Chapter 12
Assessing the Interaction Between Self-Regulated Learning (SRL) Profiles and Actual Learning in the Chemistry Online Blended Learning Environment (COBLE)

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Abstract This chapter addresses the challenges and opportunities of virtual teaching of a complex scientific topic, such as chemistry, to high-school students. Chemistry Online Blended Learning Environment (COBLE) is a learning environment for students that are willing to expand their knowledge of Chemistry but have no opportunity to do so in their schools. It is claimed that certain skills help cope with learning, in general, and are vital in advancing learning, such as Self-Regulated Learning (SRL) skills. The chapter describes a recent study that investigated and characterized the students' learning profiles, self-regulated learning processes (skills and strategies), and followed the change in these variables throughout the 3 year program learning Chemistry via COBLE in order to predict students' success in learning Chemistry this way. Such prediction may enable teachers to be aware of possible problems earlier than usual and also help personalize the teaching and learning processes according to students' profiles. Results indicate that there are some significant differences in some of the SRL categories between students studying via face-to-face and virtual environments and also among intervention students that possessed different SRL profiles when examining the involvement variable throughout their studies over time. On the basis of the data, influential indicators were isolated to enable future prediction of student success in studying Chemistry in a virtual manner and better planning of personalized support.

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1 Introduction

1.1 Virtual Teaching

E-learning means any learning that is electronically mediated and/or facilitated by software, such as course management systems for organizing courses and presenting materials (Zemsky & Massy, 2004). This type of learning is in contrast to traditional or face-to-face learning in the school classroom. Tallent-Runnels, Thomas, Lan, and Cooper (2006) address four main pillars that emerged when students' encountered e-learning: *course environment* (classroom culture, structural assistance, success factors, interaction online, and evaluations), *learners' outcomes* (understanding the teaching and learning processes in the virtual environment), *learners' characteristics* (understanding the motivation to take a virtual course, learner's goals, and needs) and *institutional and administrative factors* (clear policies for virtual courses, such as a support system, course development, and evaluation). They concluded that although no comprehensive theories or models could be derived regarding instruction online, students preferred flexibility, convenience, and autonomy of individual pacing, although it required self-management and computer-skilled students had a more positive attitude toward e-learning than others less proficient. Attempts to compare students' learning outcomes in virtual and traditional environments revealed no significant differences between the two groups. E-learning students were affected by the quality of the course design and were more successful when the course was well-designed. This finding emphasizes the importance of the designer's role in determining the educational design theory used and in the overall success rate of the students taking the course and sets the stage for the work described in this chapter.

1.2 Self-Regulated Learning (SRL)

Self-regulated learners are defined as proactive seekers of information when it is needed and as those who take the necessary steps to master it (Zimmerman, 1990). They are also conceptualized as being metacognitive, since they plan, set goals, organize, self-monitor, and self-evaluate several times during the learning process. They are motivated and hold high self-efficacy, engage in self-attributions, have intrinsic task interest, and are behaviorally active participants in their learning processes (Pintrich & De Groot, 1990; Zimmerman, 1989, 1990, 2008). Additionally, there is a distinction between self-regulating processes and strategies as the latter are designed to minimize the processes and are believed to be adaptive (Butler & Winne, 1995). Students' learning must involve the use of specified strategies in order to achieve academic goals on the basis of self-efficacy perceptions. Those perceptions are about one's capabilities to organize and implement actions necessary to attain designated performance of skills for specific tasks (Zimmerman, 1989). Self-regulated learning skills are important in all learning environments but especially in a virtual learning environment, since it lacks the immediate ability to seek help from teachers (Cho, 2004; O'Neill, Singh, & O'Donoghue, 2004). It is believed that a major requirement for using technology in a virtual environment is the ability to be a self-regulated learner (SRL) (Tsai, 2011).

Teaching students to self-regulate their academic learning can be successful only when students experience the benefits of SRL (Zimmerman, Bonner, & Kovach, 1996). Four design principles were suggested in order to promote SRL skills: (1) SRL activities are to be explicitly presented to the students; (2) learning events should include opportunities to use SRL strategies; (3) SRL skill interventions are mandatory; (4) students must experience success while using SRL skills in order to continue to use them regularly (Ley & young, 2001; Zimmerman et al., 1996).

Different tools were developed in order to assess SRL skills, such as a Likert type questionnaire, the Learning and Study Strategies Inventory (LASSI), containing 80 questions attributed to ten different categories, each of which is associated with a three letter code used later in the context of the results: anxiety and worry about school performance (ANX); attitude and interest (ATT); concentration and attention to academic tasks (CON); information processing, acquiring knowledge, and reasoning (INP); motivation, diligence, self-discipline, and willingness to work hard (MOT); self-testing, reviewing, and preparing for classes (SFT); selecting main ideas and recognizing important information (SMI); use of support techniques and materials (STA); use of time management principles for academic tasks (TMT); test strategies and preparing for tests (TST). The LASSI test was initially designed to self-assess SRL skills, among other things, in order to predict the success rate in each category for students intending to go to college (Weinstein, Palmer, & Shulte, 2002).

1.3 Chemistry Online Blended Learning Environment (COBLE)

The design of COBLE consists of three elements: *Platform Design* (with Moodle used as the basic platform with many plug-in features), *Pedagogy*, and *Organization*. Here we will only describe the principles related to the Pedagogy and the platform components, which are most relevant to students' SRL.

1. *Diagnostics*: Coming from different schools, students' preliminary knowledge was diverse and had to be acknowledged and diagnosed. The first unit was built gradually, and basic scientific concepts were taught in order to create a platform for more complex explanations later on.
2. *Diverse Learning Styles*: Several teaching methodologies were used in order to ensure each and every student's engagement in the learning process. These computerized methods were included: synchronic interactive weekly lesson, exercise work sheets, interactive internet applets, a-synchronic Moodle tasks, home lab-reports (group and singular), and periodic Chemistry projects. The following non-computerized methods were included: Laboratory work performed

at the Weizmann Institute as a group and exercises from Chemistry books and group projects (such as modeling projects).

3. *Independence and Responsibility*: In order to enhance independent learning and encourage students to take responsibility for their studies, weekly a-synchronic lessons were given following the synchronic lessons.
4. *Peer Learning*: The students used forums, chats, and WhatsApp, and were encouraged to share experiences and answer questions in the forum, as well as react to other students' comments. Occasionally, groups of students had to perform a group assignment (i.e., to write a lab report together or to give in a group task).
5. *Lesson Design*: all lessons were designed in an identical way: lesson opening, "What have we learned so far?", "former knowledge needed", acquisition of new learning material, exercising and implementing the new materials, "summary", additional enrichment materials and relevant links, homework, and important announcements. The lead idea was that the students should know at any moment where they stand with respect to the course material (regarding the curriculum and the lesson itself).

The COBLE program started in 2014 and included a full year of development of learning materials and the platform. In the following year (2015) enrollment started and, following 3 years of studying in the program in 2017, 23 students have graduated; 87 students began their studies in the 12th grade; 157 students began their studies in the 11th grade; and 110 began their studies in the 10th grade. The current research follows the first cohort (that began in 2015) during all 3 years of participation.

2 The Study

The current study seeks understanding regarding the following questions:

Q1. What are the students' SRL profiles, and how do they change during 10th–12th grades?

Q2. Is there a correlation between the intervention students' SRL profiles and the level of success in the blended Chemistry environment during 10th–12th grades?

2.1 Method

2.1.1 Participants

Three groups of students were observed and compared in two phases within this research:

Phase 1: 1. Pre-group; 2. Control group

The pre-group was composed of 109 students learning science according to the requirements of the school curriculum and served as a reference group. The control group was composed of 19 10th–12th grade students who chose to study Chemistry as a major in high school.

Phase 2: 3. Intervention group

The intervention group was composed of students who enrolled in the virtual 'Chemistry Online' course at the beginning of the 10th grade. The number of the students in this group varied owing to dropouts and newcomers over time ($N = 23$ students graduated). These students were observed for 3 years (10th–12th grade) and were compared to the Chemistry students in the face-to-face control group.

For both the control and intervention groups, the scores of the 9th grade pre-group students in the LASSI categories were considered to be at the level of self-regulated learning (LASSI reference scores) that is typical before starting 10th grade Chemistry studies.

2.1.2 Instruments and Analysis

Questionnaire

A modified and translated (from its original English to Hebrew) form of the LASSI questionnaire developed by Weinstein et al. (2002) was used. There were 48 questions related to six out of the ten categories which were part of the original LASSI questionnaire:

- Attitude and interest (ATT)
- Concentration and attention to academic tasks (CON)
- Motivation, diligence, self-discipline, and willingness to work hard (MOT)
- Use of support techniques and materials (STA)
- Use of time management principles for academic tasks (TMT)
- Test strategies and preparing for tests (TST).

Additionally, the students tested were high school students and not college students as intended in the original questionnaire.

Changes were made accordingly, and the overall reliability of the modified questionnaire was very good (α [Cronbach's coefficient] = 0.93). Reliability (after modifications) of LASSI categories (α): CON (0.88), MOT (0.86), TST (0.77), TMT (0.82), ATT (0.69), and STA (0.63).

The distribution times of the LASSI questionnaire for the three research groups were as follows (note that there were three identical distribution times for the control and intervention groups) (Table 12.1).

The control group answered the questionnaire four times during the 3 years, and the intervention group answered the questionnaire six times during the 3 years.

Table 12.1 LASSI questionnaire distribution times (pre, control, and intervention groups)

	Jun-14					
Pre-group	Before the program has begun					
Control	Sep-14 (Beginning of 10th grade)	Nov-14		Feb-16 (Middle of 11th grade)		Apr-17 (End of 12th grade)
Intervention	Sep-14 (Beginning of 10th grade)	Jun-15	Oct-15	Feb-16 (Middle of 11th grade)	Oct-16	Apr-17 (End of 12th grade)

The pre-group measurement served as a reference group by collecting the mean of students' answers: average for each category containing eight questions. Answers to the LASSI questionnaires were coded into predetermined categories. Items were grouped into categories by five expert researchers, and their coding was compared.

Analyzing Students' Tasks via Moodle

Data mining in educational systems (or Educational Data Mining, EDM), is a fast growing field that not only provides tools to gain data for statistical purposes but also allows personalization of learning processes for individual students by analyzing their personal goals, preferences, and knowledge (Castro, Vellido, Nebot, & Mugica, 2007; Chen, Liu, Ou, & Liu, 2000; Romero, Ventura, & García, 2008). Data is retrieved automatically and stored in server access logs, sketching an individual portfolio for each student. There are several advantages in using data mining in a virtual course environment, such as collecting data that possesses a bias-free quantitative nature constantly being gathered without creating a nuisance or hindering students' activities in any way. Both methods, data collecting in the traditional classroom or via electronic means, constantly evaluate the effectiveness of the course components and interventions and are used to refine them accordingly, but the latter does not rely upon face-to-face interactions with the students (Sheard, Ceddia, Hurst, & Tuovinen, 2003).

EDM via data collected through Moodle was conducted in several ways:

- Receiving reports through the *Moodle report generator*: each student's activity volume (in the system in general as well as in specific worksheets, problem solving or tests). Reports can be generated according to the teachers needs crossing various variables, participants, and dates.
- Analyzing *synchronic online chat conversations* (total chat volume and message type): All students' messages from the chat area during the synchronic lesson were counted, coded, and analyzed according to the division: (1) Chemistry content messages (related to the content matter); (2) Technical messages (expressing technical difficulties); (3) Social messages (social interactions between students); (4) Administrative messages (addressing issues that were school-related and paper work); (5) Other messages.
- *Scores*: All students' task trials were scored.

In-Depth Interviews

The interviewees belonged to the intervention group only and were interviewed by one independent interviewer. They were chosen so they were heterogeneous (weak, medium, and strong students according to their achievements). The interviewees had guiding interview questions that covered the following topics: (1) General information, (2) Opinion of Chemistry and learning environment, (3) SRL, (4) Learning strategies, (5) Administrative and Technical issues, and (6) Closure. All interview data was qualitatively analyzed. All remaining students were academically capable of studying high-level Chemistry, since they study other high-level scientific subjects at school, and study high-level English and Math (besides two students who do not study Math and English at all as part of their school policy). Fifteen students were interviewed, and their common views are presented.

3 Results

Q1. What are the students' SRL profiles and how do they change during 10th–12th grades?

The Pre-group was composed of 109 students learning science according to the requirements of the school curriculum. These students answered the LASSI questionnaire at the end of the 9th grade. In September 2014, the research study began, and the first iteration took place as the two remaining groups, control (face-to-face) and intervention (online) Chemistry students, answered the LASSI questionnaire. No significant differences between students in the three groups at the beginning of the research were found (at the beginning of the 10th grade). This meant that all students, in all groups, had the same starting point and were not different in their SRL skills according to the six questionnaire categories that were checked.

The Control group was composed of 19 10th–12th grade students who chose to study Chemistry as a major in high school. *The intervention group* was composed of 24 10th–12th grade students who enrolled in the 'Chemistry Online' course.

In order to build a student's SRL profile, the six LASSI questionnaire categories were examined. Mean score for each of the categories was calculated. In addition, a cluster analysis was applied using the statistical software and programming language R (R Development Core Team, 2017) and specifically the open-source *prcr* (person-centered analysis) package (Rosenberg, Schmidt, & Beymer, 2017). Person-centered analyses focus on common patterns in observations considered in terms of clusters, or profiles, and their change over time or differences across factors, such as groups of students (Bergman & El-Khouri, 1999).

The data was scaled (since cluster analysis is sensitive to outliers) and the different profiles that emerge from the data were identified by means of regression analysis. Calculations yielded substantial variability explained in the clustered variables (R^2 = 0.53), and the percentage of agreement from double split-half

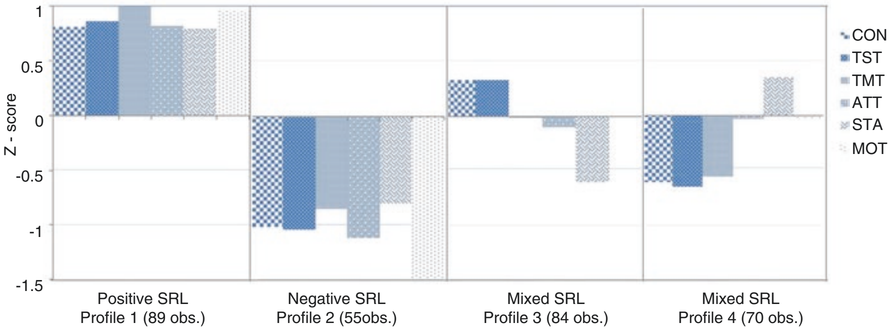

Fig. 12.1 The 4 SRL profile solution

cross-validation (all observations were split in half and each half was compared to the other in order to find similarities between the two halves) was 67.05% (κ [Cohen's Kappa] = 0.56). These calculations validated the use of a four SRL solution since 60–80% is considered a good agreement percentage (Landis & Koch, 1977; Sim & Wright, 2005).

In Fig. 12.1, we can observe the four SRL profile solution.

Distributions of the 298 SRL profile observations were found similar in size: SRL profile 1 (89 observations, 29.865% of the students) is an all-positive profile for all LASSI categories.[1] SRL profile 2 (55 observations, 18.456% of the students) is an all-negative profile for all LASSI categories. SRL profile 3 (84 observations, 28.188% of the students) is a mixed profile: ATT, MOT, STA, TMT < 0; CON, TST > 0. SRL profile 4 (70 observations, 23.49% of the students) is a mixed profile: ATT, MOT, CON, TST, TMT < 0; STA > 0. The all-positive SRL profile (profile 1) had the most observations and the all-negative SRL profile (profile 2) had the least.

Examination of the control and intervention group SRL profile percentage of appearances over time (10th–12th grades) can reveal an SRL profile pattern within the two groups. The intervention group was divided into two sub-groups: (a) remaining students (b) dropouts (Fig. 12.2a–c).

As can be seen in Fig. 12.2a–c above, the most prominent difference is in Fig. 12.2c, where dropout students barely possess the all-positive SRL profile (profile 1) at the beginning of their studies, and they quickly progressed toward the all-negative SRL profile (profile 2) up to the point when they dropped out. Furthermore, the control group and the intervention remaining student group started from approximately the same level of the all-positive SRL profile. Comparison between the two groups shows a drop in the percentage of the all-positive SRL profile (profile 1) for the control group, while the remaining student group percentage

[1]Attitude and interest (ATT); concentration and attention to academic tasks (CON); motivation, diligence, self-discipline, and willingness to work hard (MOT); use of support techniques and materials (STA); use of time management principles for academic tasks (TMT); test strategies and preparing for tests (TST).

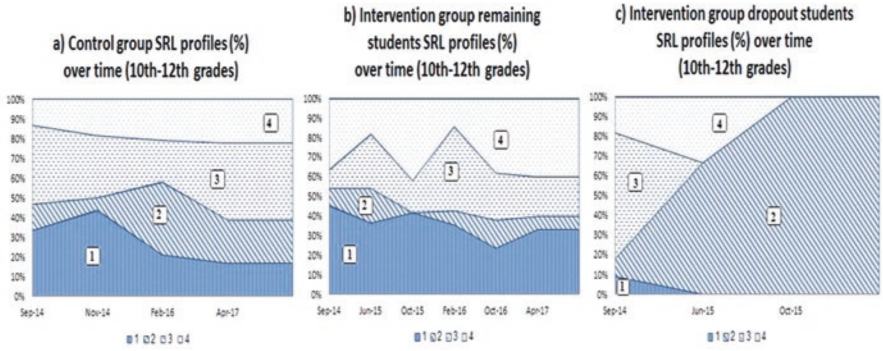

Fig. 12.2 SRL profile patterns (1–4) for (**a**) control group students, (**b**) remaining intervention group students (**c**) dropout intervention group students

of this SRL profile is higher and more or less steady. In the control group, more students were added to the all-negative SRL profile (profile 2) over time, while the remaining students displayed lower percentages of this profile, reaching the zero point on Oct 2015 (but increasing percentages somewhat after that date). As for the mixed SRL profiles (profiles 3 and 4), both groups had similar overall mixed SRL profile percentages, but the control group had steady percentages for both profiles, whereas the remaining students had SRL profile 3 decline and SRL profile 4 increase (note that SRL profile 4 is a more negative profile than SRL profile 3).

Though we present the profiles for each of the three groups over time in Fig. 12.2, we focused our analysis on overall group differences in frequencies of the profiles. A chi-square test of independence was performed comparing the frequency of student SRL profiles in each of the three groups: (a) control students (b) remaining intervention students, and (c) dropout intervention students. Significant differences were found: $\chi = 13.01$, $df = 6$, $p < 0.05$.

Intervention dropouts were less likely to possess the all-positive SRL profile 1 than remaining intervention or control students ($z = -2.2.016$, $p = 0.04328$), $p < 0.05$. Additionally, remaining intervention students were less likely to possess the all-negative SRL profile 2 than those in the control group or in the dropout intervention students ($z = -2.1676$, $p = 0.030235$), $p < 0.05$.

Results like those regarding dropout students are not surprising. It is unlikely that dropout students can possess a positive attitude, be interested, motivated, and invest time in a subject they have decided to stop studying. It is logical that any Chemistry student will possess a more positive SRL profile than dropouts.

This fits well with the other results regarding dropouts possessing an all-negative SRL profile (profile 2). We would expect a more negative SRL profile from any dropout in comparison to any Chemistry student; however, we also observed that the remaining intervention students were not likely to possess the all-negative SRL profile as much as the control students. This result shows that the remaining intervention students perhaps developed SRL skills over time since both groups were not initially different with respect to the mean scores for the LASSI categories at the beginning of their Chemistry studies.

Table 12.2 describes the LASSI questionnaire distribution times and means of the three significant LASSI categories (out of six LASSI categories that were checked) within each of the research groups.

Comparison of the two groups (control and intervention) using the Kruskal–Wallis test at the three identical distribution times: September 2014, at the beginning of the 10th grade; February 2016, in the middle of the 11th grade; and, April 2017, at the end of the 12th grade, resulted in differences found only between three of the six LASSI categories at the two latter distribution times: February 2016, in the middle of the 11th grade and April 2017, at the end of the 12th grade. Differences were found in the following categories:

- Attitude and interest (ATT) was significantly higher for the intervention group: $\chi = 4.09$, $df = 1$, $p < 0.05$. High attitude and interest was also expressed by students in the interviews regarding the interest they demonstrated in Chemistry before and after entering the program:
- Quote 1: "*Chemistry is interesting to me. The teacher teaches in an interesting way and links the material to daily life. It makes me want to listen*."
- Quote 2: "*My father bought me a second hand Chemistry book from 1963, and I read it. I enjoy Chemistry and find that I'm very interested in it*."
- Quote 3: "*Chemistry is relevant to everything in our life. When I was in junior high, we studied Chemistry, and I was mainly excited about the experiments*."
- Test strategies and preparation for tests (TST) was significantly higher for the control group: $\chi = 4.78$, $df = 1$, $p < 0.05$. According to intervention student's answers in the interviews, they all prepared for the tests, mostly by revising their notebooks since almost all had them and summarized either during the lesson or right afterwards. Most students did not prepare for the quizzes:
- Quote 4: "*In order to revise for tests, I just went through the recordings and presentations. For the quizzes, I never studied. It's also possible to go over the exercises*."

Table 12.2 Times and significant means within research groups' answers in LASSI questionnaire categories (pre, control, and intervention groups)

		Pre-group	Control		Intervention	
Category name	Category abbreviation	June 2014	Feb 2016	Apr 2017	Feb 2016	Apr 2017
		$N = 109$	$N = 19$	$N = 19$	$N = 18$	$N = 21$
Test strategies and preparation for tests	TST	3.921	3.617	4.030*	3.944	3.864*
Use of time management principles for academic tasks	TMT	3.342	3.039	3.184**	3.208	3.030**
Attitude and interest	ATT	3.533	3.496	3.451*	3.778	3.619*

*$0.01 < p < 0.05$, **$0.001 < p < 0.01$

- Quote 5: "*In order to revise for tests, I summarized the lessons and exercises. I didn't revise for the quizzes*."
- Quote 6: "*I read the summary in my notebook, and got help from my friends when I prepared for tests*."
- Use of time management principles for academic tasks (TMT) was significantly higher for the control group: $\chi = 8.98$, $df = 1$, $p < 0.005$. Students in the intervention group testify to time-management issues:

- Quote 7: "*Chemistry is time consuming if I don't understand and have to figure it out at home. If something is not clear during the lesson I revise the lesson afterwards*."

- Quote 8: "*When I have time, I do my Chemistry homework but I have more urgent things to do*."

- Quote 9: "*I feel that I can do with solving a handful of problems if I understand the principles, I don't need to spend much time on that*"

These findings can be influenced by several factors:

1. *Teacher*: each group had different teachers—a fact that may have had influence on the student's answers.
2. *Content*: in the 12th grade's curriculum there is a topic that is subject to teacher's discretion. Each group was taught a different topic and that may have been influential, affecting the student's answers.
3. *Timing*: the control group student's final external Ministry of Education (MOE) test took place at the end of the 11th grade, whereas the intervention group students were tested at the end of the 12th grade. This meant that a lot of pressure was lifted from control group students as they were left with the external laboratory exam alone (all lab work was group work, performed in the 12th grade, ending with a 15–20 min external oral test).

   - Students expressed the importance of intrinsic motivation (MOT) during their studies as a means for attaining success in a virtual environment:
     Quote 10: "*You have to be responsible for your own studies because there is no one to make you study*."
     Quote 11: "*I recheck the assignments before sending them in. If I am not content with the score, I resend them*."
     Quote 12: "*My motivation to study is intrinsic, or else I wouldn't have attended the lessons. Same goes for the face-to-face lessons at my school*."

   - They also referred to the ability to concentrate (CON) and maintain a decent level of learning without face-to-face contact with either teacher or peer-classmates (most, expressing different degrees of discontent, but showing the ability to overcome it):
     Quote 13: "*In the face-to-face classroom, there are distractions, and students do not always listen. There are many disciplinary issues. I prefer the virtual lessons because there are none of those there*."

Quote 14: "*I connect to the virtual lesson from home, because at school there are more distractions and technical problems that bother me*."

Quote 15: "*I find it very convenient to study through a virtual class setting since I have a hard time sitting in a face-to-face classroom, and I tend to bother everyone else. My functioning in the face-to-face classroom depends on if there is noise outside of the classroom or if I'm tired*."

Q2. Is there a correlation between the intervention students' SRL profiles and the level of success in the blended Chemistry environment during 10th–12th grades?

In order to answer this research question, there is a need to first define 'success' by measurable means and then track changes that have occurred in their SRL profiles throughout their studies with respect to these success measures.

3.1 Measures of Success

3.1.1 Achievements

Students in the intervention group (10th–12th grades) were divided into three groups (high, medium, and low achievers) according to their scores in the 3 year course. The division into these groups was done after statistically locating differentiating questions among all the questions that were presented to the students throughout the 3 year course and the scores of written tests and matriculation exams. In all, 251 differentiating questions were found and used for this task, defining the three intervention student achiever groups as follows.

- *Low achiever's* scores were between $0 \geq \text{score} \geq 66.4$ (five students)
- *Medium achiever's* scores were between $66.4 > \text{score} \geq 77.9$ (ten students)
- *High achiever's* scores were between $77.9 > \text{score} \geq 100$ (eight students)

No significant differences were found in GLM repeated measures performed within each group (in terms of SRL categories), and therefore the division among these achievement groups is acceptable.

There were fewer students in the low achieving group (suggesting that they might have possessed certain SRL features that enabled them to remain in the course despite their low achievements). These remaining low-achiever students were from diverse backgrounds, and their reasons for remaining in the course seemed to be different; all of these students started off with higher scores that deteriorated over time. The majority of the remaining intervention students were medium achievers and almost the same number were high achievers. In more cases than not, the students' later scores determined whether they belonged in a specific group, and if they did well on the final matriculation exam. In short, it was not the mean score but the trend that accounted for student outcomes on the matriculation exam.

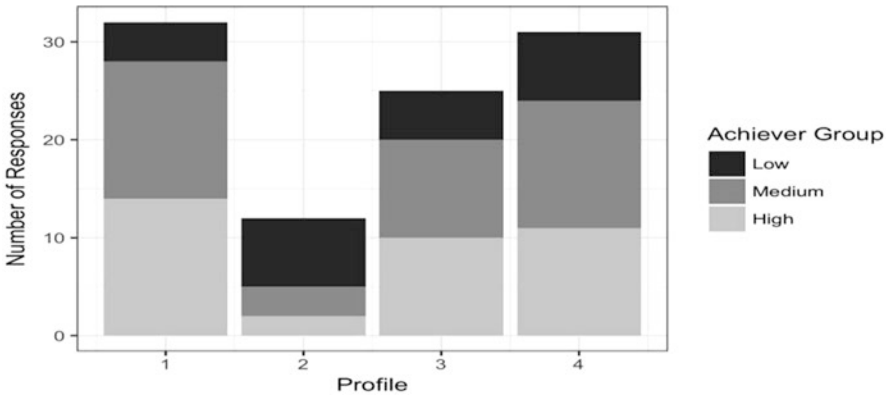

Fig. 12.3 Number of students in achievement group by SRL profiles (intervention group, 10th–12th grades)

Correlating the number of intervention students in each achievement group according to their SRL profiles, we composed the following graph (Fig. 12.3).

A χ^2 test of independence was performed comparing the frequency of the number of intervention students in each of the three achievement groups and the SRL profile they possessed. No significant interactions were found, and the student achievements were as expected according to their SRL profiles (for example: all-positive SRL profile 1 was expected to include a relatively small number of low achievers; all-negative SRL profile 2 was expected to include a relatively small number of high achievers and a relatively large number of low achievers, whereas the mixed SRL profiles 3 and 4 included students from all three achievement groups).

3.1.2 Involvement (Fig. 12.4)

Involvement in the course was imperative for the students' progress. When speaking of involvement, we can focus on the activity of students; hence, investing in an effort to succeed. This score was composed of the following.

Effort

SEM: Synchronic Effort Mark

We looked for a way to calculate and calibrate students' overall effort. As no published measure suited our needs perfectly, we developed the SEM and A-SEM measures for effort mark. All actions taking place during the synchronic lesson were recorded and stored for each student. Student effort during the lessons could be

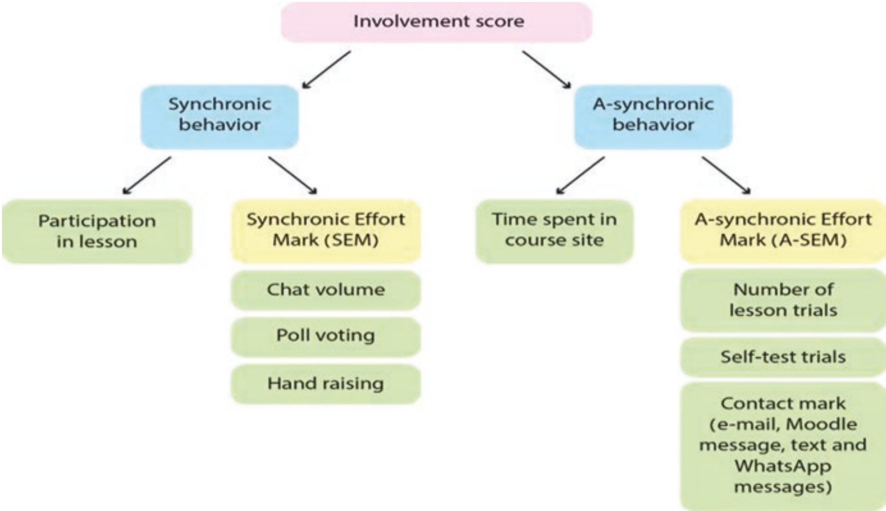

Fig. 12.4 Involvement score components

measured by voluntary actions during these lessons,[2] such as chat-volume (placing messages in the chat area), hand-raising (asking questions, participating or reacting by request) or poll-voting (poll-like questions were used as a class exercise during the lessons and students were expected to cast their vote when asked to do so). These three synchronic effort components were counted and were scaled together to form a unified synchronic effort mark (SEM).

Plotting the SEM by SRL profiles resulted in the following graph (Fig. 12.5).

There was a statistically significant difference between groups as determined by one-way ANOVA $F(3,99) = 14.77$; $p < 0.0001$; Post hoc comparisons using the Tukey HSD test indicated that the mean score for the SEM of SRL profile 1 ($M = 14.482$, $SD = 5.243$) was significantly higher than the SEM of SRL profile 2 ($M = 8.625$, $SD = 4.137$) $p < 0.01$, the SEM of profile 3 ($M = 5.624$, $SD = 3.754$) $p < 0.0001$, and the SEM of profile 4 (7.885, $SD = 6.800$) $p < 0.0001$. However, there were no other differences between the other SEMs of the other profiles.

Taken together, these results suggest that higher synchronic efforts (SEMs) might have affected the SRL profile possessed by the student. It should be noted that the difference was recorded between the all-positive SRL profile (profile 1) and all-other SRL profiles (profiles 2, 3 and 4). The results suggest that when students make an effort and keep actively involved in the lesson, they either already possess an all-positive SRL profile (SRL profile 1) or by doing so have improved their SRL skills over time and shifted their SRL profile toward a positive SRL profile.

[2] Participation in the synchronic lesson (although not a voluntary action) was also considered as synchronic behavior since it is an action related to the synchronic lesson, but since there were no differences in the SEM when absent, the existence of this component is merely acknowledged.

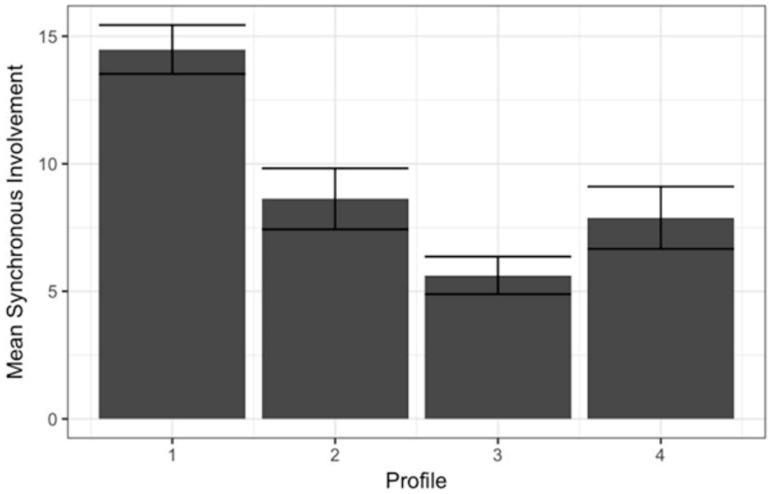

Fig. 12.5 SEM by SRL profiles (intervention group. 10th–12th grades)

A-SEM: A-Synchronic Effort Mark

Student effort during A-synchronic activity could be measured by recording all optional activities, such as number of student trials in homework task assignments: each assignment had two optional trials and students could have tried both trials (in order to improve their score), one trial (in order to do the homework duties alone), or no trials at all (if they failed to do their homework); students could self-assess their knowledge by answering self-tests and they had the option to contact the teacher in several ways: emailing the teacher using the course email address, messaging the teacher via the Moodle system, text-message or WhatsApp the teacher by cell-phone. All of these were non-obligatory features of the course, and if any students used these features, it signified as making an effort in the course.[3] These three A-synchronic effort components were counted for each student and were scaled together to form a unified A-synchronic effort mark (A-SEM). The calculated highest A-SEM for any student was 78%. Plotting the A-SEM by SRL profiles resulted in the following graph (Fig. 12.6).

There was a statistically significant difference between groups as determined by one-way ANOVA $F(3,90) = 4.96$; $p < 0.001$; Post hoc comparisons using the Tukey HSD test indicated that the mean score for the A-SEM of SRL profile 1 ($M = 46.90$, $SD = 19.298$) was significantly different than the mean score for the A-SEM of SRL

[3] Time spent at the site was also considered as a-synchronic behavior since it is an action related to the a-synchronic assignments; students could have spent more or less time at the site while performing their homework assignments or revising the learning materials. The existence of this component is merely acknowledged, since it is impossible to differentiate the actual time of student engagement or idle connectivity to the site.

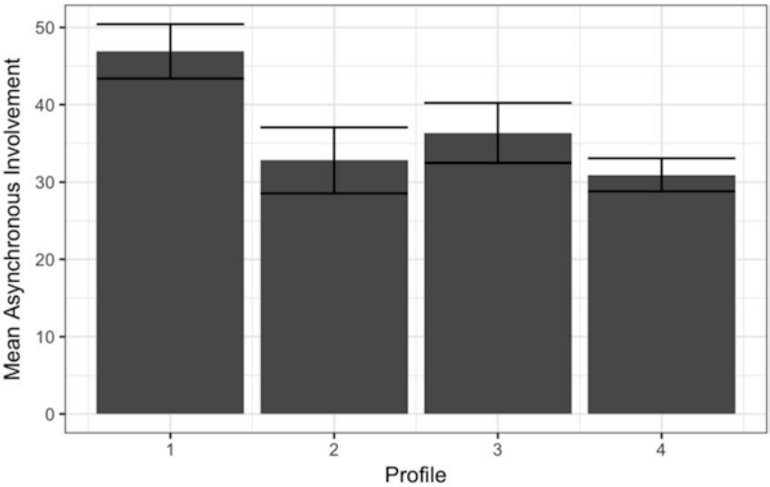

Fig. 12.6 A-SEM by SRL profiles (intervention group. 10th–12th grades)

profile 4 ($M = 30.925$, SD = 10.809) $p < 0.01$. However, there were no other differences between the other A-SEMs of the other profiles.

Taken together, these results suggest that higher A-synchronic efforts (A-SEMs) might have affected the SRL profile possessed by the student. It should however be noted that, surprisingly, the difference calculated was not between the all-positive SRL profile (profile 1) and the all-negative SRL profile (profile 2) but between the all-positive SRL profile (profile 1) and the almost all-negative SRL profile (profile 4). The results suggest that when students make an effort in non-obligatory tasks, they are more likely to possess an all-positive SRL profile (profile 1) or by doing so have improved their SRL skills and shifted their SRL profile toward a positive SRL profile over time.

- A moderate though significant correlation was found by using the Spearman non-parametric analysis between student synchronic effort marks (SEMs) and their A-synchronic effort marks (A-SEMs) ($r_s = 0.47$, $p < 0.05$).
- A moderate though significant correlation was found between student A-synchronic effort marks (A-SEMs) and their matriculation score ($r_s = 0.55$ $p < 0.05$).
- No correlation was found between student synchronic effort marks (SEM) and their matriculation scores.

Students stated in their interviews that they made various degrees of contact efforts with either teacher or tutor during their studies whenever questions or need occurred.

Quote 16: "*I ask questions by privately text messaging the teacher*."
Quote 17: "*If I don't understand something, I ask friends or family, or the class or teacher using WhatsApp. If I was in the lesson, I use the chat area*."

Quote 18: "*I write messages in the chat area during the synchronic lessons or open the microphone at the end of the lesson and ask, or WhatsApp*."

These findings mean that there is a positive relationship between different types of effort; furthermore, it is important for students to make a conscious effort in order to succeed and achieve higher scores. SEM proved to be very important in relation to a positive SRL profile; A-SEM proved to be important to success and as a means to achieve higher scores: by participating in the lesson and doing homework assignments and after-school activities that are related to the course, such as revising materials and putting extra time and thought and performing more trials in order to improve scores, as well as reaching out to the teacher in order to ask questions related to the learning material, homework or even just to talk about general interests, the students become more successful.

Chats During the Synchronic Lesson and as a Feature of Synchronic Behavior

All students' messages from the chat area during the synchronic lesson were counted and chat type percentage over the course of 3 years is shown in Fig. 12.7.

As can be seen in Fig. 12.7, the majority of chat messages were Chemistry content-related messages (63%). This indicates that students were engaged in the lesson and asked about and/or widely used the scientific terminology. Social content messages (12%), technical messages (11%), and administrative messages (11%) accounted for most of the remaining messages.

Owing to the vast amount of data collected over the period of 3 years, chats were divided into six parts (each of the 3 years of studies (y1–y3) was divided into two semesters (s1, s2)) and their mean values were calculated. We can follow the trend changes in the number of each chat category over time.

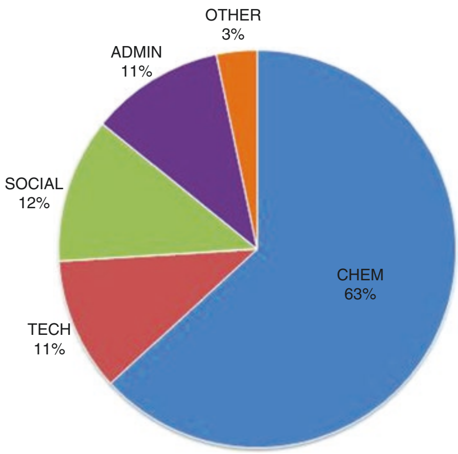

Fig. 12.7 Total 3 year chat type message percentage

Chemistry-Related Chat Messages

The number of these types of messages increased steadily until the end of the second semester of the 11th grade (y2s2), where we then notice a decrease in the number of these types of chat messages. The reason can be rooted in the methodological change of teaching the synchronic lessons in the 12th grade, which resulted in fewer lesson numbers. In the 12th grade the students practiced the material they had learned during the synchronic lessons themselves (as opposed to exercising by a-synchronic task assignments after the synchronic lesson took place). Fewer messages were generated during the lessons, but overall the trend was positive throughout the 3 years of the course.

The changes in the mean numbers of the Chemistry-related messages by grades (y1–y3) and semesters (s1, s2) are presented in Fig. 12.8.

Significant differences were found between the second semester of the 11th grade (y2s2) and the second semester of the 10th grade (y1s2): $S = 20.5$; $0.01 < p < 0.05$, between the second and first semesters of the 11th grade (y2s2, y2s1): $S = 84$; $p < 0.001$, between the first semesters of the 12th grade (y3s1) and the 11th grade (y2s1): $S = -41.5$; $0.001 < p < 0.01$, between the first semester of the 12th grade (y3s1) and the second semester of the 11th grade (y2s2): $S = -47.5$; $0.001 < p < 0.01$, and between the second semesters of the 12th grade (y3s2) and the 11th grade (y2s2): $S = -59$; $0.001 < p < 0.01$.

Technical-Related Chat Messages

The number of these types of messages decreased until the end of the second semester of the 11th grade (y2s2) where we notice an increase in the quantity of these types of chat messages. The reason can be rooted in two major changes that occurred:

1. An upgrade of the Learning Management System (Moodle), which confused the students at the beginning of the 12th grade, and since time issues arose causing student absences, constant coaxing efforts by the teaching staff in order to get the

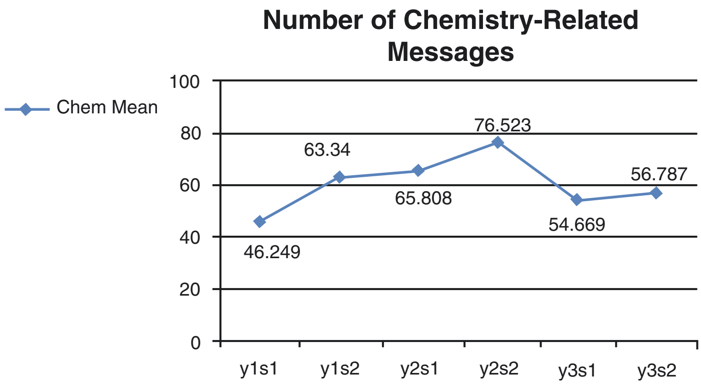

Fig. 12.8 Mean numbers of the Chemistry-related messages vs. grades (y1–y3) and semesters (s1, s2)

students to connect to the lesson in the first weeks were needed. This resulted in dealing with the same technical problems repeatedly whenever a student connected for the first time to the synchronic lesson.

2. A state of the art studio was built in order to have a place to conduct and record the synchronic lessons. Many difficulties emerged in the run-in phase during the third year (12th grade) until all technical problems were resolved. Overall, the trend was negative throughout the 3-year course. The changes in the mean numbers of the technical-related messages according to grades (y1–y3) and semesters (s1, s2) are presented in Fig. 12.9.

Significant differences were found between the second semester of the 11th grade (y2s2) and the second semester of the 10th grade (y1s2): $S = -32$; $0.001 < p < 0.01$, between the second and first semesters of the 11th grade (y2s2, y2s1): $S = -42.5$; $0.001 < p < 0.01$, between the first semester of the 12th grade (y3s1) and the second semester of the 11th grade (y2s2): $S = 33$; $0.001 < p < 0.01$, and between the second semesters of the 12th grade (y3s2) and the first semester of the 10th grade (y1s1): $S = -16$; $0.01 < p < 0.05$.

Social-Related Chat Messages

The number of these types of messages increased steadily until the end of the second semester of the 12th grade (y3s2). We do notice a slight decrease in the 11th grade (y2s1, y2s2), and this can be a result of the beginning of the MOE external exams for these students at this time. This caused them to concentrate more on their day-to-day school work rather than socialize with students outside of their own school. Overall, the trend was positive throughout the 3-year course. The changes in the mean numbers of the social related messages according to grades (y1–y3) and semesters (s1, s2) are presented in Fig. 12.10.

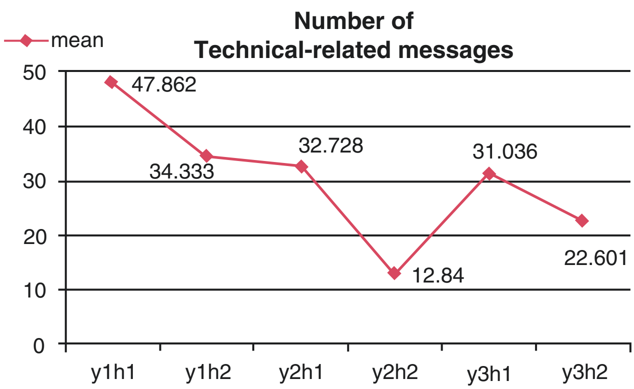

Fig. 12.9 Mean numbers of the technical-related messages vs. grades (y1–y3) and semesters (s1, s2)

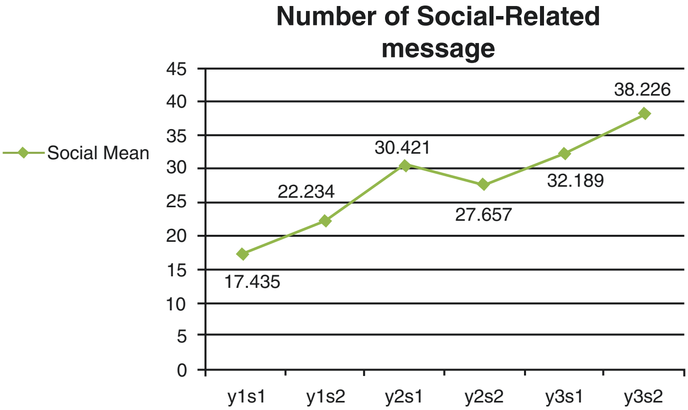

Fig. 12.10 Mean numbers of the social-related messages vs. grades (y1–y3) and semesters (s1, s2)

Significant differences were found between the first semester of the 11th grade (y2s1) and the first semester of the 10th grade (y1s1): $S = 19.5$; $0.01 < p < 0.05$, between the second semester of the 12th grade (y3s2) and the second semester of the 11th grade (y2s2): $S = 48.5$; $0.01 < p < 0.05$, and between the second semesters of the 12th grade (y3s2) and the first semester of the 10th grade (y1s1): $S = 22.5$; $0.001 < p < 0.01$.

Administrative-Related Chat Messages

The number of these types of messages increased in the 10th grade (y1s1, y1s2) and decreased only in the second semester of the 11th grade (y2s2). There was a dramatic increase in these types of chat messages in the 12th grade (then decreasing to the previous mean value (y1s2, y2s1)). This can be explained by the novelty of the program and the fact that this was the first year that schools had to deal with the unknown situation of graduation from the program, and that itself involved a great deal of bureaucratic work. Many questions were asked about the technicalities of the final matriculation exam (especially in the first semester of the 12th grade since many forms were to be filled out), and since the students were studying for other exams at their schools, many administrative issues emerged during the 12th grade that had to be addressed during the synchronic lessons. Overall, the trend was mildly positive until the end of the 11th grade (y2s2), dropped (y2s2), and shot up sharply only to continue to drop again during the 12th grade. The changes in the mean numbers of the administrative-related messages according to grades and semesters are presented in Fig. 12.11.

Significant differences were found between the second semester of the 11th grade (y2s2) and the second semester of the 10th grade (y1s2): $S = -17$; $0.001 < p < 0.01$, between the second and first semesters of the 11th grade (y2s2, y2s1): $S = -60$; $p < 0.001$, between the first semester of the 12th grade (y3s1) and

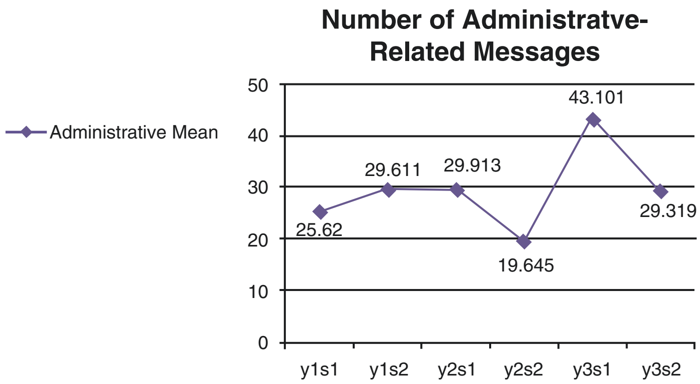

Fig. 12.11 Mean numbers of the administrative-related messages vs. grades (y1–y3) and semesters (s1, s2)

the second semester of the 11th grade (y2s2): $S = 42.5$; $0.001 < p < 0.01$, and between the second semester of the 12th grade (y3s2) and the second semester of the 11th grade (y2s2): $S = 30$; $0.001 < p < 0.01$.

Other Related Chat Messages

Other Related Chat Messages will not be discussed since they are not about any specific topic but contained sporadic messages such as "Thank you", "Sorry, I'm late", etc.

4 Conclusions

The main results that were found significant are summarized in this section:

Q1. What are the students' SRL profiles, and how do they change during 10th–12th grades?

(a) A four SRL profile solution based on modified LASSI questionnaires analysis was suggested.
(b) It is unlikely that dropout students can possess an all-positive SRL profile.
(c) Chemistry students will possess a more positive SRL profile than dropouts.
(d) The remaining intervention students were not likely to possess the all-negative SRL profile as much as the control students.
(e) Remaining intervention students developed SRL skills over time. Both intervention and control groups were not initially different with respect to the mean scores for the LASSI categories but remaining intervention students were not likely to possess the negative SRL profile as much as the control students.

Q2. Is there a correlation between the intervention students' SRL profiles and the level of success in the blended Chemistry environment during 10th–12th grades?

(a) No significant interactions were found, and the students' achievements were as expected according to their SRL profiles: (high achievers possessed all-positive SRL profile; low achievers possessed all-negative SRL profile, etc.)
(b) A significant difference was recorded between the all-positive SRL profile (profile 1) and the other SRL profiles (profiles 2, 3 and 4). There were no other differences between the SEMs of the other profiles.
(c) The difference calculated was between the all-positive SRL profile (profile 1) and the almost all-negative SRL profile (profile 4). There were no other differences between the SEMs of the other profiles.

5 Discussion

This study looks at Self-Regulation in an innovative way by analyzing high school student's SRL profiles and success with the aid of data mining, while learning in a virtual course environment that teaches Chemistry. The novelty of this research lays in the uniqueness of the learning environment setting, the interaction between the declarative SRL profile (by the LASSI questionnaires), and actual learning process and scores, and finally the length of time students were followed was large (3 years), although shorter terms were applied in different settings (Akçapınar, Altun, and Coşgun (2014); Akçapınar (2015); Preidys and Sakalauskas (2010); Ning and Downing (2015); Schmidt, Rosenberg, & Beymer, 2018). In this study, we show that SRL profiles can be isolated from data gained by student's self-declarative LASSI questionnaires and can be related to success measures that are actually derived by quantitative independent means resulting in relationships between them: a relationship between negative SRL profiles (with limitation to the categories that were checked) and students' dropout. This finding can serve in some cases as "alert-signs" for educators since they can indicate that students are prone to dropout. Both groups suffered from this phenomenon, and various reasons could have caused it: a certain image of the chosen subject (Chemistry), which might not have been realistic, the effect of novelty wearing off over time, disappointment and, therefore, a loss of concentration resulting in reluctance to apply the needed effort in their studies or difficulties, such as problems in understanding the content matter, time issues, and boredom.

Students that were more involved in the course by performing assignments of different types were more likely to attain higher scores. This finding aligns with Bannert, Reimann, and Sonnenberg (2014) who found that more regulation event types appear in successful student's behavior, such as preparing activities (orientation and planning) before they process the information to be learned and deep elaboration of information while reading. Similarly, Ning and Downing (2015) describe cognitive-oriented self-regulated learner and behavioral-oriented self-regulated learner profiles while searching for latent profiles by partly utilizing (among other tools) two of the LASSI categories used in this study: motivation (MOT) and test-strategies (TST). Motivation was found to be linked to SRL profiles by more than one researcher (Ning & Downing, 2015; Scardamalia & Bereiter, 1991, 1994; Sharp, Pocklington, & Weindling, 2002; Weinstein et al., 2002; Zusho & Edwards, 2011), although in this study, not all SRL profiles exhibit motivation, and distinction cannot be made by eyeing this LASSI category alone.

Careful application of some of the tools and patterns presented here is recommended for further applications in the educational field. These findings alone cannot be used in order to discriminate between more and less successful learners as a "one-all" solution, since educational systems are complex. We agree with Bannert et al. (2014), who state that it can only work in the same environment and context in which it has been identified and that ethical concerns can subsequently emerge by doing so; we must bear in mind that although the amount of data mined over the period of 3 years of research is great (number of chat messages, number of LASSI questionnaires etc.)—the sample size is relatively small ($N = 23$), and therefore replication studies are needed in order to reinforce the results. Further research is also needed beyond the scope of the classroom SRL profile change. It is possible to analyze the data in order to follow the personal SRL profile changes for each student over the 3 years in the course. This can supply a larger and more concrete picture that perhaps can be used to predict success in this kind of learning environment and enable educators to improve student's outcomes by mere knowledge of their personal SRL profiles and the factors that could affect them and cause changes in them over time.

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