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Esteban Villalobos, Mar Pérez-Sanagustin, Cédric Sanza, André Tricot, Julien Broisin. Supporting Self-regulated Learning in BL: Exploring Learners' Tactics and Strategies. Seventeenth European Conference on Technology Enhanced Learning ECTEL22, Sep 2022, Toulouse, France. pp.407-420, <10.1007/978-3-031-16290-9_30>. <hal-03784148>

HAL Id: hal-03784148

<https://hal.science/hal-03784148v1>

Submitted on 22 Sep 2022

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Supporting Self-regulated Learning in BL: Exploring Learners' Tactics and Strategies

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Abstract. In the past years, Blended Learning (BL) has gained traction as a methodology in Higher Education Institutions. Despite the positive effects of BL, several studies have shown that students require high levels of self-regulation to succeed in these types of practices. Still, there is little understanding of how students organize their learning in BL authentic contexts. To fill this gap, this paper presents an exploratory study to analyze the learning tactics and strategies of 119 students in a BL course using the Moodle Learning Management System. Specifically, we examined the effects on students' learning behavior before and after an intervention with a dashboard-based plug-in designed to support self-regulated learning (SRL). Using a data-driven approach based on Hidden Markov Models (HMM), we identified the tactics and strategies employed by the students along the course. The results show that students' tactics and strategies changed significantly depending on the course design and the context in which learning occurs (in or beyond the class). Also, we found evidence indicating that the main factor that correlates to the students' learning strategies is their previous knowledge and the students' SRL ability profile.

Keywords: Self-regulated Learning · Learning Analytics · Blended Learning.

1 Introduction

In the wake of the COVID-19 pandemic, Blended Learning (BL), which combines online and traditional in-person activities, has gained prominence. While this approach has been shown positive for learning, many students often have problems regulating their learning processes in these contexts [1]. This has raised a great interest in better understanding students' self-regulation and how to support it in BL. This paper aims to shed light on how students' Self-regulated Learning (SRL) manifests in BL when intervening with a dashboard-based solution to support their learning process. The following sections presents prior work on SRL and BL, students' trace analysis that supports the research questions of this work and the analytical methods employed.



Fig. 1. Examples of visualizations in the NMP plug-in

1.1 Self-Regulated Learning and BL

Self-regulated learning (SRL) is defined as a complex process that combines meta-cognitive, motivational, and emotional processes [10]. Recent literature shows that students' SRL ability is a good predictor of their behavior and success in a course [8]. However, most studies on SRL have been conducted in online contexts and little is known about how these processes manifest in BL [1].

Recent works show that students' SRL manifests differently depending on the learning context and course modality [1, 2, 6, 9]. For example, Matcha et al. [9] compared students' strategies in a BL course, in a Flipped Classroom (FC), and in Massive Open Online Courses (MOOCs), showing that students used similar strategies in BL and FC modalities, but these differed from the tactics used in MOOCs. Moreover, Broadbent [1] showed that BL students used SRL strategies less often than online students.

To support students' SRL, researchers propose different mechanisms. One of this mechanisms are tools based on dashboards providing learners with information about their progress. Although most of these tools have been designed and evaluated in online environments with encouraging results [12], only a few works show how students incorporate them into their learning strategies and have an impact on their behavior in BL courses, in which the teacher also supports the SRL [14, 16].

In this paper, we used the tool NoteMyProgress (NMP) for intervening a BL course. NMP is a plug-in for Moodle that tracks students' activity on the course and provides them with interactive dashboards for monitoring their actions and performance on the course (see Figure 1) [13]. This tool was designed to support students' self-regulated learning and offers different visualizations for supporting certain SRL processes: (1) Time management (TM), dashboards showing the number of working sessions performed along the course, showing the dates, hours in which they were performed and their duration; (2) Strategic Planning (SP), showing the resources and activities to be completed by the student each week; and (3) Self-evaluation (SE), dashboards showing students' performance on the course evaluations as well as their average compared with the mean of the course.

1.2 Inferring tactics and strategies from trace data

The community of Learning Analytics (LA) proposes techniques and methods for studying how SRL manifests in different learning contexts. One of these methods consists of using students' self-reported data about their SRL ability [17] and combine it with approaches for detecting tactics and strategies by using the trace data collected from the course LMS [2–5, 9].

To detect tactics and strategies from trace data, most studies have used techniques derived from temporal analysis and sequence mining [3, 4]. To make the connection between these techniques and the SRL theory, Fan et al. [3] used a data-driven approach to analyze the underlying SLR processes activated in the learning tactics to help develop interventions. Fincham et al. [4] studied the impact of personalized feedback to support learning strategies using HMM models and hierarchical clustering to detect tactics and strategies in a Flipped Classroom setting. While some of these studies have looked into how to detect strategies in BL courses, little is known about how they manifest across the course. In this study, we build upon the work by [4] as a basis and expand their analysis to a BL context.

1.3 Objective and Research Questions

To extend the knowledge on how SRL manifests and can be supported in BL, this paper presents an exploratory study conducted in a course with 119 students. In this course, students were provided with the NMP plug-in to monitor their study sessions, grades, course planning, and progress through interactive dashboards. The main aim of this exploratory study was to study how learning tactics and strategies manifest in a BL course having the NMP tool as a support for their self-regulatory process and how they integrate its use.

Using the data analysis techniques proposed in Fincham et al. [4], we extracted students' learning tactics and strategies from trace data (actions) and characterized those strategies that are related to performance. Three research questions were derived from the main aim:

- RQ1. How do students' learning tactics and strategies manifest along the BL course?
- RQ2. Does the NMP tool, designed to support students' SRL, have an effect on their learning tactics and strategies?
- RQ3. Is there a relationship between students' learning strategies, course performance and SRL ability profile?

2 Methodology

2.1 Exploratory Study: Context

We conducted an exploratory study in order to address the research questions. We selected this methodological approach as it is recommended for studying a phenomenon when there is insufficient prior research to establish hypotheses.

Table 1. Course description according to modality. Week 6 is excluded from this classification since it was the week of the intervention.

Weeks	Modality	Activities and tasks descriptions
1-5	Mod. 1	Objective: To get familiar with the main theoretical concepts of Databases modeling. Design: Students had a set of theoretical resources that they need to prepare before in-class sessions. A questionnaire had to be answered before the class, as a form of self-evaluation. In class, students were presented with problems that were worked in an individual manner first, discussed in groups, and presented to the rest of the class
7-11	Mod. 2	Objective: To work with an actual SQL database and solve several exercises to get familiar with the SQL management and queries with PHPMyAdmin. Design: Videos showing how to use PhPMYadmin and solve certain problems that they could see before and after the in-class session. In class, students were provided with a problem to be solved during the class. They had one week to send the results of this exercise.
12-15	Mod. 3	Objective: To work on a group project (3 per group) for setting up a DB from scratch to manage the books and members of a library. Design: The project was presented in class, and students worked autonomously on it during the rest of the sessions and from home. The teacher solved particular problems during the in-class sessions. Students had to send the project at the end of the 12th week.

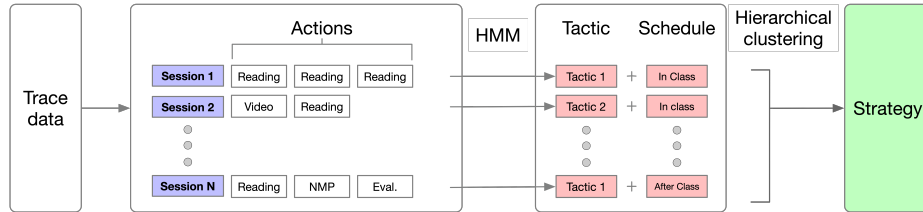
The study was conducted in a Databases course of a Degree in Management of Enterprises. The course counts with 119 students organized into 4 groups (of around 25-30 students) for theoretical sessions and 8 groups with 12-15 students for practical sessions. All students signed a consent form on the first day of the course for participating in the study and all agreed. The course was designed as a BL course using the Moodle Platform as the primary LMS. Students participated in 1.5 hours of face-to-face lessons once a week and were asked to complete online activities in Moodle and projects at home planned for 1-2 hours of dedication per week. The course lasted 15 weeks and was structured into three parts, each following a different modality of blended learning design. Table 1 shows a summary of the duration and objectives of each modality. In the sixth week of the course, the teacher introduced the NoteMyProgress (NMP) tool in a face-to-face session. Its use was not mandatory but it was presented as a support for organizing their learning in the course that students could use voluntarily whenever they needed.

2.2 Data Gathering Techniques

We used different data gathering techniques that included: (1) students' self-reported data about their SRL ability, (2) students' trace data with the course content and NMP functionalities, and (3) course metadata (see Table 2) Students' SRL was measured using the MSLQ questionnaire [11], which they completed in week 6 before the intervention with NMP. The MSLQ has 44 questions, scored based on a 7-point Likert scale and provides information on motivation (Intrinsic Value, Self-efficacy, and Text Anxiety) and self-regulated learning (Cognitive Strategy Use and Self-regulation). It was translated into French with a good level of reliability (Cronbach's alpha=0.93).

Table 2. Description of the data sources used in the study

Source Type	Source Name	Description
Trace Data	Moodle	Records of when students interacted with each element of the course in Moodle
	NMP	Records of when students interacted with elements on the NMP plug-in
Questionnaire	MSLQ	Questionnaire by Pintrich and Groot [11] that measures different components of SRL
Metadata	In-Person Class Schedule	Time table of the in person class schedule for each student
	Course Modalities	Information on how each week of the course is organized
	Students' GPA	Average accumulated grades until the start of the course
	Students' Final Grades	Final grade obtained by the students

**Fig. 2.** Diagram of the analytical approach followed in the study.

The trace data was obtained from the log files of Moodle and NMP. The Moodle log files collect information about students' interaction with the course resources: quizzes, assignments, videos, and reading material uploaded by the teacher. The NMP log files collect the students' interaction with the different visualisations and functionalities of the plug-in.

The course metadata includes: the Moodle quizzes counting for the final grade, the student's GPA, the date of the exams, the dates for delivering the practical activities and the project, and the dates of the in-class sessions for each group.

2.3 Analytical Approach

We followed the approach proposed by Fincham et al. [4] that divide the data analysis into four steps: defining actions, detecting tactics, detecting strategies and run statistical comparisons between students' based on the strategies they employed. Before starting, all the data was anonymized, and people who did not give their consent to all parts of the analysis were removed. For replicability purposes, all the scripts used for the analysis are available in the Open Science Framework platform³. Figure 2 summarizes the steps we followed for transforming trace data into actions, tactics and strategies.

Detecting Tactics A tactic is defined as the underlying process that a student is applying in a given period of time [4]. The period of time is defined as a

³ https://osf.io/s86au/?view_only=455371582ac345809e91eb844f80c5e7

Table 3. Session classification based on the schedule of the students

Schedule classification	Description
Day Before Class	Session registered 24 hours in person class
In-Class	Session registered during class time
Day After Class	Session registered 24 hours after in person class
Other Schedule	Sessions performed in all other schedules

Table 4. Library of actions in the LMS

Platform	Action Name	Description
Moodle	Class Planning	Interactions with the material containing the planning for the semester and the topics addressed in each week.
	Evaluation	Interactions with any quiz or assignment in the course.
	Hands-on Work	Interactions with practical exercises related with the management of databases
	Reading Solutions	Interactions with one of the reading materials uploaded in the platform
		Interactions with the material containing solutions to the evaluations, both practical and theoretical.
NMP	Video	Interactions with the videos uploaded in the platform.
	SRL Support	Interaction with the visualizations of the NMP plug-in.

study session, which corresponds to a sequence of actions not separated by more than 30 minutes of inactivity. Each session was classified depending on when and where it happened according to the course schedule (see Table 3). The sessions occurring between two schedules were split accordingly.

To detect students' tactics we used a Hidden Markov Model (HMM) as an unsupervised method. The hidden states represent the underlying tactic being applied during a specific session. For that, we computed for each session the proportion of each action being applied. The students' actions are described in Table 4) and are defined as their interactions with Moodle course resources, tagged by their learning purpose (planning, evaluation, hands-on work, readings, solutions or videos), and with NMP functionalities, considered as SRL support.

The number of hidden states of the model was determined using the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) as heuristics. These metrics consider both the complexity of the model (measured in terms of the number of parameters) and the likelihood of model given the data. The HMMs were fitted using the `hmmlearn-0.2.7` Python package⁴.

To answer RQ1, we analyzed how students applied different tactics over the different modalities of the course (see Section 2.1) and between the different schedule classifications (see Table 3). Class sessions dedicated to exams were excluded from the analysis.

To answer RQ2, we analyzed tactics including students' interactions with NMP. We also use the using the Kruskal-Wallis test to compare the final grades and SRL ability profiled of those students using tactics involving NMP interactions and those who did not.

⁴ <https://hmmlearn.readthedocs.io/en/latest/>

Detecting Strategies Under the analytical approach proposed by Fincham et al. [4], strategies are defined as sequences of tactics applied by the students. These are extracted by clustering the sequences of tactics of students in the course. In our analysis, we also included the schedule classification in which the session occurred in the clustering process. We added this information to understand better how students adapt to the different BL modalities of the course. Therefore, each session was represented by a token encoding the classification of the session according to the schedule (TokenSchedule) and another token encoding the most probable tactic (TokenTactics). So, each student activity was represented by a sequence of pairs composed of TokenSchedule+TokenTactics for the strategy detection process.

After defining the sequences, we computed the similarities of the sequences using a similarity ratio based on the Levenshtein distance, which is defined as the minimal number of insertions, deletions, and/or state substitutions required to transform one sequence into another. This is then normalized, considering the length of the sequences. The implementation for this similarity measure comes from the python-Levenshtein package⁵. To find the clusters, we performed an agglomerative hierarchical clustering using the scikit-learn-0.22.2 Python package⁶. For selecting the number of clusters, we analyzed the dendrogram of the clustering process and removed for the analysis those clusters containing less than 15 students, treated as outliers.

To answer RQ1, we clustered the sessions in the whole course and separating by course modality. We then analyzed the differences between them. To answer RQ3, we analyzed whether there was a correlation between previous knowledge (GPA) and their SRL ability profile with the strategy applied by the student. In each case, we performed an ANOVA test to see which variables could be significant. Then, we performed a post-hoc analysis using pairwise t-tests between clusters. In order to prevent p-value inflation, we corrected the p-values using Holm’s method. Then, we considered the strategies throughout the course without distinguishing per course modality. We then compared the differences in students’ final grades using the Kruskal-Wallis. Finally, to see the effect of the overall strategy in the final grade, we performed an ANCOVA using the GPA as a covariate.

3 Results

3.1 RQ1. Manifestations of learning tactics and strategies

We identified that **students use nine study tactics along the course, which differ in the number of actions and duration (Result 1.1)**. A general summary of these tactics is provided in Table 5. Those tactics that present a high activity in a particular action were labeled as ‘Focused’ tactics, since students focus on a particular action (F_Eval; F_HandsOn, F_Reading; F_NMP).

⁵ <https://github.com/ztane/python-Levenshtein>

⁶ <https://scikit-learn.org/>

Table 5. Description of applied tactics in terms of the mean number of actions performed, number of occurrences during the course and mean duration of the session. F=Focused tactic (mainly 1 action performed), SD=Slightly Diverse tactic (3-4 actions performed), HD=Highly diverse (almost all actions performed). E=Evaluations, H=Hands-on, R=Reading, S=Solutions, V=Video. Wo_NMP=Without NMP, W_NMP=With NMP.

Tactic Name	Mean Tactic Composition							Num. of occurrences	Mean Duration
	Class planning	Evaluation	Hands-on	Reading	Solutions	Video	SRL Support		
F_Eval	-	6.47	-	-	-	-	-	613	00:06:59
F_HandsOn	-	-	4.97	-	-	-	-	470	00:07:57
F_Reading	-	-	-	1.38	-	-	-	583	00:03:01
F_NMP	0.04	1.14	0.17	0.22	-	-	15.6	135	00:06:46
SD_EHV	-	3.77	3.07	-	-	1.61	-	485	00:18:36
SD_EHR	0.48	6.24	0.89	1.84	-	-	-	343	00:17:08
SD_HRS	-	-	1.42	1.52	1.15	-	-	500	00:13:00
HD_Wo_NMP	0.24	5.02	2.29	2.8	1.86	0.15	-	177	00:26:06
HD_W_NMP	0.12	5.77	3.62	1.05	0.42	3.1	3.09	102	00:31:46

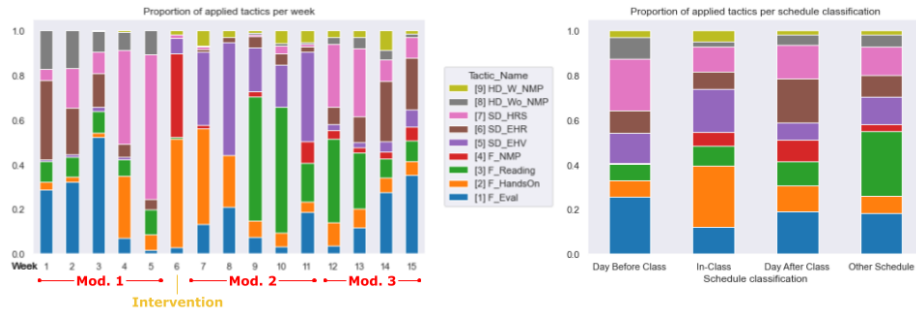


Fig. 3. Evolution of tactics applied during the course. Each vertical bar represents the proportion of tactics applied during a particular week. Below, we indicate the different modalities of the course.

Those tactics that present a variety of actions were labeled as ‘Slightly Diverse’ tactics, with 3 or 4 different actions, or ‘Highly Diverse,’ with 6 or 7 actions. We also observe that tactics differ in their duration, being the Slightly (mean 13-19 minutes) and Highly Diverse (mean 26-31 minutes) longer than the Focused ones (mean of 3-8 minutes).

We identified that **students deploy three different strategies along the course that differ in the frequency, type of tactics employed and the moment in which they take place (before, after, or during the class) (Result 1.2)**. Table 6 shows a summarized description of the strategies in terms of the frequency of tactic usage and schedule classification. All strategies (SG.1, SG.2, SG.3) involve students’ employing all tactics. However, they differ in the frequency in which tactics are deployed. First, in SG.1, the frequency of almost all tactics is higher than in the other strategies. Students using this tactic also performed significantly more sessions in other schedules beyond the in-class, before, or after-class sessions. This suggests that students employing this

strategy were more autonomous than students using the other strategies. SG.3 differs from SG.1 mainly in the frequency of tactics, including Reading actions (F_Reading, SD_EHR and SD_HRS). Finally, SG.2 included the least amount of tactics overall, meaning that students who used this strategy also invested less time in the course. They also concentrated on the least varied tactics, mainly using most of their sessions in Focused tactics such as F_Eval and F_HandsOn.

Students apply different tactics and strategies depending on the modality of the course and the characteristics of the course activity (Result 1.3). Figure 3 shows how students' tactics change from week to week and according to the schedule classification. In modality 1, where students were asked to complete activities at home before the class in a more teacher-directed course design, the most frequent tactics are the Slightly and Highly Diverse involving Reading actions, while the Focused tactics involve Evaluation actions. These tactics align with activities students were asked to do in this period: work on theoretical content before the class and do exercises to evaluate their knowledge. In modality 2, in which students were asked to practice with their database without the teacher supervision, the most frequent tactics were the Focused involving reading and hands actions, and the Slightly Diverse involving evaluation actions. Again, the tactics were related with the type of activities to be performed in this phase, in which students were asked to read how to work with a database and then practice with it. Finally, in modality 3, we saw a consistent use of Slightly Diverse tactics involving hands-on, reading, evaluation, and videos. Here, students had to work on a project in groups. At this point, they have to apply all the concepts and materials seen in the course, and they revisit particular resources to review concepts (reading and videos and evaluations) and apply them in their project (hands-on). This result suggest that there is an influence of the course design and the tactics applied by the students. This change is also represented in the overall strategies applied by the students during each modality. For the first modality, students applied two different strategies (S1.1 and S1.2). These two differ in the number of tactics that include Reading actions, again showing the relationship to the activities relevant to the modality. Students applying S1.2 also worked considerably more on schedules far from the class sessions. For the second modality of the course, we found three main strategies applied by the student (S2.1, S2.2, and S2.3). Students from S2.3 used the most tactics overall, followed by S2.1. Finally, in modality 3, we detected three different strategies (S3.1, S3.2, and S3.3). While there are changes in the tactics applied by each strategy, we found that the main differences come from the schedules in which they perform their sessions.

3.2 RQ2. Impact of SRL support on students' learning strategies

Students incorporate the use of the SRL support tool (NMP plugin) to reinforce or support their study tactics (Result 2.1). Students incorporate the SRL support in two different ways: (1) within a Highly Diverse tactic (HD_W_NMP), in which the use of NMP is an action combined with others, or (2) within a Focused tactic (F_NMP), in which they only use NMP.

Table 6. Description of strategies detected in the whole course and per course modality with respect to the mean tactic frequency, schedule, and number of students. For each strategy, the two bold entries represent the two tactics most frequently applied. We are excluding from these table the clusters considered outliers (less than 15 students).

	General			Mod. 1		Mod. 2			Mod. 3		
	SG.1	SG.2	SG.3	S1.1	S1.2	S2.1	S2.2	S2.3	S3.1	S3.2	S3.3
F_Eval	5.55	3.87	5.20	2.38	2.72	1.36	1.64	2.00	3.05	1.47	1.60
F_HandsOn	3.88	2.65	2.83	1.30	1.13	1.69	1.16	2.96	1.65	0.46	0.33
F_Reading	5.62	2.39	3.37	0.50	1.30	3.46	1.30	3.21	2.15	2.02	1.05
F_NMP	0.82	0.35	0.51	-	-	0.62	0.16	0.62	0.70	0.63	0.43
SD_EHV	4.38	2.39	4.40	0.14	0.10	2.56	3.45	5.96	2.00	2.00	1.48
SD_EHR	3.70	1.61	2.31	0.94	2.03	0.21	0.27	0.33	1.35	1.56	0.36
SD_HRS	5.40	1.43	3.94	1.38	4.20	0.18	0.11	0.21	2.25	1.12	0.40
HD_Wo_NMP	1.72	0.78	1.54	0.64	1.61	0.10	0.07	0.04	0.30	0.25	0.24
HD_W_NMP	1.08	0.52	0.63	0.02	0.04	0.56	0.39	0.67	0.60	0.68	0.17
Day Before Class	6.00	3.96	6.14	3.54	4.25	0.87	1.16	2.38	1.70	1.81	0.83
In Class	7.05	7.04	7.71	1.68	1.48	2.64	3.50	2.96	4.00	4.14	4.12
Day After Class	3.80	1.00	1.86	0.36	1.93	0.90	0.27	1.29	2.15	1.26	0.48
Other Schedule	15.30	4.00	9.03	1.72	5.49	6.33	3.61	9.38	6.20	2.98	0.62
# of students	60	23	35	50	69	39	44	24	20	57	42

Also, these two tactics are employed by students in different moments of the course. The Focus tactic (F_NMP) was mainly deployed during the first week of the intervention in which students' were presented to the tool and had time to explore it, but also during the third modality of the course, in which they had to work on the project. Since the NMP tool provides functionalities for checking which resources of the course have been or not been consulted, its usage in this period was helpful to review previous content. When incorporated with other tactics (HD_W_NMP), its use is distributed more or less equally along the course. We observe, however, that the HD_W_NMP tactics almost substitute the HD_Wo_NMP, suggesting that the use of NMP was incorporated as another action in their Highly Diverse tactics.

Students used NMP mainly in class and in other schedules beyond the class (Result 2.2). If we accumulate the use of NMP from both HD_W_NMP and F_NMP tactics, we observe that the tool was more frequently used in class (47.2%) and other schedules (27.4%) and with a much lower frequency the day after class (15.6%) and the day before class (9.7%). This suggests that students might be using the tool for checking what has to be done.

We observed that **students that had at least one use of the HD_W_NMP had a significantly higher Self-Regulation than those who did not (p-value=0.001, effect-size=0.70) (Result 2.3).** This suggests a relationship between the students SRL ability profile and the adoption of SRL support.

3.3 RQ3. Relationship between students' strategies, performance and SRL ability profile

Students' prior knowledge (GPA) has a relationship with the general strategies they apply, being those with the lowest GPA the ones using

the strategy with the least amount of tactics (Result 3.1). We found that students that applied SG.2 (mean=11.10 out of 20) had a significantly lower GPA compared with students applying SG2.1 (mean=13.22; p-val=8e-4) and SG2.3 (mean=12.86; pvalue=0.008). Since strategy SG.2 consists of applying tactics with fewer interactions with the Moodle platform than the other two strategies, this suggests that students with lower GPA could also be those less engaged with the course.

The strategy applied by the students is related to their course final grade in the course, but this association disappears when controlling for GPA (Result 3.2). We found that students performing SG.2 had a significantly lower final grade than students performing SG.1 (p-value=0.022) and those performing SG.3 (p-val=0.038). However, when controlling for GPA as a covariate, the students' strategy was no longer significantly related to their final grade (p-val=0.051). This suggests that, while GPA is the most strong predicting factor of the final grade, it is also related to the student's engagement with the course and their applied strategies.

The student's prior knowledge (GPA) has a significant relationship with the strategy chosen in each modality except for modality 2, which is related to the SRL ability profile (Result 3.3). In Modality 1, only GPA was significantly different across strategies. Students applying strategy S1.1 had a significantly lower GPA (mean=11.9) than students applying S1.2 (mean=13.2). In Modality 2, in which students are required to perform work in a more autonomous way, we found significant differences across groups for Self-Regulation. Students applying strategy S2.3 had a significantly higher level of Self-regulation than students applying strategies S2.1 (p-val=0.022, effect-size=-0.86), and S2.2 (p-val=0.032, effect-size=-0.86). We did not find significant differences in Self-regulation between strategies S2.1 and S2.2. In Modality 3, the only significant difference we found was that students applying S3.2 had a higher GPA (mean=13.2) than those applying strategy S3.3 (mean=11.8, p-val=0.016).

4 Summary of Results and Discussion

Regarding RQ1 about how students' learning tactics and strategies manifest in a BL course, we found that tactics and strategies manifested in different ways depending on the pedagogical design of the course. For example, the tactics and strategies found in this study vary according to the relevant activities (Result 1.1, Result 1.3), scheduling of the study sessions (Result 1.2), and the SRL support available (Result 2.1). Furthermore, tactics and strategies differed in scheduling as well as in frequency of actions (Result 1.1 and Result 1.2). We distinguished between focused and diverse or highly diverse tactics, depending on the number of actions and its frequency. Similar results have been obtained in prior work [9] and [4], where students use tactics involving one action (more focused) or a variety of actions. In any case, it looks like the tactics employed have a relationship with the type of activities the students are asked for, reinforcing prior work which showed that learning tactics are highly dependent

on pedagogical decisions [2, 9]. This result also aligns with prior work [5, 7] indicating that, while some students perform deep approaches to learning during the course, others use surface-level approaches where they look for specific information to pass the course. In our case, strategies SG.3 and SG.1 would be deep strategies, while SG.2 would be surface-level strategies. These results also provide further evidence on how changes in pedagogical decisions may elicit different SRL strategies from students, as shown in previous works [2, 9].

Regarding RQ2 about the impact of SRL support on students' learning strategies, we found that even though some students incorporated the SRL support tool into their learning tactics (Result 2.1), the use of the tool was relatively sparse. Students mainly used the tool during face-to-face class sessions or far from the class sessions (Result 2.2). These results suggest that students used NMP functionalities designed to support planning and self-monitoring to check their past performance. Also, we observed that the students with higher SRL self-reported ability were those who use NMP more frequently (Result 2.3). This is consistent with previous work [14], which shows that students' previous abilities influence the adoption of SRL support tools. This suggests that future interventions to support SRL should focus on those with lower SRL abilities and on improving and expanding functionalities related to student planning and self-monitoring.

Regarding RQ3 about the relationship between students' strategies, performance and SRL ability profile. Prior knowledge has been shown as the main factor related to the students' strategy in those modalities including more teacher-directed work and group work as well as in the course as a whole (Result 3.1, Result 3.3). This result is aligned with previous work showing the relationship between learning strategies and prior knowledge [14, 15]. The only exception to this is modality 2, where the main differences were in students' Self-Regulation self-reported ability (Result 3.3), in which students were required to conduct a higher amount of independent work. This reinforces the idea that different pedagogical decisions influence the students' strategies and suggests that in those requiring a more independent work the key factor is the students' SRL ability profile. In terms of the final performance, our results suggests that prior achievements are key for explaining students' final grades, although students' strategies also showed correlations with grades (Result 3.2). This suggests that students with prior knowledge are also the ones applying the most effective strategies. This is also consistent with prior work in the study of SRL, which shows a connection between the course design, the students' SRL ability profile, and the strategies applied [2, 9].

5 Conclusions, Limitations and Future Work

In this study, we found evidence that the tactics applied by students during a course can change significantly when changing the course modality. We also found evidence indicating that the main factor that correlates to the students' learning strategy is their previous achievements. In fact, even if we found evi-

dence that the students' strategy is related to their final grade, controlling for their prior achievement makes this relationship no longer significant. We found that students had a low level of engagement with the SRL support tool. Nonetheless, when interacting with the tool, they mainly performed highly focused sessions or incorporated this activity into previous highly diverse tactics. We found that students that applied the highly diverse tactic with the tool presented a significantly higher level of self-regulation.

One of the main limitations of this study comes from the data collection of actions performed by the students. As common with BL studies, we analyze the students based on self-reported and trace data. This limits the analysis since we could not capture the actions performed outside the Moodle platform. In particular, we did not include information regarding the interactions with the teachers, something that distinguished BL from other course modalities. Our current findings are also limited to the students of one course. Another limitation comes from the use of unsupervised methods, which makes it challenging to validate the accuracy of the detected tactics and strategies. For example, the use of dendrograms to select the number of clusters introduces a level of subjectivity to the results. Future work could apply the same type of analysis to different courses to see if the current study's findings are generalizable and consider the teacher's interventions in self-regulating students learning strategies using anthropological techniques to complement quantitative data.

Acknowledgements

This paper has been partially funded by the ANR LASER (156322). The authors acknowledge PROF-XXI, which is an Erasmus+ Capacity Building in the Field of Higher Education project funded by the European Commission (609767-EPP-1-2019-1- ES-EPPKA2-CBHE-JP). This publication reflects the views only of the authors and funders cannot be held responsible for any use which may be made of the information contained therein.

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