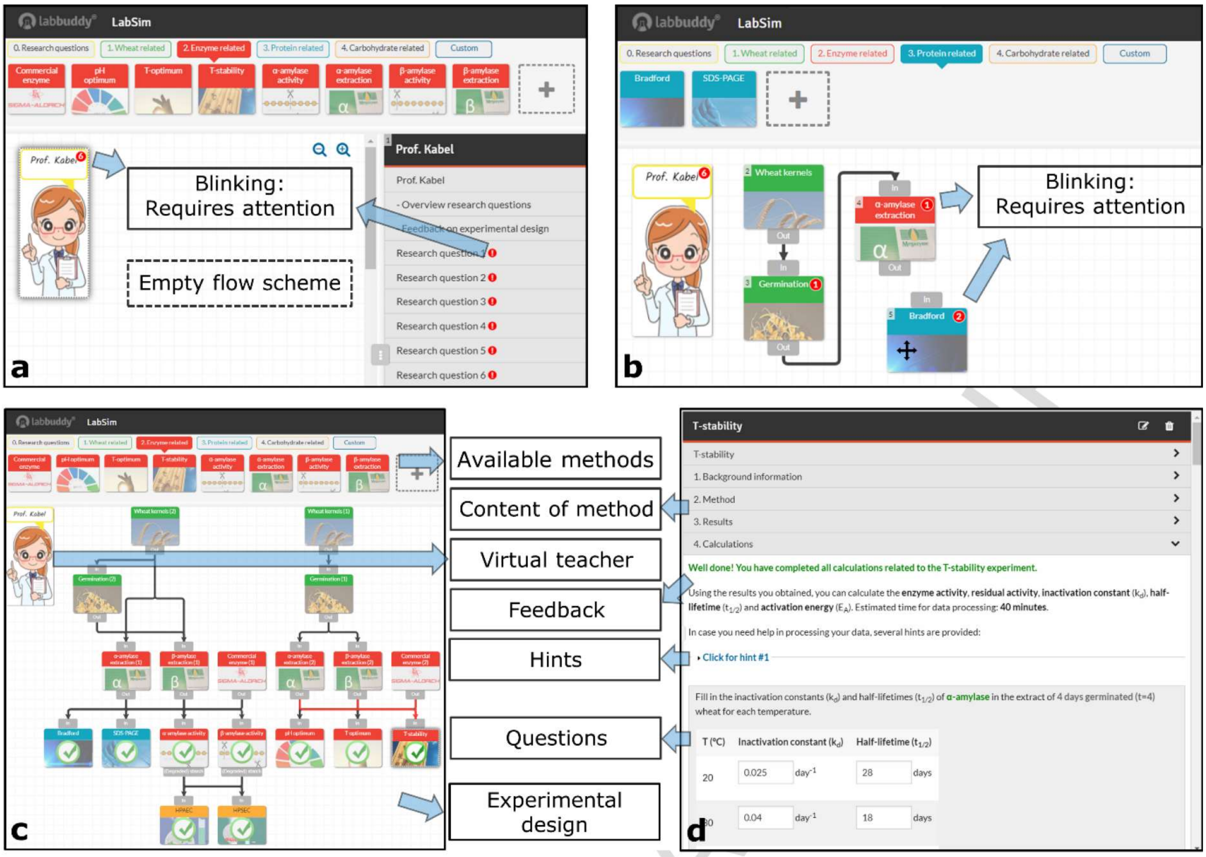

Figure 1: LabBuddy® VEE screenshots. a) Starting situation. b) Situation where three chemical methods have been added to the flow scheme, and the fourth ("Bradford") is currently being dragged into the flow scheme. c) Example of a completed flow scheme. d) Example of the content of a method.

Figure 2 depicts a schematic overview of the LabBuddy® VEE procedure including labels of the corresponding students' VEE behavior (i.e., B1 through B7), which are described later on in Table 2. Students are provided with preparation questions (B1) before entering the VEE, to ensure that they have the required basic knowledge needed to understand the topic of the VEE.

This VEE (B2) contains a self-directed learning task through which students can actively learn and apply concepts related to the laboratory class. The task consists of answering six research questions, which are provided by a virtual teacher (Figure 1a). To start off, students define a hypothesis on each research question. Next, they make an experimental design in the form of a flow scheme (Figures 1b and 1c), where each block corresponds to an available chemical method. In other words, students must select and connect the chemical methods to each other in a logical sequence. To verify the correctness of the flow scheme, students can request feedback from the virtual teacher (B3). In case the flow scheme is incorrect, the virtual teacher guides them towards the correct solution. Each chemical method, which must be further opened by students, contains the following tabs (Figure 1d): 1) background information, 2) method (containing the detailed lab protocol), 3) results (containing raw data), and, if applicable, 4) calculations. The background information tab often contains, next to general information about the method, a collapsible that students can open for more detailed information (B4) on the method. To motivate students to go through the information, the background information and method tabs incorporate one or more closed questions (B5). All questions belonging to one method must be answered correctly before any results can be unlocked.

The results obtained from the VEE are directly affected by the flow scheme made by the students. For example, in case the flow scheme is incomplete, an incomplete dataset is provided by the VEE. Simulating real laboratories, all virtual chemical methods yield raw data, which students must process and perform calculations on using for example Microsoft Excel. If a student cannot find the correct answer to a calculation, he/she can request it from the VEE (B6), after which the VEE provides him/her with the correct answer. Students can also opt to access hints (B7) that help them while processing the data and/or performing the calculations. Depending on the nature of the question, up to four hints are available per question, and 28 hints in total for the whole simulation. The results of the calculations must be entered in the calculations tab. Once all prerequisites to answer a research question are fulfilled, students can consult the virtual teacher to interpret their results, do further calculations if necessary, and finally accept or reject their hypotheses. Whenever there is something that requires the students' attention (e.g. feedback or an unanswered question), a blinking signal (Figures 1a and 1b) will appear to guide students in their progress.

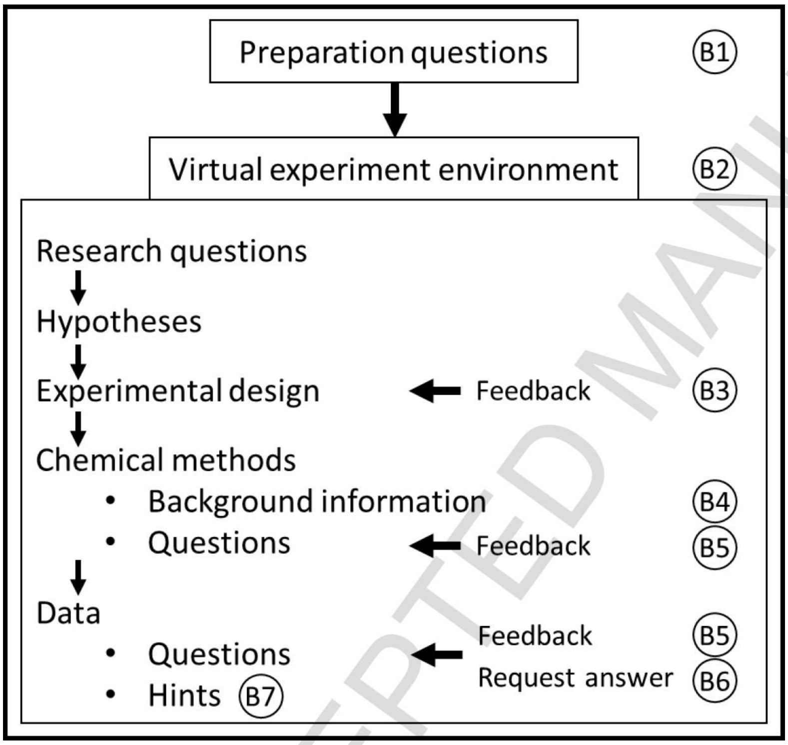

Figure 2: Flow scheme of student activities: preparation questions and virtual experiment environment. Labels B1 – B7 indicate where student behavior was measured, as further explained in section 2.4.1.

2.4 Procedure

The course in which the VEE was used, took place over a period of eight weeks. The experiment started at the beginning of the second week. Student activities in relation to the VEE with corresponding measurements and time schedule are shown in Table 1. Attendance was compulsory for all activities. Before entering the VEE, students were given 30 minutes to complete a pre-knowledge test (A1) on paper. The pre-knowledge test consisted of 13 open questions, covering all content-specific learning outcomes of the VEE. Each correctly answered question was rewarded with one point, yielding a range of scores for students between zero and 13 points. The assessment of the pre-knowledge test was done by a domain-related expert, who used a detailed key. The key included

how many points should be awarded for specific answers. A randomly selected sample (N = 10) was checked by another domain-related expert to make sure that the assessment was accurate and reproducible. The scoring by both experts was identical. Most of the students (*N* = 93) completed the pre-knowledge test, while four students were absent that day. The scores of this test (*M* = 5.1, *SD* = 2.3) were used as a measurement of their content-specific prior knowledge.
After the pre-knowledge test, students started working individually on 17 closed questions on the computer, which served as preparation (A2) for the VEE. Once the preparation questions were completed, a link was provided to access the VEE (A3). Students used the VEE for an average of 7.5 hours distributed over the first three days of the start of the experiment. Computer rooms were available and three carefully instructed supervisors were present to answer possible questions of students. However, due to the self-explanatory nature of the VEE, only few questions were raised by the students. Alternatively or additionally, students were able to access the VEE from any device connected to the Internet at any time over the period established for VEE usage (i.e., days one to three). Students took advantage of this possibility, as 19% of the digital traces were logged outside of the scheduled computer room time of days one and two of the experiment. After the scheduled time of day three, all students had completed the VEE.
The VEE was intended to prepare students for the laboratory classes. Accordingly, a post-knowledge test was conducted (A4) just before the start of the laboratory classes to determine the learning outcomes of the VEE. This test consisted of 13 open questions slightly different than the pre-knowledge test. The assessment procedure of the post-knowledge test was the same as for the pre-knowledge test. Four students were absent on the post-knowledge test day, and therefore did not complete it. The scores (*M* = 7.2, *SD* = 2.6) were used as a measure of the content-specific knowledge the students (*N* = 93) had at the time of initiating their laboratory practice.
There were no other course activities in between the pre- and post-knowledge test, other than the VEE. Students were not aware that a post-knowledge test would follow, to prevent targeted studying for it. The validity of these self-made knowledge tests was obtained through three experts including the main teacher of the course. A survey on perceived SRL level (A6) was performed at a later date, independent from the VEE.

Table 1: Student activities with corresponding measurement(s) and time indications.

Code	**Student activity**	**Measurement**	**Day***	**Duration**
A1	Pre-knowledge test	content-specific prior knowledge	1	30 min
A2	Preparation questions	student behavior	1	60 min
A3	Virtual experiment environment (VEE)	student behavior	1-3	7.5 h
A4	Post-knowledge test	content-specific knowledge	9	30 min
A5	Laboratory classes	N/A	9-12, 15-19	27 h
A6	Survey	perceived SRL level	26	15 min

*Running days relative to the start of the experiment. There were no course activities in between the VEE and the post-knowledge test.

2.4.1 Measurement of students' VEE behavior

Students' behavior in the LabBuddy® VEE (Figure 2, labels B1 – B7) was measured by digital trace data, which is most commonly aggregated by frequency counts in studies linked to SRL (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007; Van Laer & Elen, 2018). Therefore, aligned with the literature and particularizing for the LabBuddy® VEE, the seven aspects of students' behavior measured are described in Table 2.

The focus was clearly on count measures, while time-on-task measures have been excluded on the twofold basis of measurement challenges and relevancy, which is elaborated on next. Kovanović and colleagues (2015) conducted a thorough study of 15 different time-on-task estimation strategies, and how they compare to count measures in explaining differences in students' learning outcomes. They conducted experiments in two different settings: blended learning and fully online learning. Based on their findings, they concluded that "with all the challenges in accurate estimation of time-on-task, given the off-task behaviours, [...] perhaps using time-on-task measures should be reconsidered and counts measures be more promoted" (Kovanović et al., 2015, p. 104). Still, they found time-on-task to be an important variable to consider in fully online learning settings, but not in blended learning, which is the case in our study. This was explained by evidence that "the relative amount of activity per student is much higher in the fully online course" (Kovanović et al., 2015, p. 103).

Further clarification needed in relation to some of the count measures used follows. Meaningful clicks (B2) were considered those necessary to carry out the VEE assignment, including use of the support provided by the environment. For example, when a student clicked to open a hint within an analysis method, the click was added to the count of meaningful clicks, but the click to close it afterwards was not counted. This is because it was optional to close a tab or hint, and after switching to, for example, another analysis method, all previously opened hints were closed automatically. Moreover, access to a specific background information unit (B4) or hint (B7) was only logged the first time it was accessed.

Table 2: Explanation of the student behavioral aspects analyzed.

Code	Behavioral aspect
B1	Number of extra attempts to complete the preparation questions (= total number of attempts minus minimal attempts possible for completion (17))
B2	Number of meaningful clicks in the simulation
B3	Number of times student accessed the virtual teacher for feedback on the experimental design
B4	Number of unique background information units accessed
B5	Number of extra attempts to complete all questions in the simulation (= total number of attempts minus minimal attempts possible for completion (49))
B6	Number of times a student requested the answer to a calculation
B7	Number of unique hints accessed

2.4.2 Measurement of perceived SRL level

The self-regulation scale of the Inventory of Learning Styles (ILS) (Vermunt, 1998), a questionnaire for higher education, was used to measure students' self-reported SRL level (A6). ILS was chosen, because the ILS inventory was developed based on qualitative and quantitative empirical studies with university students and has been applied and validated in many studies ever since (Vermunt & Donche, 2017). The scale consists of seven items on self-regulation strategies, such as "When I have difficulty grasping a particular piece of subject matter, I try to analyze why it is difficult for me" and "I do more than I am expected to do in a course". Students rated each item on a five-point Likert scale ranging from "I do this seldom or never" to "I do this almost always". The reliability and validity of these scales have been reported as adequate in various contexts (Roth, Ogrin, & Schmitz, 2016; Vermunt & Vermetten, 2004). In this study, the reliability coefficient for the self-regulation scale of the ILS was satisfactory (*Cronbach's* α = .80). A small number of participants (N = 8) was not considered for the analysis since five students were absent and three failed to complete the questionnaire. Based on the scale scores of those who completed it, students were subdivided into three groups of approximately equal size: low self-reported SRL level (N = 31, M = 2.0, SD = 0.4), medium self-reported SRL level (N = 30, M = 2.8, SD = 0.1), and high self-reported SRL level (N = 28, M = 3.4, SD = 0.3). This categorization resulted in statistically highly significantly different groups ($F(2, 86) = 128.16$, $p < .001$, $\eta^2 = .75$).

2.5 Analysis

Univariate analyses of variance were used to find out whether the three self-regulation groups were significantly different in terms of their VEE behavior, and significantly different in terms of their VEE learning outcomes as indexed by the post-knowledge test results. The results of the post-knowledge test were corrected for variance in prior knowledge by considering prior knowledge as a covariate. This method was justified and chosen over a repeated measurement analysis, since the pre- and post-knowledge questions tested the same concepts but were not identical. If a significant overall difference between the three groups was found, repeated contrast analyses were carried out to examine statistical differences among the various groups.

A correlation analysis for each perceived SRL level was performed to investigate the relationship of the VEE learning outcomes to the students' prior knowledge and their VEE behavior.

3 Results

3.1 Perceived level of SRL in relation to VEE behavior

The results for the behavior of students with high, medium, and low level of perceived self-regulation in the preparation questions and the VEE are shown in Table 3.

The attempts to complete the preparation questions (B1) were found to be significantly lower ($F(3, 80) = 3.13$, $p = .05$, $\eta^2 = .07$) for students with a low level of SRL (M = 15, SD = 9) compared to students with a medium level of SRL (M = 25, SD = 16). The total number of meaningful clicks in the simulation (B2) was found to be significantly lower ($F(3, 80) = 4.10$, $p = .02$, $\eta^2 = .09$) for students with a low level of SRL (M = 1154, SD = 376) compared to students with a medium level of SRL (M = 1630, SD = 744). The total number of answers requested (B6) was found to be significantly higher ($F(3, 80) = 5.27$, $p = .01$, $\eta^2 = .12$) for students with a medium level of SRL (M = 48, SD = 30), compared to students with a low level of SRL (M = 24, SD = 20) and students with a high level of SRL (M = 29, SD = 20). No significant differences were found between the three levels of SRL and the other behavioral aspects including the number of times students accessed the virtual teacher for feedback on the experimental design (B3), the number of unique background information units accessed (B4), the number of extra attempts to complete the VEE (B5), and the number of unique hints accessed (B7).

Table 3: Quantitative data on each behavior variable, grouped by perceived self-regulating ability.

Code	Variable	SRL	M	SD	F	Sig	η²

B1	Attempts preparation questions	Low	15.67 [a]	9.25	3.13*	.05	.07
		Medium	24.68 [b]	16.02			
		High	21.62	11.23			
		Total	20.51	12.89			
B2	Number of meaningful clicks	Low	1154.20 [a]	375.66	4.10*	.02	.09
		Medium	1630.21 [b]	744.77			
		High	1482.00	605.49			
		Total	1414.33	617.89			
B3	Feedback on experimental design	Low	7.73	5.92	0.13	.88	.00
		Medium	8.11	5.19			
		High	8.54	7.08			
		Total	8.11	6.02			
B4	Background information	Low	5.20	3.27	0.80	.45	.02
		Medium	5.71	2.62			
		High	5.81	3.29			
		Total	5.56	3.05			
B5	Attempts simulation questions	Low	74.17	31.36	0.76	.47	.02
		Medium	87.29	26.99			
		High	81.04	37.40			
		Total	80.67	32.12			
B6	Answer requested	Low	23.90 [a]	20.32	5.27*	.01	.12
		Medium	47.50 [b]	29.83			
		High	28.77 [a]	19.95			
		Total	33.27	25.69			
B7	Hints accessed	Low	18.60	5.30	0.95	.39	.02
		Medium	20.96	4.13			
		High	19.92	5.84			
		Total	19.80	5.16			

* Significant at the .05 level.

[a] Self-regulation group is significantly different from [b] in terms of the behavior variable.

3.2 Perceived level of SRL in relation to VEE learning outcomes

The descriptive statistics of the pre- and post-knowledge tests are shown in Table 4. A univariate analysis of variance showed that the three perceived self-regulation groups were significantly different in terms of students' VEE learning outcomes as measured by the post-knowledge test ($F(2, 77) = 5.36$, $p < .01$, $\eta^2 = .12$). The follow-up repeated contrast analysis showed a statistically significant difference ($p = .02$) in VEE outcomes between students with low level of self-regulation and medium level of self-regulation. There was also a statistically significant difference ($p < .01$) in the post-knowledge test between students with medium and high level of self-regulation. The sample size for this statistical test was 81, which was the number of students who completed both the survey and the post-knowledge test.

Table 4: Descriptive statistics of knowledge tests by perceived SRL level.

Perceived SRL level	**Pre-knowledge test**		**Post-knowledge test**	
	M	*SD*	*M*	*SD*

Low	5.4	2.4	7.8	2.4
Medium	4.3	1.7	5.8	2.4
High	5.8	2.3	8.3	2.0

3.3 VEE learning outcomes in relation to VEE behavior, prior knowledge, and perceived SRL level

The results of the correlation analyses for each perceived SRL level are shown in Table 5. Many of the correlations were statistically significant, and moderate to strong. The VEE learning outcomes showed positive strong correlation to the prior knowledge for the low and medium groups of perceived SRL level, and moderate positive correlation with the high group. In general, the VEE behavior correlated negatively with the learning outcomes.

Table 5: Correlation of VEE learning outcomes to prior knowledge and VEE behavior by perceived SRL level.

		VEE behavioral variables						
Perceived SRL level	Prior knowledge	B1	B2	B3	B4	B5	B6	B7
Low	.74**	-.29	-.60**	.03	-.45	-.48**	-.46*	-.42*
Medium	.69**	-.41*	-.28	.16	-.20	-.25	-.53**	.01
High	.41*	-.62**	-.46	-.07	-.18	-.46**	-.43*	-.46*

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

4 Discussion

4.1 Perceived level of SRL in relation to VEE behavior

A clear pattern emerged for the three VEE behavioral variables with significant differences in terms of perceived SRL levels, namely the total number of attempts to complete the preparation questions (B1), the number of meaningful clicks (B2), and the number of times the answer was requested (B6). The average values for the three variables were ascending for low, high, and medium SRL levels, in that order (i.e., low < high < medium). Low self-regulated learners showed the lowest level of activity, engaging the least with the VEE and its resources. Aligned with the SRL theory, low self-regulated learners thus proved to be the least agentic and least active group, with students taking minimum control of their learning process (De Bruin & Van Merriënboer, 2017). At the following level in the SRL hierarchy, the VEE activity of medium self-regulated learners peaked. It is known that SRL skills develop with time and practice (Panadero, 2017). Our findings suggest that, as students develop their SRL skills from low to medium, they go from the lowest to the highest measured level of activity and use of learning resources at their disposal. Their agency and willingness to own their learning process increase, but their use of strategies is not mature, and their behavior shows low level of planning (too much unnecessary activity). Finally, as the students evolve from medium to high levels of SRL, their activity decreases to a more optimum level in between that of low and medium self-regulated learners. The findings are thus consistent with the current body of SRL knowledge (cf. Bjork, Dunlosky, & Kornell, 2013; Zimmerman, 1998), which characterizes the behavior of highly self-regulated learners as more goal-directed, relevant to their learning process, involving a more carefully considered and purposeful use of strategies, and a more rational use of resources.

The preparation for the VEE (B1) consisted of closed questions designed to compensate for the differences in prior knowledge by providing content-specific feedback to incorrect answers. Therefore, although the number of attempts to complete the preparation questions (B1) follows the pattern described above, it is affected also by prior knowledge differences, still important at this point of the course. This might explain why students with low SRL level required the least number of extra attempts. It is important to note that least number of attempts does not necessarily mean greater learning at this stage. Errors and mistakes are typically viewed as something to avoid during the learning process, but research suggests, by contrast, that making errors creates opportunities that are often an essential component of efficient learning (Bjork et al., 2013). Feedback on errors is especially effective for learning if the errors were made with high confidence (Butterfield & Metcalfe, 2001). Thus, the content-specific feedback may lead the students to learning gains if properly used. Again, the same pattern was found when it comes to the number of answers requested. Medium self-regulated learners went beyond having significant differences with both low and high ones, to account, on average, for twice as many requested answers as low self-regulated learners (48 vs. 24). This conspicuous result clearly shows that medium self-regulated learners followed a minimum effort approach and abused the VEE's functionality of providing the answers to the calculations, rather than doing the calculations themselves. Attempting to succeed in an interactive learning environment (a VEE in this case) by exploiting properties of the system rather than by learning the material is a strategy known as "gaming the system" (Baker, D'Mello, Rodrigo, & Graesser, 2010). Previous work has shown that one of the common ways in which learners become careless and disengaged, is precisely gaming the system (Azevedo, 2015). Because learners intentionally decide how to regulate their engagement in (or disengagement from) learning, gaming the system, as procrastination and other self-handicapping techniques, is a form of SRL (Winne, 2015). In other words, SRL is not always beneficial and we should be talking of particular forms of SRL that lead to better learning, rather than SRL in general. Our results highlight medium self-regulated learners as clearly engaging in gaming the system, significantly more than low and high self-regulated learners. However, it is worth noting that independently of the SRL levels, on average, all students engaged in gaming the system, 24, 48, and 29 times for the low, medium, and high SRL levels respectively. Lack of motivation and interest have been found among the leading causes associated with this behavior (Baker et al., 2008). User interface features designed to increase interest have been reported to decrease gaming (Graesser, Hu, & Sottilare, 2018). Nonetheless, apart from designing to enhance interest, it is important to explore various forms of SRL instruction to prepare students to learn in relatively new contexts (Cutumisu, Blair, Chin, & Schwartz, 2015) such as VEEs.

The other VEE behavioral variables, namely the feedback requested on the experiment scheme (B3), the additional background information requested (B4), the number of attempts to answer the questions (B5), and the number of hints used (B7), showed no statistically significant difference among the three levels of SRL. The feedback on the experiment scheme (B3) and the use of hints (B7) can be associated to the SRL strategy of help seeking, during the performance phase (Zimmerman, 2013). When students do not ask for help when they need it, they run the risk of undermining their learning and achievement (Ryan, Pintrich, & Midgley, 2001). Normally, one would expect that students with different SRL level vary in their help-seeking behavior. However, the specificity of the feedback on the tasks usually available in online learning environments (e.g., VEEs), may not give enough room for differences to appear, as opposed to more open learning situations where knowing when and how to seek and apply help is an important part of SRL (Greene & Azevedo, 2010; Roll, Baker, Aleven, & Koedinger, 2014).

Similarly, the specificity and format of additional information (B4) available to the students, which can be associated with the performance phase SRL strategy of seeking information (Zimmerman, 2013), together with the other support features available (e.g., feedback on scheme, hints, and answers), might explain the lack of significant differences in this variable.

4.2 Perceived level of SRL in relation to VEE learning outcomes

SRL is regarded as "constitutive of success in learning, problem solving, transfer, and academic success in general" (Winne, 1997, p.397). Based on previous findings (Broadbent & Fuller-Tyszkiewicz, 2018; Schunk, 2012), students with a high level of self-regulation skills are expected to have higher learning outcomes, as was the case in our study. However, by showing medium self-regulated learners to have the worst results, our findings indicate that there is no linear relationship between the level of (perceived) SRL and learning outcomes. Rather, as learners progress in their SRL skills in between low and high, there seems to be an intermediate phase that is detrimental for learning. Apparently, this phase (i.e., medium SRL) is characterized on the one hand by an increase in the students' perceived agency (as reflected in higher scores in the SRL questionnaire used), and on the other hand, by an abuse or random use of resources available, showing lack of both planning and goal-directed activity, as clearly evidenced in the VEE behavior discussed in 4.1. The agency in these learners is not yet matched by a strategic control of their learning process (Järvelä, Hadwin, Malmberg, & Miller, 2018). Effective learners seek deeper help (Luckin & Hammerton, 2002), while excessive help is associated with shallower learning (Mathews & Mitrović, 2008). Particularly, of the help and support available to the students in the VEE used, medium SRL learners abused the request of answers, thus avoiding obtaining the results by themselves and learning to do so. In other words, as previously discussed, they engaged in gaming the system behavior. Their lower learning outcomes come then as no surprise, since gaming the system has been repeatedly reported to be conducive to poorer learning (Azevedo, 2015; Baker et al., 2008; Cutumisu et al., 2015; Roll et al., 2014).

Low self-regulated learners outperformed medium, and actually, they were not that far from students with high SRL, which seems to be explained by the fact that they had a higher prior knowledge compared to medium self-regulated learners, and similar prior knowledge compared to high self-regulated learners (Table 4).

4.3 VEE learning outcomes in relation to VEE behavior, prior knowledge, and perceived SRL level

Two main ideas clearly arise from the results. First, prior knowledge as measured by the pre-knowledge test showed statistically significant and moderate to strong correlations with the VEE learning outcomes. This is an expected result since, historically, prior grades tend to be the best predictors of subsequent academic success (Zimmerman, 2013). As the perceived level of SRL increased from low to high, the correlations of outcomes to prior knowledge decreased from strong to moderate.

Prior knowledge is undeniably an advantage, and highly self-regulated learners activate this automatically (Pintrich, 2000). But, in the case of insufficient prior knowledge, highly self-regulated learners have the skills to cover the knowledge gap using effective strategies. This can also explain the reduced correlation of prior knowledge of highly self-regulated learners to their learning outcomes, as compared to students at the low and medium levels of SLR. Aligned with the previous discussions, prior knowledge accounted for more than half of the variance (R^2 = .55) of the learning outcomes of low SRL students, and almost half of the variance of (R^2 = .48) of medium, while 17% of the variance (R^2 = .17) of high SRL students, the latter having obtained the best results in the post-knowledge test.

Second, in general, VEE behavior negatively correlated with the outcomes. Previous studies indicate that there is indeed a link between student activity in online learning environments and outcomes as measured by final grades (Chen, 2002; Cho & Kim, 2013; Colthorpe, Zimbardi, Ainscough, & Anderson, 2015). Higher levels of activity are often associated with better outcomes and greater student satisfaction (Lowes et al., 2015). Our results support that there is a relationship between VEE behavior and outcome, but a negative one in this case. The explanation is found in the number of answers requested (B6). Table 5 shows that, apart from prior knowledge, the number of answers requested is the only variable with statistically significant (and at least) moderate correlations. The highest negative correlation of this variable (B6) to VEE outcomes is found in the medium SRL group, which had the poorest outcomes. As discussed in previous sections, this gaming the system behavior (Baker et al., 2008) evidences disengagement (Azevedo, 2015) and impairs learning. The generally negative correlations of VEE behavior to outcomes suggest that it would have been more efficient for the medium self-regulated learners to not interact that much with the VEE, mostly because they tried to "abuse" its resources. This result should be taken into account for the design of online learning environments.

5 Conclusions

In many disciplines, laboratory education is an essential part of the curriculum, as it gives students the possibility to put the learned theories and procedures to the test, and gain practical, hands-on experience on the subject matter. However, laboratory education is expensive, and it has been shown that, often, students do not come to the laboratory sufficiently prepared, which prevents them from obtaining the proper skills from this practical learning opportunity. To mitigate this issue, VEEs such as the LabBuddy® VEE used in our experiment, have been developed to take advantage of online learning environments for supporting students in familiarizing with the laboratory environment, its methods, content-specific knowledge, and resources. Nonetheless, it is important that students take ownership of their learning processes. Students differ in their ability to set goals, plan how to meet their goals, use strategies to address tasks, monitor their progress towards their goals, evaluate their performance, and adapt their learning processes cyclically based on monitoring and control loops. In other words, students vary in their level of SRL, but SRL can be taught and supported so that learners become better at it (Winne, 1997), leading them to better learning outcomes (Bjork et al., 2013).

In this study, students' perceived SRL level (i.e., low, medium, high) was explored in relation to their VEE behavior (e.g., number of attempts and hints, number of answers requested) and their VEE learning outcomes, while controlling for their prior knowledge. In addition, the relationships between VEE behavior and VEE learning outcomes depending on their SRL level were investigated. The results showed that, on the one hand, as expected, students with a high SRL level obtained better outcomes, but on the other hand, the relationship between these variables was not linear, since medium self-regulated learners obtained the worst results. The medium groups' VEE behavior suggested lack of goal-directed activity and planning, and showed the highest level of activity with the VEE but overusing resources that impair learning, such as number of attempts at answering the questions. This suggested random behavior, and excessive request of answers (statistically significantly more than both their low and high counterparts, and twice as many times as the students with low SRL). Such behavior, known as gaming the system, has been repeatedly reported to be detrimental to learning (Roll et al., 2014). The findings thus suggest the existence of an intermediate SRL level between low and high, characterized by an increase in perceived agency, ownership over the learning process and use of strategies and resources, but still lacking goal-directed activity and appropriate planning and execution to meet the goals. The medium SRL level seems to be a developing but not yet mature SRL level, a transitional state between the low and high levels. The random and detrimental to learning behavior of this group, indicates that special attention should be paid in SRL interventions to this group, and to support students to move to a higher SRL level as soon as possible, where they will benefit from their increase in agency, but use it in a purposeful way in the accomplishment of their goals, and improving their learning outcomes. The phases of the SRL process have been largely studied and reflected in a variety of models (Panadero, 2017). However, to the best of our knowledge, the phases of how the SRL skills develop over time have received less attention.

In this study, it was also shown that prior knowledge correlated with the learning outcomes, aligned with a historical tendency, and showed an inverse relation to the SRL level. The more self-regulated students perceived they were, the less they relied on their prior knowledge for their learning outcomes, since their ability to acquire new knowledge was likely to be superior.

In general, and independently of SRL level, VEE behavior correlated negatively with VEE learning outcomes. This has important implications for the design of VEEs, given their role of supporting students' laboratory practice. It is paramount to iteratively design VEEs to maximize students' engagement and minimize the harmful gaming the system behavior (Graesser et al., 2018). Students might benefit from a limited access to ready-made answers, and only been provided with task solutions when there is evidence in the VEE that they have been attempting the solution. Instead, the use of hints and seeking information should be encouraged and seen by the students as the standard procedure. Challenges are recognized as triggers of SRL (Perry, 1998). The VEE should be designed for information and help-seeking strategies, giving answers only exceptionally. In the real laboratory, this support is not available, and they need to learn how to perform the calculations. The VEE acts as a scaffold to support learning that is removed in the real laboratory practice. SRL is paramount to optimizing learning and performance, but formal training is scarce (Bjork et al., 2013). Accordingly, it might be important to embed SRL support in the VEE, for example, through prompts (Hadwin, Wozney, & Pontin, 2005).

The use of a questionnaire in this study has its limitations (Winne, 2015). It is known that students are not always accurate when reporting their own use of strategies (Boekaerts & Corno, 2005), and that questionnaires are static tools (Greene & Azevedo, 2010). However, self-reported data is still the most frequent measure of SRL (Panadero, 2017), and the field has heavily relied on them (Hadwin et al., 2011). Self-reported data is still regarded as a valid tool when it is sufficiently tailored to the specific context in which the study is being conducted (Panadero, Klug, & Järvelä, 2016).

Future research could focus on the development phases of SRL, on how to prevent students from staying at a medium SRL level, and on the effects of VEEs designed to avoid gaming the system behavior and to promote SRL.

6 References

Abdulwahed, M., & Nagy, Z. K. (2009). Applying Kolb's experiential learning cycle for laboratory education. *Journal of Engineering Education, 98*, 283-294. doi:https://doi.org/10.1002/j.2168-9830.2009.tb01025.x

Azevedo, R. (2015). Defining and measuring engagement and learning in science: conceptual, theoretical, methodological, and analytical issues. *Educational Psychologist, 50*, 84-94. doi:https://doi.org/10.1080/00461520.2015.1004069
Baker, R., D'Mello, S. K., Rodrigo, M. M. T., & Graesser, A. C. (2010). Better to be frustrated than bored: the incidence, persistence, and impact of learners' cognitive–affective states during interactions with three different computer-based learning environments. *International Journal of Human-Computer Studies, 68*, 223-241. doi:https://doi.org/10.1016/j.ijhcs.2009.12.003
Baker, R., Walonoski, J., Heffernan, N., Roll, I., Corbett, A., & Koedinger, K. (2008). Why students engage in "gaming the system" behavior in interactive learning environments. *Journal of Interactive Learning Research, 19*, 185-224.
Bandura, A. (1986). Social foundation of thought and action: a social-cognitive view. Englewood Cliffs, NJ: Prentice-Hall.
Bannert, M. (2002). Managing cognitive load—recent trends in cognitive load theory. *Learning and Instruction, 12*, 139-146. doi:https://doi.org/10.1016/S0959-4752(01)00021-4
Bjork, R. A., Dunlosky, J., & Kornell, N. (2013). Self-regulated learning: beliefs, techniques, and illusions. *Annual Review of Psychology, 64*, 417-444. doi:https://doi.org/10.1146/annurev-psych-113011-143823
Boekaerts, M., & Corno, L. (2005). Self-regulation in the classroom: a perspective on assessment and intervention. *Applied Psychology, 54*, 199-231. doi:https://doi.org/10.1111/j.1464-0597.2005.00205.x
Brinson, J. R. (2015). Learning outcome achievement in non-traditional (virtual and remote) versus traditional (hands-on) laboratories: a review of the empirical research. *Computers & Education, 87*, 218-237. doi:https://doi.org/10.1016/j.compedu.2015.07.003
Broadbent, J., & Fuller-Tyszkiewicz, M. (2018). Profiles in self-regulated learning and their correlates for online and blended learning students. *Educational Technology Research and Development*, 1-21. doi:https://doi.org/10.1007/s11423-018-9595-9
Broadbent, J., & Poon, W. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: a systematic review. *Internet and Higher Education, 27*, 1-13. doi:https://doi.org/10.1016/j.iheduc.2015.04.007
Bruck, A. D., & Towns, M. (2013). Development, implementation, and analysis of a national survey of faculty goals for undergraduate chemistry laboratory. *Journal of Chemical Education, 90*, 685-693. doi:https://doi.org/10.1021/ed300371n
Buntine, M. A., Read, J. R., Barrie, S. C., Bucat, R. B., Crisp, G. T., George, A. V., . . . Kable, S. H. (2007). Advancing chemistry by enhancing learning in the laboratory (ACELL): a model for providing professional and personal development and facilitating improved student laboratory learning outcomes. *Chemistry Education Research and Practice, 8*, 232-254. doi:https://doi.org/10.1039/B6RP90033J
Butterfield, B., & Metcalfe, J. (2001). Errors committed with high confidence are hypercorrected. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 27*, 1491-1494. doi:https://doi.org/10.1037/0278-7393.27.6.1491
Chen, C. (2002). Self-regulated learning strategies and regulated learning strategies and achievement in an introduction to information systems course. *Information Technology, Learning, and Performance Journal, 20*, 11-25.
Cho, M.-H., & Kim, B. J. (2013). Students' self-regulation for interaction with others in online learning environments. *Internet and Higher Education, 17*, 69-75. doi:https://doi.org/10.1016/j.iheduc.2012.11.001
Coates, H., James, R., & Baldwin, G. (2005). A critical examination of the effects of learning management systems on university teaching and learning. *Tertiary Education and Management, 11*, 19-36. doi:https://doi.org/10.1080/13583883.2005.9967137
Colthorpe, K., Zimbardi, K., Ainscough, L., & Anderson, S. (2015). Know thy student! Combining learning analytics and critical reflections to develop a targeted intervention for promoting

self-regulated learning. *Journal of Learning Analytics, 2*, 134-155. doi:https://doi.org/10.18608/jla.2015.21.7

Crandall, P. G., Engler III, R. K., Beck, D. E., Killian, S. A., O'Bryan, C. A., Jarvis, N., & Clausen, E. (2015). Development of an augmented reality game to teach abstract concepts in food chemistry. *Journal of Food Science Education, 14*, 18-23.

Cutumisu, M., Blair, K. P., Chin, D. B., & Schwartz, D. L. (2015). Posterlet: a game-based assessment of children's choices to seek feedback and to revise. *Journal of Learning Analytics, 2*, 49-71. doi:https://doi.org/10.18608/jla.2015.21.4

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. doi:https://doi.org/10.1016/j.learninstruc.2017.06.001

Diederen, J., Gruppen, H., Hartog, R., & Voragen, A. G. (2006). Design and evaluation of digital assignments on research experiments within food chemistry. *Journal of Science Education and Technology, 15*, 227. doi:https://doi.org/10.1007/s10956-006-9010-x

Domin, D. S. (1999). A review of laboratory instruction styles. *Journal of Chemical Education, 76*, 543-547. doi:https://doi.org/10.1021/ed076p543

Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: the effects of instructional conditions in predicting academic success. *Internet and Higher Education, 28*, 68-84. doi:https://doi.org/10.1016/j.iheduc.2015.10.002

Graesser, A. C., Hu, X., & Sottilare, R. (2018). Intelligent tutoring systems. In F. Fischer, C. E. Hmelo-Silver, S. R. Goldman, & P. Reimann (Eds.), *International Handbook of the Learning Sciences* (pp. 246-255). New York, NY: Routledge.

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*, 203-209. doi:https://doi.org/10.1080/00461520.2010.515935

Hadwin, A. F., Järvelä, S., & Miller, M. (2011). Self-regulated, co-regulated, and socially shared regulation of learning. In B. J. Zimmerman & D. H. Schunk (Eds.), *Handbook of Self-regulation of Learning and Performance* (Vol. 30, pp. 65-84). New York, NY: Taylor & Francis.

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. doi:https://doi.org/10.1007/s11409-007-9016-7

Hadwin, A. F., Wozney, L., & Pontin, O. (2005). Scaffolding the appropriation of self-regulatory activity: a socio-cultural analysis of changes in teacher–student discourse about a graduate research portfolio. *Instructional Science, 33*, 413-450. doi:https://doi.org/10.1007/s11251-005-1274-7

Hartog, R. J., Van der Schaaf, H., Beulens, A. J., & Tramper, J. (2009). Virtual experiments in university education. In M. Ebner & M. Schiefner (Eds.), *Looking Toward the Future of Technology-Enhanced Education: Ubiquitous Learning and the Digital Native* (pp. 373-393). Hershey, PA: IGI Global.

Hawkes, S. J. (2004). Chemistry is not a laboratory science. *Journal of Chemical Education, 81*, 1257.

Hawkins, I., & Phelps, A. J. (2013). Virtual laboratory vs. traditional laboratory: which is more effective for teaching electrochemistry? *Chemistry Education Research and Practice, 14*, 516-523. doi:https://doi.org/10.1039/C3RP00070B

Hoadley, C. (2018). A short history of the learning sciences. In F. Fischer, C. E. Hmelo-Silver, S. R. Goldman, & P. Reimann (Eds.), *International Handbook of the Learning Sciences* (pp. 11-23). Abingdon: Routledge.

Järvelä, S., Hadwin, A. F., Malmberg, J., & Miller, M. (2018). Contemporary perspectives of regulated learning in collaboration. In F. Fischer, C. E. Hmelo-Silver, P. Reimann, & S. R. Goldman (Eds.), *Handbook of the Learning Sciences* (pp. 127-136). New York: NY: Routledge.

Kay, J., Reimann, P., Diebold, E., & Kummerfeld, B. (2013). MOOCs: so many learners, so much potential ... *IEEE Intelligent Systems, 28*, 70-77. doi:https://doi.org/10.1109/MIS.2013.66

Kirschner, P., & Huisman, W. (1998). ‘Dry laboratories’ in science education; computer-based practical work. *International Journal of Science Education, 20*, 665-682. doi:https://doi.org/10.1080/0950069980200605

Kirschner, P., & Meester, M. (1988). The laboratory in higher science education: problems, premises and objectives. *Higher Education, 17*, 81-98. doi:https://doi.org/10.1007/BF00130901

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. doi:https://doi.org/10.1016/j.compedu.2016.10.001

Koehler, B. P., & Orvis, J. N. (2003). Internet-based prelaboratory tutorials and computer-based probes in general chemistry. *Journal of Chemical Education, 80*, 606-608. doi:https://doi.org/10.1021/ed080p606

Kovanović, V., Gašević, D., Dawson, S., Joksimović, S., Baker, R. S. J. D., & Hatala, M. (2015). Does time-on-task estimation matter? Implications for the validity of learning analytics findings. *Journal of Learning Analytics, 2*, 81-110. doi:https://doi.org/10.18608/jla.2015.23.6

Limniou, M., & Whitehead, C. (2010). Online general pre-laboratory training course for facilitating first year chemical laboratory use. *Cypriot Journal of Educational Sciences, 5*, 39-55.

Lowes, S., Lin, P., & Kinghorn, B. (2015). Exploring the link between online behaviours and course performance in asynchronous online high school courses. *Journal of Learning Analytics, 2*, 169-194. doi:https://doi.org/10.18608/jla.2015.22.13

Luckin, R., & Hammerton, L. (2002). *Getting to know me: helping learners understand their own learning needs through metacognitive scaffolding.* Paper presented at the International Conference on Intelligent Tutoring Systems, Berlin, Heidelberg.

Mathews, M., & Mitrović, T. (2008). *How does students’ help-seeking behaviour affect learning?* Paper presented at the International Conference on Intelligent Tutoring Systems, Berlin, Heidelberg.

Moos, D. C., & Ringdal, A. (2012). Self-regulated learning in the classroom: a literature review on the teacher's role. *Education Research International, 2012*, 1-15. doi:https://doi.org/10.1155/2012/423284

Panadero, E. (2017). A review of self-regulated learning: six models and four directions for research. *Frontiers in Psychology, 8*, 1-28. doi: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*, 723-735. doi:https://doi.org/10.1080/00313831.2015.1066436

Perry, N. E. (1998). Young children's self-regulated learning and contexts that support it. *Journal of Educational Psychology, 90*, 715-729. doi:https://doi.org/10.1037/0022-0663.90.4.715

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: Academic Press.

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: a systematic review and meta-analysis. *Psychological Bulletin, 138*, 353-387. doi:https://dx.doi.org/10.1037/a0026838

Roll, I., Baker, R. S. J. d., Aleven, V., & Koedinger, K. R. (2014). On the benefits of seeking (and avoiding) help in online problem-solving environments. *Journal of the Learning Sciences, 23*, 537-560. doi:https://doi.org/10.1080/10508406.2014.883977

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*, 225-250. doi:https://doi.org/10.1007/s11092-015-9229-2

Rutten, N., van Joolingen, W. R., & van der Veen, J. T. (2012). The learning effects of computer simulations in science education. *Computers & Education, 58*, 136-153. doi:https://doi.org/10.1016/j.compedu.2011.07.017

Ryan, A. M., Pintrich, P. R., & Midgley, C. (2001). Avoiding seeking help in the classroom: who and why? *Educational Psychology Review, 13*, 93-114. doi:https://doi.org/10.1023/a:1009013420053

Schunk, D. H. (2012). *Learning theories an educational perspective (sixth edition)*. Boston, MA: Pearson.

Schunk, D. H., & Zimmerman, B. (2011). *Handbook of self-regulation of learning and performance*. New York, NY: Taylor & Francis.

Spagnoli, D., Wong, L., Maisey, S., & Clemons, T. D. (2017). Prepare, do, review: a model used to reduce the negative feelings towards laboratory classes in an introductory chemistry undergraduate unit. *Chemistry Education Research and Practice, 18*, 26-44. doi:https://doi.org/10.1039/c6rp00157b

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior, 47*, 157-167. doi:https://doi.org/10.1016/j.chb.2014.05.038

Van der Kolk, J., Beldman, G., Hartog, R., & Gruppen, H. (2012). Students using a novel web-based laboratory class support system: a case study in food chemistry education. *Journal of Chemical Education, 89*, 103-108. doi:https://doi.org/10.1021/ed1005294

Van der Kolk, J., Beldman, G., Hartog, R., Moerland, G., & Gruppen, H. (2013). *ExperD: web-based support for laboratory class workflow design.* Paper presented at the 5th International Conference on Computer Supported Education, Aachen, Germany.

Van Laer, S., & Elen, J. (2018). Adults' self-regulatory behaviour profiles in blended learning environments and their implications for design. *Technology, Knowledge and Learning*, 1-31. doi:https://doi.org/10.1007/s10758-017-9351-y

Vermunt, J. D. (1998). The regulation of constructive learning processes. *British Journal of Educational Psychology, 68*, 149-171. doi:https://doi.org/10.1111/j.2044-8279.1998.tb01281.x

Vermunt, J. D., & Donche, V. (2017). A learning patterns perspective on student learning in higher education: state of the art and moving forward. *Educational Psychology Review, 29*, 269-299. doi:https://doi.org/10.1007/s10648-017-9414-6

Vermunt, J. D., & Vermetten, Y. J. (2004). Patterns in student learning: relationships between learning strategies, conceptions of learning, and learning orientations. *Educational Psychology Review, 16*, 359-384. doi:https://doi.org/10.1007/s10648-004-0005-y

Verstege, S., Van der Kolk, J., Diederen, J., Hartog, R., & Gruppen, H. (2016). *Exploring the potential of simulations as preparation tools for university laboratory classes.* Paper presented at the EDULEARN16 Conference, Barcelona, Spain.

Winberg, T. M., & Berg, C. A. R. (2007). Students' cognitive focus during a chemistry laboratory exercise: effects of a computer-simulated prelab. *Journal of Research in Science Teaching, 44*, 1108-1133. doi:https://doi.org/10.1002/tea.20217

Winne, P. H. (1997). Experimenting to bootstrap self-regulated learning. *Journal of Educational Psychology, 89*, 397-410. doi:https://doi.org/10.1037/0022-0663.89.3.397

Winne, P. H. (2015). Self-regulated learning. In J. D. Wright (Ed.), *International Encyclopedia of the Social & Behavioral Sciences (Second Edition)* (pp. 535-540). Oxford: Elsevier.

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277-304). Mahwah, NJ: Lawrence Erlbaum Associates.

Winne, P. H., & Perry, N. E. (1994). Educational psychology. In V. S. Ramachandran (Ed.), *Encyclopedia of Human Behavior* (pp. 213-223). San Diego, CA: Academic Press.

Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology, 81*, 329-339. doi:https://doi.org/10.1037/0022-0663.81.3.329

Zimmerman, B. J. (1998). Comparing skillful and naive self-regulated learners. In D. H. Schunk & B. J. Zimmerman (Eds.), *Self-regulated learning: from teaching to self-reflective practice* (pp. 6-10). New York, NY: Guilford.

Zimmerman, B. J. (2000). Attaining self-regulation: a social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 13-39). San Diego: Academic Press.

Zimmerman, B. J. (2013). From cognitive modeling to self-regulation: a social cognitive career path. *Educational Psychologist, 48*, 135-147. doi:https://doi.org/10.1080/00461520.2013.794676

Zimmerman, B. J. (2015). Self-Regulated Learning: Theories, Measures, and Outcomes. In J. D. Wright (Ed.), *International Encyclopedia of the Social & Behavioral Sciences (Second Edition)* (pp. 541-546). Oxford: Elsevier.

Zimmerman, B. J., & Moylan, A. R. (2009). Self-regulation: where metacognition and motivation intersect. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Handbook of Metacognition in Education* (pp. 311-328). New York, NY: Routledge.

Zimmerman, B. J., & Pons, M. M. (1986). Development of a structured interview for assessing student use of self-regulated learning strategies. *American Educational Research Journal, 23*, 614-628. doi:https://doi.org/10.3102/00028312023004614

Zimmerman, B. J., & Schunk, D. H. (2003). Albert Bandura: the scholar and his contributions to educational psychology. In B. J. Zimmerman & D. H. Schunk (Eds.), *Educational psychology: a century of contributions.* (pp. 431-457). Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.

Self-regulated learning (SRL) level determines behavior and outcomes in VEEs

Students with a high SRL level benefited the most from the VEE

Students with a medium SRL level engaged more in gaming the system behavior

Students with a low SRL level engaged the least with the VEE

All students might benefit from a limited access to ready-made answers in VEEs