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Learning Analytics to Unveil Learning Strategies in a Flipped Classroom

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1. Introduction

Prior education studies have consistently emphasized the importance of sustained and active student engagement to aid academic performance and achievement of learning outcomes (e.g., Michael, 2006; Hockings, Cooke, Yamashita, McGinty, & Bowl, 2008). The positive impact of such active learning models on academic outcomes has been well established, particularly, in the STEM disciplines. For example, Freeman et al (2014) demonstrated that students undertaking STEM courses incorporating active learning models received (on average) higher academic grades and were less likely to fail in comparison to peers in more traditional and lecture based modes of teaching. While active learning has clear benefits for student learning outcomes, the process of implementation is often more complex than first anticipated (Gillies & Boyle, 2010; Hung, 2011). For instance, student engagement in active learning does not occur spontaneously and educators must employ careful consideration of the curriculum design, activity sequencing and progression as well as the diversity of learners, including learners' prior experience and motivation, background and knowledge.

Flipped learning (FL) is a form of blended learning that requires students' active participation in learning activities both before and during face-to-face sessions with the teacher (Lage, Platt, & Tregua, 2000). However, students frequently lack the necessary skills, time, and/or motivation to fully participate in pre-class activities and therefore do not commit to the level of involvement in the learning process that effectively complements the intended design (Lai & Hwang, 2016; Mason, Shuman, & Cook, 2013). Clearly, the reasoning for why students may or may not engage in pre-class activities is complex and multi-dimensional. However, if provided with a deeper insight into the types of learning strategies students employ in such active learning models, teaching staff can make better informed decisions regarding student support and course design processes (Stief & Dollar, 2009).

Despite the increasing popularity of FL and similar active learning models, there has been limited attention devoted to understanding the types of learning strategies that students employ when engaged in this model of education. Studies on FL have to date, primarily focused on examining students' satisfaction with this mode of learning and their course performance (O'Flaherty & Phillips, 2015; Bishop & Verleger, 2013). However, considering that FL encourages students' sense of autonomy and ownership of learning and is quite different to the 'traditional' lecture model, it is

important to shed some light on how students approach and manage this new learning setting, and how they organize and regulate their learning process. The relevance for undertaking such research is further strengthened by studies noting that students often lack sufficient skills and proficiency to modify their learning strategies to better suit the specificities of newly encountered learning situations (Lust, Elen, & Clarebout, 2013a). Consequently, students often employ suboptimal learning tactics and strategies (Winne & Jamieson-Noel, 2003).

Research into student learning tactics and strategies has primarily relied on self-reports that are typically collected through questionnaires or think-aloud protocols (Bannert, Reimann, & Sonnenberg, 2013; Chamot, 2005; Hill & Hannafin, 1997). While these studies have provided insights into the student learning process, there are several inherent deficiencies that have effectively limited the generalizability of the findings. For instance, self-reports are often inaccurate due to the poor recall of prior behavior related to the use of study tactics (Winne & Jamieson-Noel, 2002). Similarly, think aloud protocols are negatively impacted by the increased level of cognitive load placed on the participants (Winne, 2013). However, given that contemporary FL activities are typically delivered via an online medium (e.g. Learning Management System - LMS) there is a new opportunity to draw on alternate analytic approaches derived from the fields of learning analytics and educational data mining (Siemens, 2013; Gašević, Dawson, & Siemens, 2015). Essentially, the deficiencies commonly associated with self-report protocols can be overcome by grounding the analysis in the users' trace data i.e. data collected from the tools and services the students interact with during the learning process (Winne, 2013; Stief & Dollar, 2009). Such learning analytic approaches provide a direct analysis of the users' "actual" behavior in lieu of the students' perception and recall of events.

The present study examined students' learning strategies by using the trace data collected from the University's LMS. The study focuses on the trace data originating from the preparatory activities that students were requested to complete prior to the scheduled face-to-face sessions (i.e., lectures) in a first-year undergraduate course in computer engineering. The rationale for focusing on this component of the FL design centers on the importance of the preparation activities to facilitate and enable student participation in the face-to-face sessions (Rahman, Aris, Rosli, Mohamed, Abdullah, & Zaid, 2015).

The educational research community offers a diversity of interpretations on what constitutes a learning strategy. In this work we rely on the broad definition developed by Weinstein, Husman, & Dierking (2000, p. 227) suggesting that a learning strategy includes "*any thoughts, behaviors, beliefs or emotions that facilitate the acquisition, understanding or later transfer of new knowledge and skills*". We consider students' learning strategies as latent constructs that cannot be directly observed in the collected traces, but have to be mined/detected using appropriate analytical methods and techniques. Unsupervised methods such as clustering and sequential pattern mining have proven beneficial for mining latent, unobservable constructs from learning traces (see e.g., Perera, Kay, Koprinska, Yacef, & Zaïane, 2009; Jeong, Biswas, Johnson, & Howard, 2010; Kovanovic, Gašević, Joksimović, Hatala, & Adesope, 2015; Lust et al., 2013a; Blikstein et al., 2014). In this study, we make a combined use of exploratory sequence analysis and agglomerative hierarchical clustering to detect patterns in student behaviour that are indicative of the adopted learning strategies.

1.1 Active learning and Flipped learning

The earlier work of Trigwell, Prosser, & Waterhouse (1999) clearly demonstrated the impact that a teaching model can play on a student's approach to learning. In essence, Trigwell, et al. noted that a student's choice between a surface or deep approach to learning is dependent on the instructor's approach to teaching. For instance, a teacher-focused approach oriented towards information transmission tends to evoke a surface approach to learning. In contrast, a student-focused approach aimed at assisting learners in changing their conceptions of the studied phenomena results in a deeper approach to learning. This latter model of teaching is akin to active learning and shares a lot of similarities with FL. Hence, the study by Trigwell et al. (1999), with 48 first year science classes, strongly suggests that active learning strategies can engage students in a deep approach to learning, and therefore lead to the development of higher learning outcomes (Trigwell & Prosser, 1991). FL assumes that students are not only actively participating in the classroom activities, but that they are also actively engaging in pre-class and/or post-class activities. This level of active engagement in studies throughout the course, leads to improved academic outcomes.

To compare student performance in undergraduate STEM courses with traditional lecturing and active learning approaches Freeman et al. (2014) undertook a meta-analysis of 225 studies. The authors examined two outcome measures: the failure rate in courses and student performance on tests. They observed that students in traditional lecture courses were 1.5 times more likely to fail than students in courses with an active learning design. Regarding the test performance, the meta-analysis showed that on average, student performance on identical or comparable tests increased by about a half a standard deviation when active learning methods were deployed compared to traditional lectures. The observed benefits of active learning in the Freeman et al. meta-analytic study were consistent across all STEM disciplines, including different levels of courses, and different experimental methodologies. The highest impacts were observed in primary studies where the majority of class time was devoted to active learning. Freeman et al. (2014) also pointed to evidence that active learning tends to have a greater impact on student mastery of higher versus lower-level cognitive skills.

Although FL as a form of active learning has been around for over 15 years, it has only recently seen an increase in adoption and interest within the education community (Bishop & Verleger, 2013; Hamdan, McKnight, & McKnight, 2013). As such, FL as an approach to enhance student learning remains under-evaluated and under-researched in general (Abeysekera & Dawson, 2015). Previous studies examining FL predominantly relied on questionnaires and interviews to collect students' opinions and perceptions of FL, whereas pre- and post-tests and course grades were used to assess the extent of improvement in students' performance (O'Flaherty & Phillips, 2015). The majority of the reported studies confirmed the educational benefits associated with FL models, such as increased student satisfaction (e.g., Forsey, Low, M., & Glance, 2013), higher course grades (e.g., Pierce & Fox, 2012), and increased attendance (e.g., Prober & Khan, 2013). Despite these noted benefits to learners, O'Flaherty & Phillips (2015) warn fellow educators not to rush to conclusions regarding the advantages of FL over more traditional lectures. In particular, O'Flaherty & Phillips found that there were "*very few studies that actually demonstrated robust evidence to support that the flipped learning approach is more effective than conventional teaching methods.*" (p.94). Clearly, further work is required to provide greater methodological rigor associated with such comparative analyses.

An important and challenging aspect affecting student success in FL setting is the high level of learner autonomy associated with a FL design (Kim, Kim, Khera, & Getman, 2014). This model of

active learning requires students to be self-regulated learners in order to undertake and complete the preparatory activities (Lai & Hwang, 2016; Mason et al., 2013; Sletten, 2015). However, many students have underdeveloped self-regulation skills and need support and scaffolding to manage their learning in less familiar and more intensive settings that often characterize FL designs. To address this need, the FL design examined in this paper has a well-defined structure that is consistent throughout the entire course duration (see Section 2.1).

1.2 Learning strategies and Self-regulated learning

There has been much research undertaken related to student learning strategies. Authors such as Pask & Scott (1972) examined learning strategies in relation to students' cognitive competences. The authors identified discrete learning strategies as behavioral patterns that were adopted by students when attempting to solve a given learning task. Pask and Scott (1972), demonstrated that the adopted strategies were related to a student's cognitive competence. In particular, they noted that students with similar cognitive competences tended to adopt similar behavioural patterns (i.e. learning strategies), and that the students' learning success was dependent on how well the adopted learning strategy matched the instructor's teaching strategy. Pintrich & de Groot (1990) examined the relationship between students' motivation, self-regulation, cognitive strategies used, and performance on classroom academic tasks. They found that self-regulated learning (SRL) was closely tied to a student'' efficacy beliefs and the intrinsic value they associated with the study tasks. However, self-efficacy and intrinsic values, as motivational components, are not sufficient to lead to successful academic performance, but have to be concomitant with SRL components (self-regulation and cognitive strategy use) as the latter are noted to be more directly implicated in the students' academic performance. Moreover, Pintrich & de Groot's (1990) findings suggest that the adopted cognitive strategy must be coupled with self-regulation to aid overall academic performance. In other words, apart from being aware of possible learning strategies, students must also know how and when to use specific strategies. This is particularly the case in FL settings where learners are expected to take control of and be responsible for their own learning, including making decisions on how to utilize the available learning resources and what strategies to apply (Lai & Hwang, 2016). Considering these findings, and confirmed by several other research studies (see Section 1.4), the present study models our understanding of learning strategies through the lens of SRL. We view SRL as a set of actions and processes that are well thought of, planned and employed for the purposes of learning new skills and knowledge. The employment of such actions and processes implies there is a level of learner agency and autonomy to monitor and evaluate the effectiveness of the adopted learning strategy and modify where necessary (Winne, 2013).

The capacity of a student to choose and adapt their learning strategy in accordance with the requirements of the learning setting is a key self-regulatory skill (Winne, 2006). Unfortunately, students often have poorly developed self-regulation skills and tend to choose suboptimal learning strategies (Winne & Jamieson-Noel, 2003). Furthermore, previous research has shown that learners are not accurate reporters of how they study and what strategies they apply (Zhou & Winne, 2012). These findings have two important implications. First, learners would benefit from scaffolds that make them aware of their learning strategies, so that they can identify if, when and where they can make adjustments to enhance their learning experience. According to Winne, to improve learning, students "*might profit from (a) feedback that accurately represents how they actually studied and (b) information about tactics and strategies that might be more effective than those they actually used*" (Winne, 2013, p.387). Second, the inaccuracy of students' self-reports indicates that such data collection methods should not be used as the primary or sole source of data for examining students

learning strategies. This approach would be better complemented by, or substituted with, digital learning traces (Winne, 2013).

1.3 Analytics for detecting patterns in student behaviour

The use of trace data for the detection of learning strategies requires appropriate analytical methods and techniques that allow for the detection of strategies as latent constructs emerging from the observable student behaviour. For instance, Jeong et al. (2008) used an approach incorporating hidden Markov models (HMM) to examine learning behaviour of middle school students as they undertook 'learning through teaching' activities. Specifically, the students were requested to 'teach' a computer agent called Betty specific science concepts, and the trace data were used to provide insight into students' patterns of activities. In a later study, Jeong et al. (2010) applied the same HMM approach to study learning behaviour of adult professionals in an asynchronous online learning environment. In particular, their exploratory study was aimed at identifying the main phases of the students' learning process in the examined course, and investigating the differences between high and low-performing students in terms of their transitions through the identified phases of the course.

Clustering techniques have also been successfully applied to detect learner profiles based on the way students interacted with and made use of the technology/tools offered in online and blended learning environments. For instance, Kovanovic et al. (2015) used clustering to identify students' technology-use profiles in an online graduate engineering course. Their study was theoretically grounded in the Communities of Inquiry (CoI) framework (Garrison & Arbaugh, 2007), and particularly focused on examining the effect of the identified technology-use profiles on the development of cognitive presence, a key component of the CoI model. Perera et al. (2009) made a combined use of sequential pattern mining and clustering in order to gain a better understanding of how students worked in small groups. In particular, their work was aimed at *i*) detection of patterns that are suggestive of potential problems in some key aspects of group work, *ii*) providing support for self-monitoring, and *iii*) gaining an improved understanding of how effective groups make use of the online collaboration tools. Berland, Martin, Benton, Smith, & Davis (2013) also used clustering and sequence analysis to examine students' learning behavior as they learn to program in an open-ended, semi-formal, and collaborative learning setting. In particular, the authors employed these analytic techniques to explore how novices progress along a pathway that starts with exploration, and goes through tinkering, towards refinement. This led to the identification of patterns in students' learning activities, and showed that "*the students generally wandered through a few relatively similar patterns of activity*" (Berland et al., 2013; p.587).

The abovementioned contributions provide solid evidence of the power of analyzing event sequences to identify learning strategies. In this study we used similar techniques to shed light on how students prepare for face-to-face sessions in a FL context. In particular, to contribute to better understanding of students' learning behavior in FL settings, our study aimed to identify patterns in students' class preparation activities, considering such patterns as manifestations of the adopted learning strategies. We also aimed to detect and compare strategy-based student profiles, i.e., groups of students who exhibited similarities in the adopted learning strategies. Accordingly, we defined our first research question (RQ1) as follows:

RQ1: Can we detect patterns in student learning behavior that are indicative of the learning strategies that students adopted when preparing for face-to-face sessions in a FL setting? If so, what kinds of learning strategies do the identified patterns suggest?

1.4 Learning strategies and academic performance in flipped classroom

Numerous research studies have demonstrated that regulation of learning strategies can lead to higher academic achievements (e.g., Pintrich & Grove, 1990; Zimmerman, 1990; Stief & Dollar, 2009). This is an expected association since regulation is about monitoring and adapting learning strategies for the purpose of improving the effectiveness and/or efficiency of studying. However, for majority of students, regulation of learning does not come easy (Winne, 2013). This is primarily due to the underdeveloped self-regulation skills, which in turn often leads to the selection of suboptimal learning strategies. For instance, Lust et at. (2013a) examined students' capacity to effectively use the available learning affordances (i.e., tools and resources), that is, to use the affordances in a way that can maximize their educational opportunities and outcomes. Lust et al. found that while students regulated their tool-use throughout the course, suggesting that they were aware of the cues in the learning environment, only a small proportion (3%) of students regulated their tool-use in line with the course phases and the changing instructional requirements. Similar findings come from Ellis, Marcus, & Taylor (2005).

One possible cause for the students' low ability to effectively regulate their learning strategies may lie in the differences between the newly faced learning context and those that students have been previously exposed to. For instance, Hattie, Biggs, & Purdie (1996) noted that the transfer of the acquired study skills, while common in case of similar learning situations (so-called near transfer), was infrequent in case of quite different learning contexts (far transfer). Considering substantial differences between FL model and traditional lecturing, it is reasonable to expect that students who have experienced lecturing as the main or even the only teaching approach would face difficulties with strategy regulation in FL settings.

On the positive side, the very features of FL model may lead to an increase in a students' motivation for learning. By examining FL from the perspective of self-determination theory (Deci & Ryan, 2008), Abeysekera & Dawson (2015) proposed that learning environments created by the FL approach are likely to satisfy a student's need for competence, autonomy and relatedness and, thus, may positively affect their motivation for learning (both intrinsic and extrinsic). Considering that higher motivation levels are often associated with a higher level of regulation of learning, higher academic achievements can therefore be expected.

The above given considerations suggest that a FL setting can both positively (motivation) and negatively (far transfer) affect a student's selection and regulation of learning strategies, and consequently, their academic performance. Previous research has shown that when students manage to quickly adjust to the FL model (i.e., resolve the transfer problem), their academic achievements are comparable to or better than that of students attending traditional lecturing model (Mason et al., 2013; McLaughlin et al., 2013). However, it has not been sufficiently explored how regulation of pre-class activities affect the overall course performance. Aiming to fill this gap, we focused our second research question (RQ2) on the strategies students adopt when preparing for classes and how these relate to students' learning achievements:

RQ2: What is the association between the identified patterns in students' learning behaviour (i.e. manifestations of the adopted learning strategies) when preparing for face-to-face sessions in a FL setting and student overall course performance?

2. Methods

2.1 Study context

The examined FL design was deployed in a first year engineering course in Computer systems at an Australian research-intensive higher education institution. The course lasted 13 weeks and had an enrollment of approximately 300 students. Trace data were available for 290 students, 81.5% male, 18.5% female. The students had limited previous experience with FL.

The FL strategy of the course consisted of two key elements: 1) a set of preparatory online activities to be completed prior to the plenary face-to-face session with the instructor (i.e., the lecture); and 2) redesigned lecture framed as an active learning session requiring students' preparation and participation in collaborative problem solving tasks (Anonymous, 2016b).

The study focused on the lecture preparation activities. These activities retained the same structure and flow throughout the course. The activities included:

- *Videos with multiple-choice questions (MCQs)*: short videos introduced and explained relevant concepts. They were followed by MCQs covering the concepts discussed in the video and promoting simple factual recall. Students could answer a question, have the answer evaluated, and if it was incorrect, they could either request to see the solution or try again. These questions were framed as formative assessment.
- *Documents with embedded MCQs*: the students were required to read the document and answer the embedded MCQs. These questions were conceptualized in the same way as MCQs that accompanied course videos, in terms of the students' interaction with them, and also framed as formative assessment.
- *Problem (exercise) sequences*: these sequences were summative assessments. If an exercise was correctly solved, the student's score was increased, and the exercise was removed from the sequence. Alternatively, a new exercise was randomly selected and the current problem remained in the sequence. Students received exercises randomly until they solved all of them correctly. To be counted towards their final course mark, the exercises had to be solved before the start of the weekly lecture. This requirement was introduced as an incentive for students to prepare for the lecture.

Students were provided with real-time feedback on their level of engagement with the preparation activities and their activity scores via an analytics dashboard (Anonymous, 2016a). Through the dashboard, students could monitor their engagement with the video resources, success in answering MCQs that followed the videos, and MCQs that were embedded in the course related documents, as well as the percentage of correctly solved problem sequences. Next to the students' personal scores, the dashboard displayed the overall class scores, thus allowing for social comparison. The displayed data was updated every 15 minutes, and the magnitudes were reset each week.

2.2 Learning traces

The study relied on student interaction data obtained from the students' engagement with and completion of the preparatory learning activities during the active period (weeks 2-13) of the 2014 delivery of the course. In particular, the analyses were based on the events data (trace data) collected from the Learning Management System (LMS) used in the course. Each event is represented as a quadruple comprising of event id, student id (anonymized), type of learning action, and timestamp. Table 1 provides an overview of the types of learning actions that were considered in the analyses.

Learning sessions were extracted from the events data, as continuous sequences of events where any two consecutive events are within 30 minutes of one another (Anonymous, 2016a). This resulted in 11,317 learning sessions for the 12 active weeks of the course and 290 students.

Table 1 Types of learning actions examined in the study

Action code	Description
EXE_CO	a correctly solved summative assessment item (exercise)
EXE_IN	an incorrectly solved summative assessment item (exercise)
MCQ_CO	a correctly solved formative assessment item (multiple choice question - MCQ)
MCQ_IN	an incorrectly solved formative assessment item (MCQ)
MCQ_SR	a solution requested for a formative assessment item (MCQ)
VIDEO_PLAY	activation of a course video
CONTENT_ACCESS	access to a page containing reading materials
MC_EVAL	access to the dashboard; this is considered a metacognitive evaluation action
MC_ORIENT	access to the schedule and the learning objective pages; this is considered a metacognitive orientation action

2.3 Data analysis techniques

2.3.1 Exploratory learning sequence analysis

To address research question 1, learning sessions were encoded as sequences based on a representation format of the TraMineR R package (Gabadinho, Ritschard, Müller, & Studer 2011). Figure 1 shows examples of learning sequences encoded in this format. As the examples indicate, the sequences can be rather heterogeneous, both in terms of their length (sequence [1] vs. sequence [5]) and the diversity of learning actions they consist of (sequence [1] vs. sequence [6]). The sequences were first used for an exploratory analysis and subsequently for clustering.

```
[1] (CONTENT_ACCESS,3)
[2] (EXE_IN,3)-(EXE_CO,1)-(EXE_IN,1)-(EXE_CO,1)-(EXE_IN,2)
[3] (CONTENT_ACCESS,3)-(EXE_IN,4)
[4] (MC_EVAL,4)
[5] (EXE_IN,5)-(EXE_CO,1)-(EXE_IN,3)-(EXE_CO,1)-(EXE_IN,2)-(EXE_CO,1)-(EXE_IN,9)-
(EXE_CO,4)-(EXE_IN,4)-(EXE_CO,1)-(EXE_IN,2)-(EXE_CO,2)-(EXE_IN,3)-(EXE_CO,3)-
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(EXE_IN,1)-(EXE_CO,2)-(EXE_IN,1)
[6] (MCQ_IN,2)-(MCQ_CO,2)-(CONTENT_ACCESS,1)-(MCQ_CO,2)-(MC_EVAL,3)-(CONTENT_ACCESS,1)
-(VIDEO_PLAY,5)-(MCQ_CO,2)-(MCQ_IN,1)-(MCQ_CO,1)-(VIDEO_PLAY,2)
```

Figure 1. Examples of learning sequences encoded in the TraMineR format

For the exploratory sequence analysis, we focused on a comparison of the highest and lowest performing students with respect to the midterm and final exam results. This type of exploratory analysis (i.e. analysis based on two extreme groups) has been previously adopted for examining patterns and strategies in students' regulation of learning (Bannert et al., 2013), and is recommended for situations when the prior research is either absent or does not provide sufficient knowledge regarding the expected effects (Preacher, Rucker, MacCallum, & Nicewander, 2005).

The two examined groups included students with midterm and final exam scores above the 90th percentile and those with the scores below the 25th percentile. For the low performing group, we initially chose students with the exam scores below the 10th percentile. However, there was a large disproportion in the number of learning sessions (and therefore, learning sequences) completed by the students from the two groups: those with the midterm and final exam scores above the 90th percentile ($N_{above90th}$=15) collectively produced 829 sequences, whereas those with the scores below the 10th percentile ($N_{below10th}$=7) had only 128 sequences in total. To obtain samples of comparable sizes, we extended the latter group to include students with the exam scores below the 25th percentile ($N_{below25th}$=31). This process generated a more comparative and representative total of 721 learning sessions.

To gain an insight into the general patterns of learning sessions of the two student groups, we removed the outliers. In particular, we removed overly short sequences, i.e., those comprising of only one event, as well as those that were overly long, i.e., those that were above the 95th percentile in terms of the number of events. After pruning the outliers, the sizes of the two groups were: 786 sequences for the students with the scores above the 90th percentile, and 684 sequences for the group with scores below the 25th percentile.

2.3.2 Clustering

Clustering was used for:

- grouping similar learning sequences (N=11,317) to detect patterns in students' learning behaviour (i.e., adopted learning strategies), and
- grouping students (N=290) based on the identified sequence patterns (i.e., learning strategies) to check if student groups can be detected based on the students' distinct use of learning strategies.

In both cases, we used agglomerative hierarchical clustering, based on Ward's method. This clustering technique was suggested as particularly suitable for detecting student groups in online learning contexts (Kovanovic et al., 2015). The first cluster analysis was used to address research question 1, whereas the second one was used to set the grounds for addressing research question 2.

The computation of the distance (similarity) between learning sequences, required for the clustering algorithm, was based on the optimal matching distance metric (Gabadinho et al., 2011), which is a variant of the Levenshtein's edit distance (Levenshtein, 1966). According to this metric, the distance

between any two learning sequences is the minimal cost, in terms of insertions, deletions and/or substitutions of learning actions, required for transforming one sequence into another.

The sequence clustering algorithm produced four variables, $seq.clust_i$, i=1:4, for each student, where $seq.clust_i$ is the number of learning sequences in cluster *i* for a particular student. These variables plus the variable (*seq.total*) representing the total number of learning sequences per student were used for the second cluster analysis applied to students; the objective was to examine if different student profiles could be detected based on the adopted learning strategies. All variables were normalized, i.e., reduced to the [0,1] range. The Euclidian metric was used for this step to compute distance between the vectors with five values for each student.

Kruskal Wallis tests followed by Mann Whitney U tests were used to compare the resulting student clusters based on the midterm and final exam scores. False Discovery Rate (FDR) was used as a recommended correction for preventing alpha inflation when doing multiple tests (Cramer et al., 2015).

3. Results

3.1 Exploratory sequence analysis

The plot on Figure 2a shows the distribution of learning actions along the learning sequences of students with midterm and final exam scores above the 90th percentile. Figure 2b presents the same kind of distribution for students with scores below the 25th percentile. Each learning sequence comprises a sequence of actions (as described in the figure legend and Table 1), and each point on the X-axis refers to a corresponding 'point' of a learning sequence (i.e., one action). The length of each plot is equal to the length of the longest sequence in the corresponding set of learning sequences (87 in case of the top performing group, and 100 in the case of the lower-performing group). Since the plots represent the distribution of learning actions throughout a learning session, the Y-axis represents the proportion of a certain type of action in each 'point' of the learning sequence. For example, in the case of students with scores above the 90th percentile (Figure 2a), the first action in ~65% of the learning sequences was reading (green color); in ~10% of the sequences the first action was successful completion of the summative assessment (yellow color), and so on.

The figures suggest that there is a considerable difference in the distribution of learning actions along learning sequences between the two examined groups. High performing students were observed to be giving roughly equal attention to all types of actions throughout their learning sessions. In contrast, their lower performing peers were almost exclusively focused on the summative assessment tasks. Furthermore, this group of students was often failing to correctly complete the assigned summative assessment items (exercises). This initial insight suggested that further analysis of students' learning sequences might lead to the identification of patterns in students' learning behaviour, potentially indicative of the adopted learning strategies.

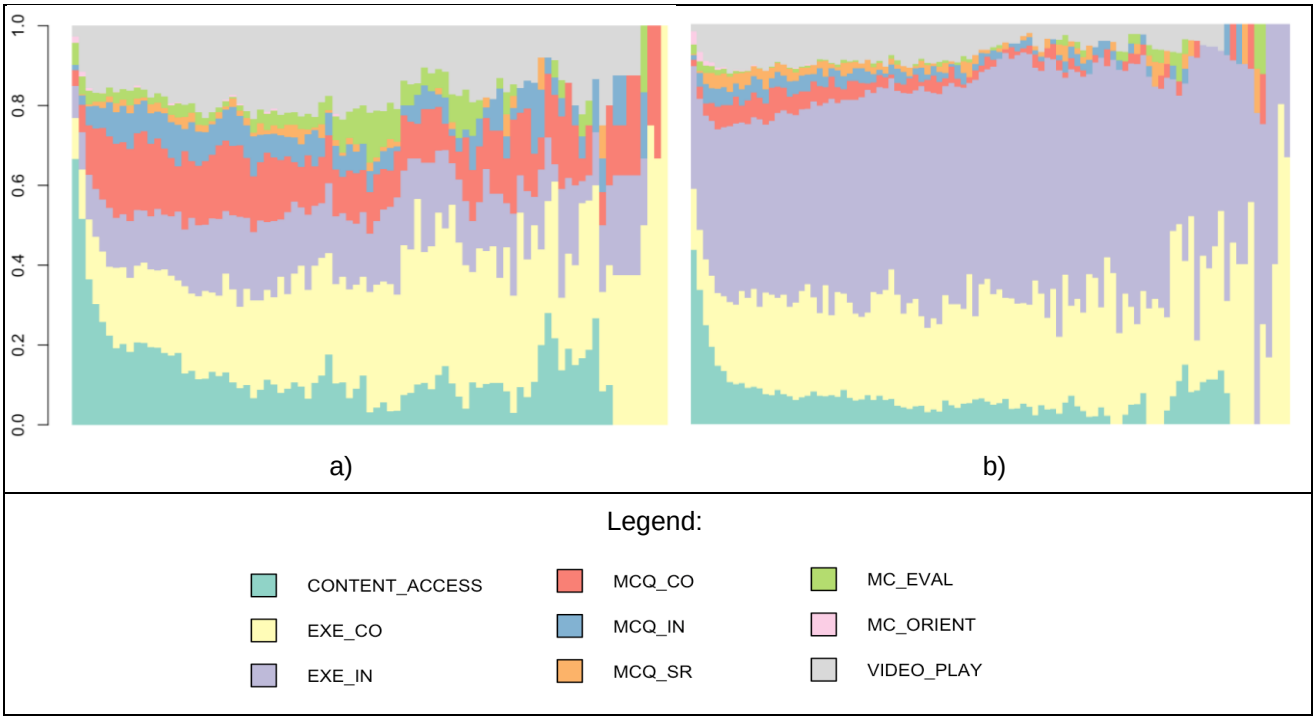

Figure 2. Distribution of learning actions throughout learning sequences (sessions) of (a) students with the exam scores above the 90th percentile, and (b) students with scores below the 25th percentile. The Y axis represents the proportion of certain type of action in each 'point' of the sequences, e.g., in case of top performing students (a), the first action in ~65% of the learning sequences was reading (green color); in ~10% of the learning sequences the first action was successful completion of the summative assessment (yellow); in ~5% of the sequences, the first action was summative assessment done incorrectly (violet), and so on. Learning action abbreviations are outlined in the figure legend and briefly explained in Table 1.

3.2 Clusters of learning sequences as manifestations of student learning strategies

Agglomerative hierarchical clustering of learning sequences of all the students during the 12 active weeks of the course led to a solution with 4 clusters as the optimal one (Figure 3). The resulting clusters are:

- Cluster 1 (1448, 12.79%) is the smallest cluster. This grouping comprises learning sequences that are dominated by formative assessment activities (MCQ_CO, MCQ_IN, MCQ_SR), with actions related to summative assessment (EXE_CO, EXE_IN) almost absent. Actions related to the reading materials for the class (CONTENT_ACCESS) are not frequent, though they tend to be more present at the beginning and towards the end of this group of learning sequences.
- Cluster 2 (4736, 41.85%) is the most dominant cluster with a clear focus on actions related to summative assessment. In this group, incorrectly solved exercises considerably outnumber the correctly completed exercises, thereby suggesting that students are adopting a trial-and-error learning approach. The sequences tend to end with metacognitive evaluation actions (MC_EVAL), that is, access to the dashboard.
- Cluster 3 (3240, 28.63%) sequences are predominantly focused on the reading materials for the class with a fraction of formative assessment. These sequences tend to be shorter than sequences in the other groups, and typically end by watching course videos. Hence, this pattern indicates a low level of active engagement with the learning content (i.e. passive 'consumption' of the provided materials).

- Cluster 4 (1893, 16.73%) sequences predominantly focus on the course videos. Formative assessment actions are also present though they are gradually and mostly towards the end of the sessions substituted by summative assessment actions. These seem to be sessions where students were primarily watching videos, then doing the follow-up multiple-choice questions, and finally trying the exercises. It is interesting to note the presence of metacognitive actions (MC_EVAL, MC_ORIENT) at the beginning of these sessions.

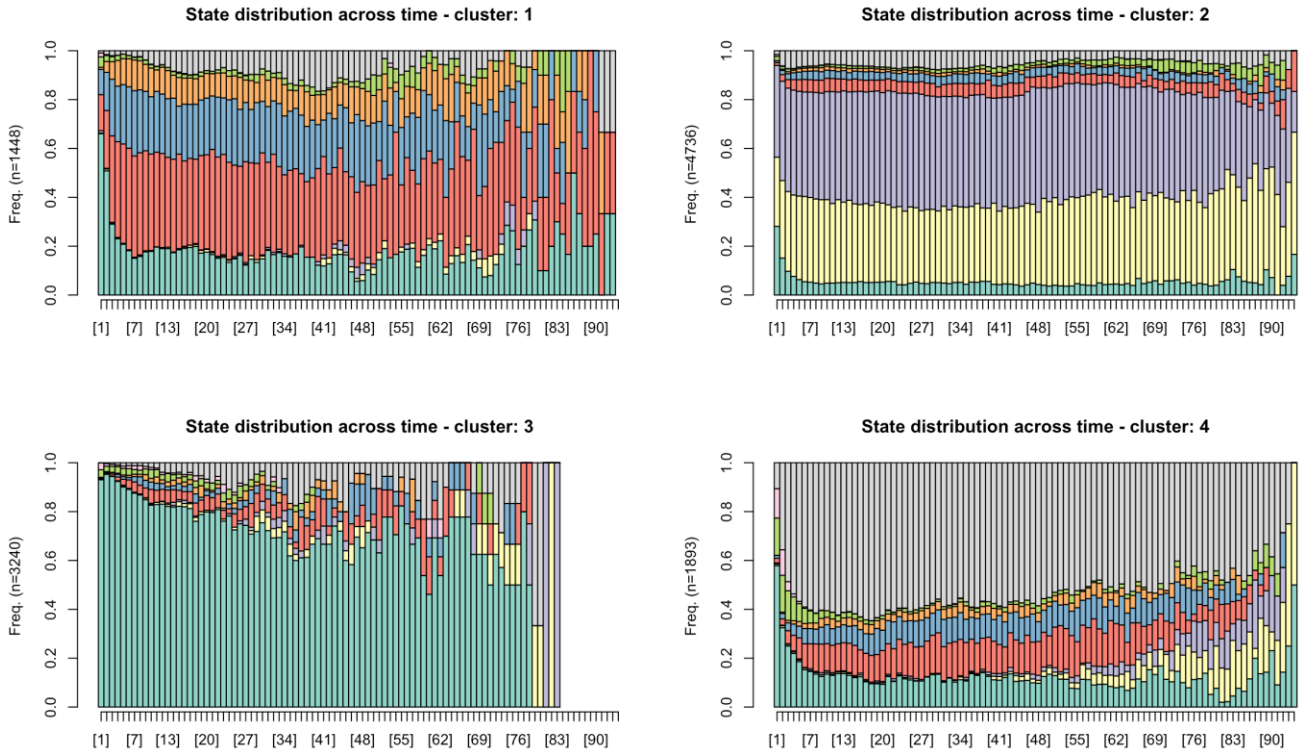

Figure 3. Clusters of learning sequences, indicative of students' learning strategies. Legend from Figure 2 applies here, as well; interpretation of the axes is also the same as for Figure 2.

3.3 Clusters of students based on the shared learning strategies

Student clustering was performed based on the identified patterns in students' behavior (i.e., clusters identified in Section 3.2) and their overall level of engagement (i.e., total number of learning sequences). To select the optimal number of clusters we inspected the resulting dendrogram, depicting the clustering results, and examined different ways of cutting the tree structure (i.e., different numbers of clusters). This led to choosing the solution with 5 clusters as the best one.

Table 2 describes the resulting clusters in terms of i) the five variables used for clustering (seq.clust1 – seq.clust4, and seq.total); ii) the midterm exam score (midterm.score); and iii) the final exam score (final.score). For all the variables the table shows the median, 25th and 75th percentiles.

Table 2. Summary statistics for the 5 student clusters: median, 25th and 75th percentiles

	Cluster 1 (19, 6.55%) (*Intensive*)	Cluster 2 (35, 12.07%) (*Strategic*)	Cluster 3 (50, 17.24%) (*Highly strategic*)	Cluster 4 (128, 44.14%) (*Selective*)	Cluster 5 (58, 20%) (*Highly selective*)
seq.clust1	14 (12, 19.5)	10 (5, 13)	5.5 (3, 7)	3 (1, 5)	1 (0, 3)

seq.clust2	23 (20, 24.5)	19 (15, 22)	20 (17, 23)	17 (14, 19)	9.5 (6, 12)
seq.clust3	31 (26.5, 36.5)	17 (12, 21)	17 (15, 19.75)	7 (5, 10)	3 (2, 5)
seq.clust4	12 (10, 17.5)	13 (11, 18)	7 (4.25, 9)	5 (3, 7)	1 (0, 2)
seq.total	83 (76, 89.5)	59 (55.5, 63.5)	50 (46, 55)	32 (27, 37)	17 (12, 19.75)
midterm.score	16 (13, 18)	15 (13, 17)	16 (13, 17)	13 (11, 16)	11 (8, 14.75)
final.score	24 (18.5, 30)	19 (14.5, 29)	21 (16, 30.75)	15 (12, 23)	14 (9.25, 18.75)

From the perspective of variables outlined in Table 2, the clusters can be described as follows:

- Cluster 1 – *Intensive* (19, 6.55%): the most active group representing students who undertook a variety of learning strategies, among which strategies 3 (focus on reading materials) and 2 (focus on summative assessment) were the most prominent. This group also represents the students with the highest median values of midterm and final exam scores. Considering the high level and diversity of engagement of these students, we refer to them as the *Intensive group*.
- Cluster 2 – *Strategic* (35, 12.07%): this group is similar to Cluster 1, but with a lower activity level and a reversed level of importance placed on strategies 2 (focus on summative assessment) and 3 (focus on reading materials). Whereas this cluster had lower median values for the midterm and final exam scores in comparison to Cluster 1, the differences were not statistically significant. These students demonstrated strategic approach (Biggs, 2012) to class preparation: their primary focus on assessment activities (both summative and formative) suggests that they regulated their learning based on performance-oriented objectives, whereas their overall level of engagement – lower than that of the *Intensive* group – suggests a preference for efficiency. Considering that the exam scores of this group did not significantly differ from the *Intensive* group, it can be concluded that these students did well in choosing their strategies; accordingly, we refer to them as the *Strategic* group.
- Cluster 3 – *Highly strategic* (50, 17.24%): this group is similar to Cluster 2 in terms of the presence and relevance of strategies 2 (focus on summative assessment) and 3 (focus on reading materials). However, compared to Cluster 2, these students had a significantly lower adoption of strategies 1 (focus on formative assessment) and 4 (video watching followed by assessment activities). In terms of exam performance, this group had higher median values than group 2, though the differences were not statistically significant. Being similar to Cluster 2, this group can also be considered strategic in their behaviour. In fact, students in this group seem to be even more successful in regulating their learning as they achieved the performance level of the other two high performing groups – Clusters 1 and 2 – in spite of their lower level of overall engagement. Therefore, the group is considered to be *Highly strategic*.
- Cluster 4 – *Selective* (128, 44.14%): this cluster forms the largest grouping. In this group, strategy 2 (focus on summative assessment) was the most dominant, although students also experimented with other learning strategies. The group's overall level of activity and exam scores were significantly lower than those of the previous three clusters (1, 2 and 3). Considering the group's primary focus on one learning strategy and only occasional experimentation with the other strategies, we named its members *Selective* students.
- Cluster 5 – *Highly selective* (58, 20%): represents the least active group. Students in this cluster were almost exclusively applying strategy 2 (focus on summative assessment). The group also represents students who received the lowest scores on both midterm and final exams. Compared to Cluster 4, this group demonstrated a lower level of effort and higher attachment to only one learning strategy; therefore, its members were considered to be *Highly selective*.

Tables 3 and 4 give pairwise comparisons of clusters with respect to the students' midterm and final exam scores. All the cluster pairs, except for the cluster pairs 1-2, 1-3, and 2-3, were significantly different (even after applying the FDR correction for multiple testing) in terms of both midterm and final exam scores, with effect sizes (r) ranging from small to medium.

Table 3 Pairwise comparison of clusters with respect to the students' midterm exam scores

C1	C2	Z	p	alpha	r
3	5	4.6192	0.000002*	0.005	0.4445
2	5	4.3495	0.000007*	0.010	0.4510
1	5	3.7428	0.000105*	0.015	0.4265
3	4	3.2830	0.000927*	0.020	0.2461
2	4	3.1829	0.001289*	0.025	0.2493
4	5	2.8440	0.004264*	0.030	0.2085
1	4	2.7099	0.006095*	0.035	0.2235
1	3	0.5415	0.593483	0.040	0.0652
1	2	0.2824	0.783782	0.045	0.0384
2	3	0.1890	0.852660	0.050	0.0205

Note: * marks statistically significant differences, i.e., comparisons where p value is below the FDR corrected alpha

Table 4 Pairwise comparison of clusters with respect to the students' final exam scores

C1	C2	Z	p	alpha	r
3	5	4.7092	0.000001*	0.005	0.4531
1	5	3.8737	0.000056*	0.010	0.4414
2	5	3.7237	0.000145*	0.015	0.3861
3	4	3.6342	0.000236*	0.020	0.2724
1	4	2.8127	0.004350*	0.025	0.2320
2	4	2.5720	0.009722*	0.030	0.2015
4	5	2.3889	0.016636*	0.035	0.1752
1	2	0.6168	0.543737	0.040	0.0839
1	3	0.4371	0.667051	0.045	0.0526
2	3	-0.3040	0.764090	0.050	0.0330

Note: * marks statistically significant differences

The degree of variation in learning strategies adopted by students within each cluster was also examined. Figure 4 illustrates how the median number of learning sequences per learning strategy (sequence cluster) changed over the 12 weeks of the course. The figure suggests that:

- *Intensive* students (Cluster 1) used all learning strategies until week 7, and then mostly abandoned strategy 1 (focus on formative assessment); until the end of the course, they used the other three strategies, but gave more attention to strategies 2 (focus on summative assessment) and 3 (focus on reading materials) than to strategy 4 (focus on course videos and video follow-up activities). The peak of their activities and strategy use was in week 6, right before the midterm exam.
- Similar to their colleagues from the *Intensive* group, *Strategic* students (Cluster 2) engaged with all learning strategies until week 7, and were the most active right before the midterm exam (week 6). From week 7, they abandoned strategy 1 (focus on formative assessment), and while still retaining the other three strategies, they showed preference for strategy 2 (focus on summative assessment).

- *Highly strategic* students (Cluster 3) practiced different learning strategies only during the first two weeks of the course and when preparing for the midterm exam (week 6). In all other weeks, they opted for strategies 2 (focus on summative assessment) and 3 (focus on reading materials), with the former being the preferred one.
- The *Selective* students (Cluster 4) had almost exclusive focus on strategy 2 (focus on summative assessment) throughout the course, with the exception of the first few weeks, i.e., weeks up until the midterm exam when they were occasionally undertaking strategy 3 (focus on reading materials).
- The *Highly selective* group (Cluster) 5 is characterized by a complete focus on strategy 2 (focus on summative assessment) for the entire duration of the course.

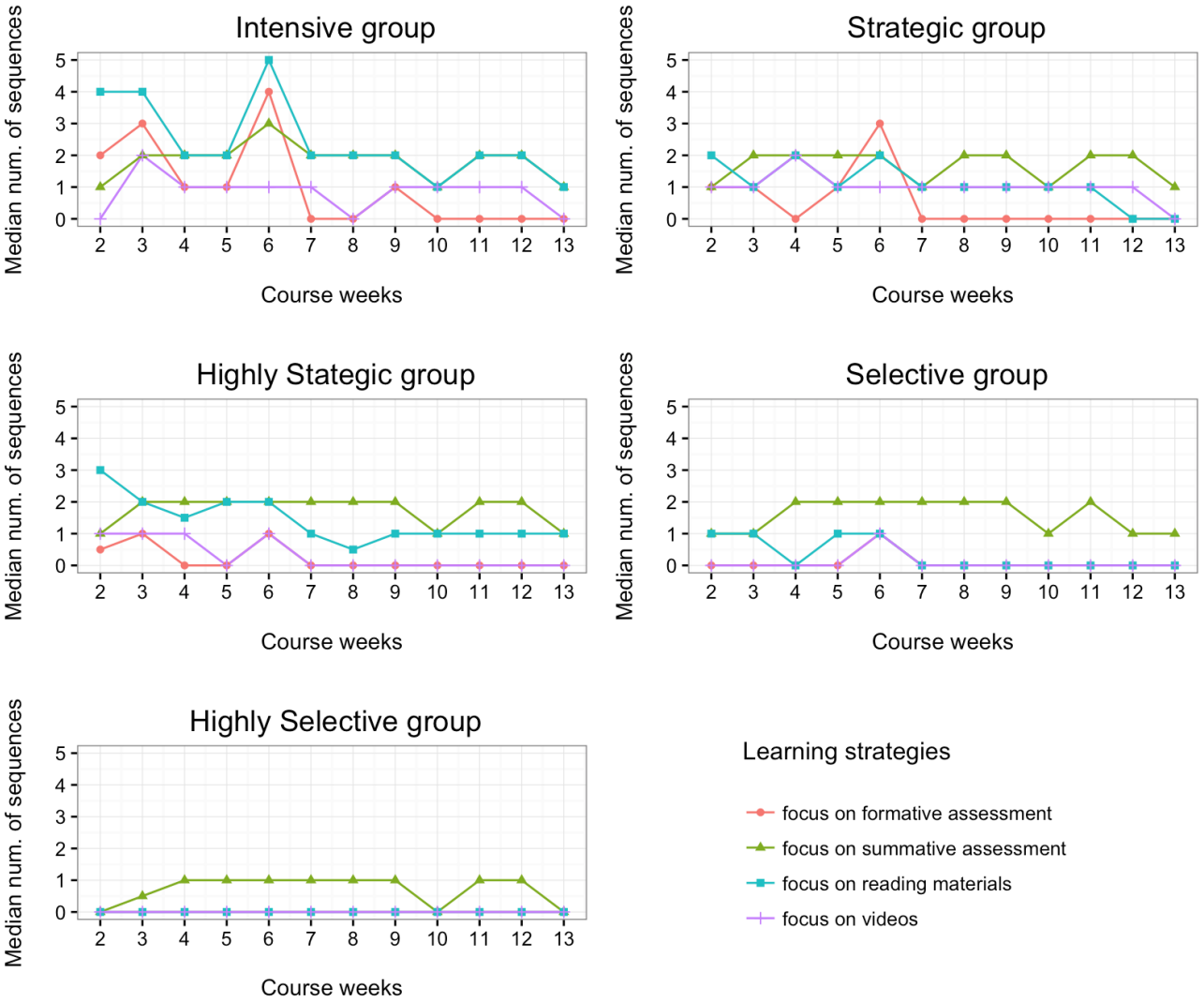

Figure 4. Change in the applied learning strategies for each of the five student clusters over the 12 weeks of the course. Y-axis represents the median number of learning sequences per each of the 4 learning strategies.

4. Discussion

4.1 RQ1: Learning strategies in flipped learning settings

The identified clusters of learning sequences (Sect. 3.2) are well differentiated, and as such they suggest the presence of patterns in students' learning behavior in the examined FL setting. These patterns can be thought of as *manifestations* of students' learning strategies (Winne, 2013). As manifestations they provide insight into the specific strategies students employ to navigate the tasks associated with a particular FL setting. However, the data and analyses do not address the question of *why* students may have opted for particular strategies nor why they may have abandoned or continued with such strategies for the course duration. This is particularly perplexing when considering students that under-performed or failed on the mid-term exam or received low scores in the ongoing summative tasks. For instance, it would be anticipated that students scoring poorly on the mid-term would alter and increase their level of engagement in the FL preparation activities after receiving their exam results. Generally, this was not the case in the present study. We return to the *why question* when discussing the limitations of this work (Sect. 4.3).

Student clustering derived from the observed patterns in learning behavior, led to the detection of several strategy-based student profiles. The identified profiles reflect those reported in previous research (e.g., Lust et al., 2013a; Lust, Elen, & Clarebout, 2013b; Valle & Duffy, 2009). The prior research is well summarized by Kovanovic et al. (2015) who identified three re-occurring technology-use profiles and interpreted these in terms of approaches to learning (deep vs. surface) (Biggs, 2012) and achievement goal orientations (performance vs. mastery) (Senko, Hulleman, & Harackiewicz, 2011):

- Profile/group characterized by low activity level, surface approaches to learning, and performance-goal orientation. This group of minimalists corresponds to our cluster of *Highly selective* students whose level of activity is considerably low, approaching complete disengagement.
- Group with a very high activity level, deep approach to learning and mastery-goal orientation. Students from our *Intensive* and *Strategic* groups (clusters 1 and 2, respectively) seem to match the features of this group, since they are highly active students who practiced a variety of learning strategies, obviously trying to adapt to the course requirements. The fact that these students were among the best in terms of exam performance suggests that they tended to be successful in adapting/regulating their learning.
- Group of selective and efficiency-oriented users who typically exhibit performance goal-orientation, and tend to regulate their learning, but often in a non-desirable way. This group largely matches our *Selective* group (cluster 4) where students are fastidious about learning activities they engage with and aimed at achieving high scores (performance-orientation) through minimal engagement (high efficiency). However, their low exam scores evidence that their regulation of learning is far from optimal.

The additional profile detected in our study – *Highly strategic*, cluster 3 – bears features of effective students (*Strategic*, cluster 2) and those who are selective and efficiency-oriented (*Selective*, cluster 4). We refer to this group as *Highly strategic* learners since they proved successful in finding and applying learning strategies that led them to high course performance. As Figure 4 indicates, during the first few weeks of the course, these students experimented with different learning strategies, and then narrowed their selection to two strategies (2 and 3) that they practiced till the end of course.

To deepen our understanding of the identified student groups/profiles, we relate to the Winne & Hadwin model of self-regulated learning (SRL) (Winne & Hadwin, 1998; Winne, 1997). According to this model, the learning process is, among other things, influenced by internal and external conditions. External conditions include factors such as the time available, guidelines provided by the teacher, and access to feedback. Internal conditions refer to the learner's personal characteristics such as, confidence, motivation, and his/her repertoire of learning strategies (developed over previous learning experiences). The specific FL design we focused on in this study determined the external conditions. Since the students had limited previous experience with FL, the external conditions in the examined course differed markedly. Therefore, the repertoire of study tactics and strategies they possessed were not well suited for the external conditions they faced. To cope with this gap, they initially experimented with different learning strategies – as can be seen in Figure 4 for all groups except the *Highly selective* cluster. However, after a few weeks, only the *Intensive* and *Strategic* clusters, and to a small extent the *Highly strategic* group continued to employ a variety of learning strategies. This finding may in part be explained through the concept of "utilization deficiency" (Miller & Seier, 1994) – one of the barriers to applying learning strategies as identified by Winne (2013). Since students were faced with a new learning setting (FL) where the available repertoire of learning strategies did not (fully) apply, they had to develop/adopt a new learning strategy that would better complement the instructional setting. This could have led to an increase in cognitive load since students would have needed to simultaneously adopt new learning strategies and work on the development of the subject specific knowledge and skills concurrently. The increased cognitive burden might have initially resulted in performance that was lower than expected (e.g., in case of the *Selective* group), or might have proven too demanding (requiring more effort than students were willing or able to devote). As a result, students reverted to prior established practices (focus on summative assessment) without giving the new tactics a full consideration and opportunity to evaluate their impact on performance and learning outcomes.

The findings from this study also suggest that students have a tendency to change their learning strategy over the duration of the course, which is something to be expected (Pask & Scott, 1972). As noted by Winne in relation to SRL theory, a change in learning strategy reflects changes in the internal and external conditions (Winne, 1997; Winne & Hadwin, 1998). The present study has shown that students tended to turn to less effective study strategies, which was evident in their engagement with summative assessment and passive learning strategies such as video watching and reading / browsing through reading materials instead of self-testing afforded by formative assessment. This is also consistent with the previous research that offered evidence that *"people often have a faulty mental model of how they learn and remember, making them prone to both misassessing and mismanaging their own learning*" (Bjork, Dunlosky, & Kornell, 2013, p. 417).

An important practical implication of the presented findings is that instructors should occasionally, and especially after the midterm, remind their students about the importance of choosing effective learning strategies, particularly those strategies that rely on active engagement with the learning resources (e.g., different forms of formative assessment). To assure the students' attentiveness to such recommendations, instructors should make the students aware of the value and relevance of the recommended strategies for both learning and academic achievement. Furthermore, learning strategies are skills, and as all skills they have to be practiced to develop proficiency (Ericsson, Krampe, & Tesch-Romer, 1993; Winne, 2013). Hence, the instructors should consider altering the learning design, in particular the preparation part of the FL design, to scaffold the development of the desired learning strategies.

4.2 RQ2: Association between learning strategies and course performance

Comparison of the identified student groups (clusters) with respect to the students' midterm and final exam scores (Tables 3 and 4) demonstrated that there are significant differences in the scores of 7 out of the 10 group pairs. Specifically, only in the case of group pairs 1-2, 1-3, and 2-3 differences in the exam scores are not statistically different. This indicates that there is an association between the learning strategies that students adopted in the FL setting and their course performance. Specifically, students who experimented with different learning strategies (clusters 1, 2, and 3) had high course performance, whereas those who reduced their engagement to solving summative assessment items had low performance. This is consistent with previous research findings in Self-Regulated Learning (SRL) that students who are experimenting with different tactics and strategies are engaged in more metacognitive monitoring and, hence, more active SRL (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007), which in turn leads to higher achievements (Bannert et al., 2013).

This finding is also consistent with empirical findings of research studies that examined students' approaches to learning and how these approaches impact academic performance. Three approaches to learning have been recognized (Biggs, 2012): i) deep approach, characterized by critical evaluation and syntheses of information, and driven by intrinsic motivation; ii) surface approach, dominated by shallow cognitive strategies and associated with extrinsic motivation; and iii) strategic approach, which assumes alterations between deep and surface approaches, depending on the characteristics of the task at hand. Learning strategies practiced by students from the *Intensive* group (cluster 1) might be considered as indicative of deep approach; clusters 2 and 3 gather strategic learners, whereas the *Selective* and *Highly selective* groups seem to be practicing surface approach to learning. Course performance of the five clusters is consistent with the performance levels characterizing the three learning approaches. Specifically, meta-analysis by Richardson, Abraham, & Bond (2012) demonstrated positive, though small, correlations between students' performance and both deep and strategic approaches to learning, whereas surface approach was found to be negatively correlated with academic performance.

4.3 Limitations and future research

Analysis of trace data allows for detection and description of regularities in a series of learning events, but it has limited power in explaining the detected patterns (Reimann, Markauskaite, & Bannert, 2014). In this particular case, the applied analytical method led to the unfolding of *manifestations* of learning strategies, but it did not allow for a complete understating of these strategies. In particular, it did not provide us with answers to the questions such as i) why students decided to approach a learning task in the given way; ii) what learning objectives they set for themselves, and iii) what kind of learning motivation drove their actions. For instance, we observed among a majority of students an extensive focus on summative assessment coupled with a tendency to neglect formative assessment tools (clusters 4 and 5, comprising 64% of all the students). The observed deficiency in regulating their use of available learning tools and strategies suggests that students had erroneous conditional knowledge (Winne, 1996). This in turn can be caused by the 'objective' facet of the conditional knowledge, i.e., the students' perception of the learning tasks, the learning requirements and the available learning support. Alternatively, or in addition, the cause might originate in the 'subjective' facet of conditional knowledge, that is, students' motivation and epistemological beliefs (Winne,1996; Winne, 2011; Greene & Azevedo, 2007).

To be able to understand the reasons for the observed behavior, we would need to extend our investigation with a qualitative method capable of providing deeper insight into the identified learning strategies and the corresponding student profiles. In other words, what is needed is a follow-up multi-modal study where the analysis of learning traces is combined with the analysis of data obtained from other sources (e.g., students' self reports, interviews with students and instructors) to better understand the students' learning behavior.

A gradual approach to building knowledge and understanding of students' learning behavior is a practice also applied by other researchers in the field. For instance, in their initial examination of students' interaction with the Lectopia lecture recording system, Phillips et al. (2010) identified eight student groups characterized by different patterns of Lectopia use. While the identified groups were reflective of patterns in the students' learning behaviour, they did not allow for explaining that behaviour. Therefore, in their follow-up study, Philips et al. (2011) conducted semi-structured interviews with a small sample of students from different behaviour categories. Most of the interviewed students refuted the assigned group label and provided explanation for their interaction pattern with Lectopia. The discrepancy between the algorithmic group assignment and the students' opinion on the group they should have been assigned to seems to originate in the students' perception of those groups as descriptors of their overall learning behavior, whereas the groups reflected only the pattern of use of the lecture recording tool. This suggests an important practical implication regarding the design of qualitative data collection instruments to be used for triangulation with the results originating from the trace data. In particular, there is a need for carefully designed interviews with clearly and precisely formulated questions and statements that students are expected to respond to, to prevent the abovementioned and similar kind of mismatch between the purpose of a qualitative data collection instrument and the students' comprehension of the constructs they were asked about.

An important direction for future work will be to examine connections between the identified strategy-based learner profiles and learners' motivation and goal orientation. The rationale for this research direction comes from the achievement theory according to which students' personal goals are regulators of their learning behavior (Elliot & McGregor, 2001). There is also empirical evidence of the effect that students' personal goals have on the selection of learning strategies (Greene & Miller, 1996; Neuville, Frenay, & Bourgeois, 2007). We refer here to the prominent model of achievement goal orientation (Elliot & McGregor, 2001) based on two orthogonal dimensions: approach – avoidance and mastery – performance. The most desirable are mastery-approach goals since they are associated with the intrinsic motivation, engagement in learning activities for the sake of self-improvement, and elaborated study strategies. On the opposite spectrum are performance-avoidance goals, which are rooted in the fear of failure relative to others, and often associated with anxiety, low competence expectations, and surface level strategies. Lust et al. (2013b) examined the use of LMS tools in an undergraduate blended course and found that differences in the students' use of learning tools could be explained in terms of students' goal orientation. Specifically, they found a connection between i) mastery goal orientation and active and intensive tool-use pattern (indicative of deep level study strategy), and ii) performance goal orientation and selective tool-use pattern (reflective of surface level strategy).

Collection of data required for identifying students' goal orientation is not straightforward. Traditional self-report measures are not capable of capturing the dynamics of students' goals (Zhou & Winne, 2012), which, although generally stable, can change along with changes in learning tasks (Fryer & Elliot, 2007). In addition, the ability of students to give valid and objective reports on their goal orientations is questionable (Richardson, 2004). Hence there is a need to extend learning

environment with instruments that would allow for seamless and unobtrusive collection of data about the dynamics of students' goal orientation. An illustrative example is an annotation tool that allows students to associate selected pieces of content with one or more tags (from a predefined tags collection) reflective of their goal orientations (Zhou & Winne, 2012). By capturing data indicative of the students' goal orientation, we would be able to better understand and interpret the insights that our method provides about the students' use of learning strategies.

5. Conclusion

If properly communicated, results of the analytical method applied in this study can be useful in multiple ways:

- To inform the instructor on whether the deployed FL design was effective in sustaining student engagement and preparing them for active participation in the class (i.e., face-to-face session).
- To provide grounds for selective/adaptive inclusion of scaffolds (e.g., hints, guidelines) to help students improve their learning behavior.
- To make students aware of their learning strategies, and how those strategies compare to the strategies of well performing peers. Students in a FL setting often require more awareness of their learning process than students in more traditional settings (Frederickson, Reed, & Clifford, 2005); they need to reflect on their learning activities in order to properly connect them with the course materials and requirements, and make necessary adjustments in their learning approach (Strayer, 2012).

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