Identifying and Comparing Multi-dimensional Student Profiles Across Flipped Classrooms

Paola Mejia-Domenzain[1(✉)], Mirko Marras[2], Christian Giang[1,3], and Tanja Käser[1]

[1] EPFL, Lausanne, Switzerland
{paola.mejia,christian.giang,tanja.kaeser}@epfl.ch
[2] University of Cagliari, Cagliari, Italy
mirko.marras@acm.org
[3] University of Applied Sciences and Arts of Southern Switzerland, Locarno, Switzerland

Abstract. Flipped classroom (FC) courses, where students complete pre-class activities before attending interactive face-to-face sessions, are becoming increasingly popular. However, many students lack the skills, resources, or motivation to effectively engage in pre-class activities. Profiling students based on their pre-class behavior is therefore fundamental for teaching staff to make better-informed decisions on the course design and provide personalized feedback. Existing student profiling techniques have mainly focused on one specific aspect of learning behavior and have limited their analysis to one FC course. In this paper, we propose a multi-step clustering approach to model student profiles based on pre-class behavior in FC in a multi-dimensional manner, focusing on student effort, consistency, regularity, proactivity, control, and assessment. We first cluster students separately for each behavioral dimension. Then, we perform another level of clustering to obtain multi-dimensional profiles. Experiments on three different FC courses show that our approach can identify educationally-relevant profiles regardless of the course topic and structure. Moreover, we observe significant academic performance differences between the profiles.

Keywords: Clustering · Time series · Self-regulated learning

1 Introduction

Flipped Classrooms (FC) courses are a form of blended learning where students complete pre-class activities before attending interactive face-to-face sessions. These courses allow students to conveniently access learning resources and independently manage their studying time, which requires a high degree of self-regulation. While pre-class activities are essential for course success [2,16], students often do not engage with such activities due to a lack of motivation, time,

M. M. Rodrigo et al. (Eds.): AIED 2022, LNCS 13355, pp. 90–102, 2022.
https://doi.org/10.1007/978-3-031-11644-5_8

or necessary skills [22]. Understanding student behavior in pre-class activities can hence help the teaching staff identify these reasons and timely intervene.

Nevertheless, a large number of prior studies on FC have mainly focused on the effectiveness and implementation of the approach rather than on students' learning strategies during the course [22]. Moreover, the studies on learning strategies have formerly used self-evaluating questionnaires [9,26], which can be biased and do not acknowledge the dynamic nature of learning. Fewer works have used log data from pre-class activities to predict student success. For instance, [3] showed that the video usage frequency is correlated to student success, [1] predicted homework grades by modeling student strategies as clickstream event n-grams, and [17,28] identified at-risk students based on clickstream features.

Regarding clustering approaches to profile student learning behavior in FC, [12] identified student learning strategies by examining the distribution of learning actions in students' pre-class online sessions. In subsequent work, the same authors examined student regularity of pre-class activities and its association with course grades [13]. Other works used clustering techniques to analyze student time management skills [6], study the evolution of video usage indicators [23], and analyze consistency in student learning [25].

However, most of the aforementioned studies have investigated one specific FC course only (e.g., [12,23]) and/or focused on one specific aspect of student learning behavior (e.g., consistency [25], time management [13]). In other digital learning environments, such as massive open online courses, [18] identified rule-based clusters and explored the movement of students across clusters over time. However, no groups of students with similar changing behavior were studied. In contrast, [5] analyzed how students changed their studying strategies during the course, but did not incorporate multiple student behavioral aspects like [18].

In this paper, we investigate the integration of multiple dimensions of student behavior, including self-regulated learning (SRL), in data-driven student profiles. To this end, we propose a multi-step clustering pipeline based on previous findings on SRL in online education. In the first step, we model students' log data as time series and cluster student behavior individually in terms of effort, consistency, regularity, proactivity, control, and assessment. Through a second level of clustering, we integrate the obtained behavioral patterns into interpretable multi-dimensional profiles. With our approach, we aim to combine multiple behavioral dimensions to obtain interpretable student profiles in FC and study how these profiles compare across FC courses (**RQ1**); as well as analyze the relationship between the detected profiles and academic performance (**RQ2**). Our analysis on three FC courses shows that profiles integrating multiple dimensions can be identified and interpreted using clusters' prototypes and that sometimes similar profiles emerge regardless of the course topic and structure. We also find a significant variance in academic performance across profiles. The obtained profiles hence contribute to teachers' understanding of student behavior, enabling better-informed course decisions and student interventions.

2 Method

To investigate student behavior in FC, we propose the multi-step clustering pipeline depicted in Fig. 1. We first extract features from pre-class log data to explain relevant dimensions of learning behavior (Sect. 2.1). Instead of clustering the multiple features in a single step, we propose a multi-step approach that allows a better interpretation and understanding of the cluster composition and characteristics. Thus, we perform a first clustering step separately for each dimension (Sect. 2.2); and a second clustering step, in which we integrate the obtained behavioral patterns into multi-dimensional profiles (Sect. 2.3). Source code accompanying this paper: https://github.com/epfl-ml4ed/fc-clustering.

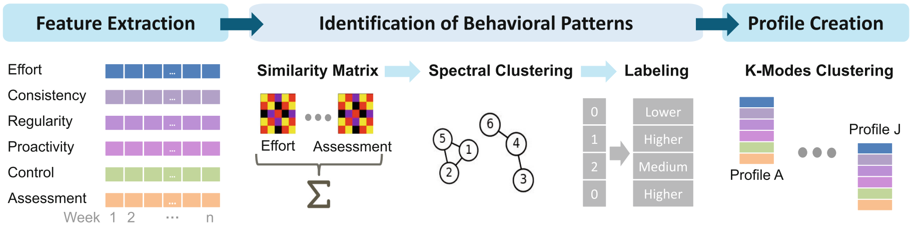


Fig. 1. Overview of the clustering pipeline.

2.1 Feature Extraction

Different aspects of SRL have been researched extensively (e.g., [9,25]). In a meta-analysis on online education, [7] found significant associations with academic achievement for five sub-scales of SRL: effort regulation (persistence in learning), time management (ability to plan study time), metacognition (awareness and control of thoughts), critical thinking (ability to carefully examine material), and help-seeking (obtaining assistance if needed). Based on these findings, we use the following dimensions to represent student behavior: effort regulation (*Effort*), time management (*Consistency*, *Regularity*, *Proactivity*), and metacognition (*Control*). The nature of our log data does not allow us to represent critical thinking and help-seeking. Assuming that there will be a significant association between performance in pre-class activities and course grades (e.g., [16,17,28]), we add a sixth dimension (*Assessment*) to our representation of student behavior. We measure these dimensions using features that proved to be relevant in prior work analyzing learning strategies in online or blended learning (e.g., [6,8,15,17,20]). Table 1 shows the dimensions and their respective features.

The first dimension, ***Effort***, aims to monitor the intensity of student engagement in the course, which is fundamental for learning success [9]. In contrast, ***Consistency*** is concerned with the relative shape of student events, measuring how student effort varies over time. Specifically, it estimates the intra-course time management skills of the students, an important SRL aspect [7,25]. The ***Regularity*** dimension is also associated with time management; it estimates the

Table 1. Features are grouped into six different dimensions. Each feature stems from a relevant prior study and is accompanied by a short description.

Dimension[a]	Feature	Description
Effort	Total time online [8]	Sum of session durations
	Total video clicks [8]	Video events (play, pause, stop, seek)
Consistency	Mean session duration [8]	Time measured in minutes
	Relative time online	Unit vector of total time online
	Relative video clicks	Unit vector of total video clicks
Regularity	Periodicity of week day [6]	Studying on certain day(s) of the week
	Periodicity of week hour [6]	Studying at certain hours of the day
	Periodicity of day hour [6]	Studying on certain day(s) & hours of the week
Proactivity	Content anticipation [17]	Fraction of videos (from subsequent weeks) watched before the scheduled due date
	Delay in lecture view [6]	Time interval between the first views and the due date of videos of prior weeks
Control	Fraction spent [20]	Real time spent watching the video divided by its duration, averaged across videos
	Pause action frequency [15]	Mean number of pauses divided by the time spent watching a video per video
	Average change rate [20]	Mean playback speed used to watch videos
Assessment	Competency strength [17]	Highest grade achieved by the student on a quiz divided by the number of attempts
	Student shape [17]	Student's tendency of obtaining the maximum grade in a quiz in the first attempt

[a]Features names taken from original papers and implementation from [17].

intra-week and intra-day time management patterns (i.e., capturing whether a student is regularly engaged on specific weekdays or day times), which have been proved to be predictive of student success in MOOCs [6] and FC [13]. Another dimension of time management, ***Proactivity***, attempts to measure the extent to which students are on time or ahead of the schedule [11]. Engagement in pre-class activities has shown to be associated with exam performance [2,16]. The ***Control*** dimension models the in-video behavior as a proxy of student ability to control the cognitive load of video lectures (metacognition). The flow of video information can result in cognitive overload and thus regular pauses can improve learning outcomes [4]. In the platform, students are provided with functionalities (e.g., pause button) to control video flows [4]. Finally, the ***Assessment*** dimension assumes that there is a relation between student performance in voluntary non-graded online quizzes and the final course grade (e.g., [16,17,28]). Given that learning is dynamic in nature [27], we model features as week-wise time series (length equal to the number of course weeks). The only exceptions are the *Regularity* features, whose computation requires evidence from all course weeks and thus are computed for the whole course as a scalar.

2.2 Identification of Behavioral Patterns

The first clustering step is done separately per dimension: we compute a pairwise similarity matrix, feed it into a spectral clustering, and interpret its labels.

Similarity Matrix. First, we compute a pairwise distance matrix between students separately for each feature. To compute distances between student time series, we use the Dynamic Time Warping (DTW) distance [25]. DTW can identify similar patterns (e.g., peaks) regardless of small variations (shifts) in time. In contrast, we use the Euclidean distance for the *Regularity* features, since they are scalars and not time series. Second, we apply a Gaussian kernel to transform the distance matrix into a similarity matrix. The standard deviation (σ) of the kernel controls the blurring degree, which is useful to reduce the impact of students with extreme behavior. We then add the similarity matrices of the features of each dimension to get the dimension similarity matrix. We optimize the DTW window size (w) and the width of the Gaussian kernel (σ) per dimension via a grid search maximizing the clusters' *Silhouette* score (see next paragraph).

Spectral Clustering. We apply *Spectral Clustering* [21] to cluster the similarity matrix of each dimension separately. This clustering algorithm treats points as nodes in a graph and then solves the graph partitioning problem. Unlike *K-Means*, it is not limited to convex clusters. The algorithm outputs a vector containing the cluster identifiers for each student. In total, there are as many vectors as behavioral dimensions, and each vector length is equal to the number of students. We perform a grid search separately for each dimension using $k = 2, ..., 10$ clusters. We use the *Silhouette* score [24] to determine the optimal number of clusters as this heuristic is easy to interpret (higher scores indicate high separability between clusters).

Labeling. We label the obtained clusters for each dimension according to the intensity, shape (including peaks), and relation to key aspects of the course (e.g., exams), by thoroughly inspecting the time series of the students in each cluster. When the patterns differ in more than one attribute (e.g., intensity and shape), we choose the attribute that better explains each dimension. Labels are created relative to other clusters and not in absolute terms. For instance, labeling a cluster as *Higher Effort* does not mean effort exceeds a given threshold, but that students in this cluster work more intensively than those in the other clusters.

2.3 Profile Creation

The second clustering step integrates all dimensions into a single learner profile, enabling us to describe student behavior across dimensions (e.g., a cluster with *Higher Effort*, *Lower Assessment*, *Higher Control*, etc.). We are hence able to gain insights into the dependencies across dimensions. We take as input the five/six annotated labels (one per dimension) from Sect. 2.2 and cluster them using *K-Modes* (selecting K as in Sect. 2.2). *K-Modes* extends K-Means to use the mode (most frequent element) instead of the mean to compute cluster centroids from categorical data. These centroids provide insights into the cluster composition (e.g., [25]) and will be analyzed in the next section.

3 Experimental Evaluation

We evaluated our approach on three different FC courses. We first analyzed and compared the obtained profiles across courses (**RQ1**) and then investigated their relation to academic performance (**RQ2**). The study was approved by the institutional review board (HREC No. 058-2020/10.09.2020).

Table 2. Characteristics of the FC courses.

Course	Year	Semester	Students	Female	Event type	No. events	Fail
LA	2018/19	1	292	29%	Video + Quiz	1,033,962	41%
FP	2018	3	216	20%	Video	464,115	2%
PC	2019	4	147	14%	Video	156,375	11%

Data Set. Our analysis is based on the log data collected from an EPFL online institutional platform (custom Open edX installation) that tracked student pre-class activities (watching video lectures and solving quizzes) in three FC courses. The log entries are tuples reporting the user, the activity, and the timestamp (e.g., user: 10, activity: play video 32, timestamp: 05-03-2018 12:06:01). The three considered FC courses (Table 2) are compulsory courses for the Computer Science and Communication Systems Bachelor degrees in EPFL. The first data set was collected from two consecutive FC editions of the *Linear Algebra* (LA) course, taught by the same lecturer and with a flipped duration of 10 weeks. Among the three courses, this is the only one including online quizzes. The second data set was collected from the FC edition of a *Functional Programming* (FP) course with a flipped duration of 11 weeks. The third data set stems from a FC course in *Parallelism and Concurrency* (PC) lasted 15 weeks. It is important to note that this course was taught in a traditional way between weeks 4–7.

3.1 Behavioral Patterns and Multi-dimensional Profiles

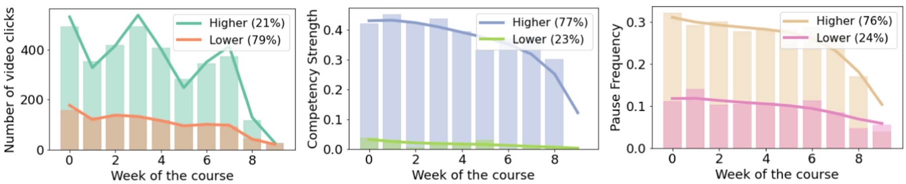
We first examined the profiles obtained for LA and then compared the profiles and behavioral patterns across courses (LA, FP, PC). Table 3 shows the characteristics of the identified profiles for all courses, i.e., the centroids from the *K-Modes* clustering. The centroid is the mode (majority label) of each learning dimension. For instance, for profile A, the majority of students were labeled *Lower Effort*.

Profiling for LA. We identified five profiles (A, B, C, D and E) for LA. To visualize their patterns, we inspected the barycenters (centroid) of each cluster. To compute the barycenter, we used the DTW Barycenter Averaging method that averages time series considering the DTW alignment and window constraint.

Figure 2 shows the barycenters as lines and the Euclidean mean of each week as bars for *Effort*, *Assessment*, and *Control*. Concerning the *Effort* dimension, the students with *Lower Effort* were less active (in terms of online time and number of video clicks) than the students with *Higher Effort*. One profile (C) exhibits

Table 3. Percentage of students per profile for each course and profile description.

Profile	%			Dimension					
	LA	FP	PC	*Effort*	*Consistency*	*Regularity*	*Proactivity*	*Control*	*Assessment*
A	24			Lower	Uniform	Lower Peaks	Delayed	Lower	Lower
B	18	28	35	Lower	Uniform	Lower Peaks	Delayed	Higher	Higher
C	19		18	Higher	Uniform	Higher Peaks	Anticipated	Higher	Higher
D	21			Lower	Uniform	Higher Peaks	Delayed	Higher	Higher
E	18			Lower	Uniform	Higher Peaks	Anticipated	Higher	Higher
F		15	27	Higher	Midterm	Higher Peaks	Delayed	Higher	
G		25		Higher	Midterm	Lower Peaks	Anticipated	Higher	
H		14		Lower	Midterm	Lower Peaks	Delayed	Lower	
I		18		Higher	Midterm	Higher Peaks	Anticipated	Higher	
J			20	Lower	Midterm	Lower Peaks	Anticipated	Lower	



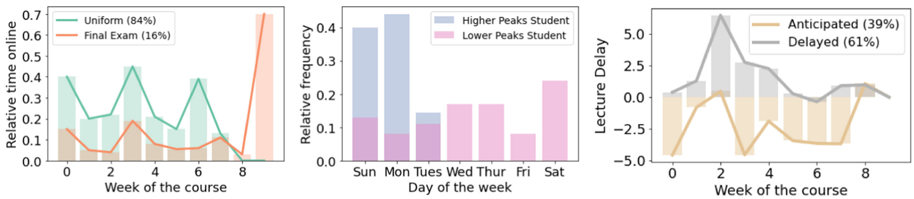
(a) (b) (c)

Fig. 2. Patterns for *Effort* (a), *Assessment* (b), and *Control* (c) for LA.

patterns of higher effort compared to the other four profiles. For *Assessment*, the difference between the detected patterns again lies mainly in the intensity (Fig. 2b). We observed two clusters, with one cluster (denoted as *Higher Assessment*) exhibiting a higher pattern than the other cluster (labeled as *Lower Assessment*). Different from *Effort*, most profiles showed *Higher Assessment*. The difference in competency strength between the two clusters is very large, with the *Lower Assessment* cluster having very low values. This observation could suggest that *Assessment* is reflecting the differences in students' willingness to solve the quizzes rather than measuring their actual quiz performance. For the *Control* dimension (Fig. 2c), we observed two groups: the *Higher* cluster (76%) had a greater ratio indicating that it pauses the video more often than the *Lower* cluster (24%). Higher pause frequency and longer pauses can be a result of students taking time to reflect on unclear or interesting parts of a video [15]. It is worth noting that *Control* and *Assessment* are the only dimensions that are paired. It is not surprising that the students that have *Higher Control* and manipulate the video content more are also the students with *Higher Assessment* that are engaged with the optional quizzes.

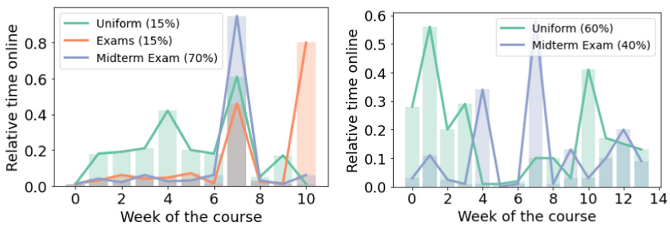
While the aforementioned dimensions mostly capture the differences in the intensity of student activity, *Consistency* captures differences in the relative intensity (in terms of online session time and video clicks) over the whole course. We obtained two distinct patterns shown in Fig. 3a. The majority of students (84%) worked consistently over time with little or no peaks (*Uniform*), while only a few students (16%) worked considerably more in the last week of the semester (*Final Exam*). Interestingly, all the `LA` profiles are labeled with *Uniform Consistency* (see Table 3). This means the *Uniform Consistency* students outnumber the *Final Exam Consistency* students in all profiles, indicating that the differences in other dimensions were more significant or separable.

Regarding the *Regularity* patterns, Fig. 3b shows an example of the relative frequency of events per day of the week for two example students. The (*Higher Peaks*) student worked only on Sundays, Mondays, and Tuesdays. In contrast, the student with (*Lower Peaks*) worked some weeks on Saturdays and other weeks on the other days of the week without a clear pattern (Fig. 3b). The in-person part of the course was taught on Tuesdays; this can explain the relative peak in activity for (*Higher Peaks*) on Monday. Students in profiles A, and B exhibit less regular working patterns than students in profiles C, D, and E.



(a) (b) (c)

Fig. 3. Patterns for *Consistency* (a), *Regularity* (b) and *Proactivity* (c) for `LA`.



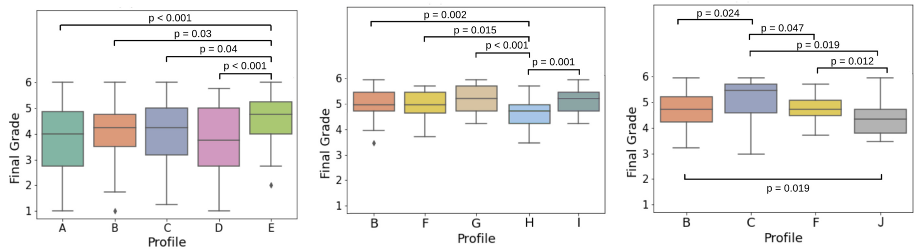
(a) (b)

Fig. 4. *Consistency* patterns for `FP` (a) and `PC` (b). In `FP`, most of the students show increased activity for exams. In `PC`, the majority works consistently.

Unlike other dimensions, *Proactivity* includes two features with contrasting behavior: content anticipation and delay in lecture view. Figure 3c shows that the *Anticipated* cluster (39%) has negative values in delay in lecture view, while the *Delayed* cluster (61%) has positive values with a peak in the beginning.

Comparison Across Courses. In a second analysis, we compared the profiles from `LA` with the ones identified for the other two courses (`FC` and the `PC`). We obtained a total of 10 profiles, listed in Table 3. Profile B was found in all three courses and profile C and F were found in two out of three courses.

From Table 3, it seems that *Consistency* has peculiar behavioral patterns between courses. Figure 4 presents the relative time online for `FP` and `PC`. In `FP`, three different patterns were identified (Fig. 4a). The students that worked strongly for the midterm (*Midterm*), those that had more activity before both the midterm and final exam (*Exams*), and those that had a normal-shaped activity with a visible peak one week before the midterm (*Uniform*). For `PC`, we observed two distinct behaviors (Fig. 4b). A group of students worked more during the weeks before the midterm (*Midterm*), whereas another group worked more consistently over the semester (*Uniform*). Note that there were no videos from weeks 4 to week 7 in this course, which explains the drop in activity during these weeks for the *Uniform* group. In contrast to `FP` and `PC`, there is no pattern in `LA` (see Fig. 3a) in which students work more intensely for the midterm exam; this could be a result of the weekly online quizzes that kept the majority of the students engaged almost uniformly during the semester.



(a) (b) (c)

Fig. 5. Academic performance for `LA` (a) and `FP` (b) and `PC` (c).

In summary, our approach can identify meaningful multi-dimensional profiles across courses with different topics and structures. We observed profiles with varying compositions and no completely aligned dimensions. The multiple combinations of dimensions reflect the complexity of learning behavior ***(RQ1)****.*

3.2 Relation to Academic Performance

We finally explored the relationship between the profiles and academic performance, measured using the students' final course grade[1]. For LA, a significant Shapiro-Wilk normality test ($W = 0.96$, p = 2.6e−07) indicated that the grades were not normally distributed. We hence used the non-parametric Kruskal-Wallis test to identify significant differences between profiles ($\chi^2(4) = 12.7$, p = 5.3e−03). We then performed pairwise comparisons between profiles using the Wilcoxon Rank Sum test[2]. Subsequently, we replicated the analysis using the grades from PC and FP[3]. Figure 5 shows the distribution of grades per profile.

In LA, students in profile E have significantly higher grades than the students in profiles A, B, C, and D. These differences in performance also emerge in the failure rate for each profile. Students in profile E have a lower chance of failing the course (failure rate: 19%) compared to students in profiles D (57%), A (48%), C (38%), and B profiles (36%). When we compare the four other profiles to profile E, we observe that *Proactivity* is the only difference between profiles E (the best performing profile) and D (the profile with the highest failure rate). Therefore, it seems that delaying lecture material and not being proactive results in worse academic performance. Likewise, profile E and C only differ in the *Effort* dimension, but surprisingly, profile E with *Lower Effort* outperforms profile C with *Higher Effort*. We hypothesize that in this case, *Effort* is an indicator of students struggling rather than a measure of commitment as expected [9].

In PC, profile C outperforms the other three profiles B, F, and J; while students in J perform poorly compared to profiles B, C, and F. In FP, students in profile H perform significantly worse than the students in B, I, F, and G. As shown in Table 3, these poor performing profiles (profiles H and J) are quite similar. The results are as expected since both have *Lower Effort*, *Lower Peaks* in *Regularity*, *Lower Control*, and increased activity before the midterm exam. For PC, it is hard to identify the dimension responsible for the worse academic performance of profile J, as the other profiles differ in several dimensions. For example, it would be inaccurate to say that profile F outperforms profile J despite having *Delayed Proactivity* because it is not the only dimension that varies. For PC and FP, the combination of dimensions explains the differences in performance rather than an isolated dimension.

In summary, we found significant differences in academic performance in all three courses. Although the level of significance varies across courses, we found coherent results between the shared profiles ***(RQ2).***

[1] Grades range from 1 to 6, with 6 being the best and 4 being the passing grade.

[2] Correcting for multiple comparisons via a Benjamini-Hochberg (BH) procedure.

[3] Shapiro-Wilk test for FP: $W = 0.97$, $p = 5.6\text{e}{-05}$; and PC: $W = 0.97$, $p = 3.1\text{e}{-03}$. Kruskal-Wallis Test for FP: $\chi^2(4) = 21.8$, $p = 2.2\text{e}{-04}$; PC: $\chi^2(3) = 13.4$, $p = 3.8\text{e}{-03}$.

4 Discussion and Implications

In this work, we combined multiple behavioral dimensions to obtain interpretable student profiles in FC and analyzed how these profiles and their behavioral patterns compare across courses (**RQ1**). We then showed the relation between those profiles and academic performance (**RQ2**). Unlike prior work mostly focusing on a single FC course [12,23], we applied our pipeline to three courses (`LA`, `FP` and `PC`) with different topics, instructors, FC period length, and study level.

Our results showed that our pipeline can identify interpretable student profiles in FC, with some of them showing similar behavior across different courses and others associated with a behavior unique to a specific course (**RQ1**). In addition, our results emphasize the importance of taking into account the dependencies between learning dimensions and analyzing them in combination rather than focusing on an isolated dimension. It is noteworthy that despite *Effort*, *Consistency*, *Regularity* and *Proactivity* are SRL skills, they do not always go hand-to-hand in the profiles description. For example, *Effort* appears to be constant in several profiles, and the profiles with the same effort magnitude differ based on other dimensions (e.g., *Consistency*). This is in line with [19], where three groups showed the same effort but a different consistency. Interestingly, a profile with a *Lower*, *Decreasing*, and *Delayed* patterns in all dimensions was also found among university students with high dropout rates [14] and profiles A and H resemble the minimalist behavior identified by [23].

Our analyses also confirmed that there were some significant differences in academic performance between the profiles (**RQ2**). From a pedagogical perspective, these results are mostly coherent with findings from prior work (e.g., [4,6,10,25]) showing that achievement is significantly higher for students with high SRL skills (focusing on a single dimension). In `LA`, surprisingly, counter to the work of [9], keeping all the other dimensions equal, the *Lower Effort* profile (E) outperformed the *Higher Effort* profile (C). In contrast, in `PC`, profile C (with *Higher Effort*) was the best performing profile. These differences exemplify how the proposed pipeline expresses the profiles relative to the classmates of each course. Likewise, the results from `LA` showed that *Proactivity* appeared to be the most indicative behavioral dimension for academic performance: watching the lecture videos ahead of schedule (like profile E) was associated with good academic performance, while delaying lecture material (like profile D) was related to inferior academic performance, in line with [17]. Nevertheless, in `PC`, profile F with *Delayed Proactivity* outperformed profile J with *Anticipated Proactivity*. This does not rule out the importance of *Proactivity* but rather the limitations of analyzing dimensions separately. Profiles F and J also differ in *Effort*, *Regularity* and *Control*, thus, the differences in academic performance in `PC` and `FP` can be better explained with multi-dimensional profiles. Instructors should acknowledge this to foster learning profiles beneficial to their course (e.g., profile E), and prevent counterproductive behaviors (e.g., profile H).

In this work, we used three different data sets to provide a diverse evaluation of our approach. From a research perspective, we proposed a method to help both researchers and practitioners improve the understanding of student learning in FC. From a teacher's perspective, this study enables data-driven course modifications (e.g., weekly quizzes) and better-informed student interventions. In addition, students could receive automatic personalized feedback and recommendations depending on their profile. Overall, our work contributes to the ongoing research of reusable analytics and to the generality of theories and patterns of SRL. Nevertheless, further work is needed to assess the generalizability of our results in other educational contexts.

References

1. Akpinar, N., Ramdas, A., Acar, U.: Analyzing student strategies in blended courses using clickstream data. In: Proceedings of the EDM, pp. 6–17 (2020)
2. Bassett, K., Olbricht, G.R., Shannon, K.B.: Student preclass preparation by both reading the textbook and watching videos online improves exam performance in a partially flipped course. CBE Life Sci. **19**(3), ar32 (2020)
3. Beatty, B.J., Merchant, Z., Albert, M.: Analysis of student use of video in a flipped classroom. TechTrends **63**(4), 376–385 (2019)
4. Biard, N., Cojean, S., Jamet, E.: Effects of segmentation and pacing on procedural learning by video. Comput. Hum. Behav. **89**, 411–417 (2018)
5. Boroujeni, M.S., Dillenbourg, P.: Discovery and temporal analysis of latent study patterns in MOOC interaction sequences. In: Proceedings of the LAK, pp. 206–215 (2018)
6. Boroujeni, M.S., Sharma, K., Kidziński, Ł., Lucignano, L., Dillenbourg, P.: How to quantify student's regularity? In: Proceedings of the EC-TEL, pp. 277–291 (2016)
7. Broadbent, J., Poon, W.L.: Self-regulated learning strategies & academic achievement in online higher education learning environments: a systematic review. Internet High. Educ. **27**, 1–13 (2015)
8. Chen, F., Cui, Y.: Utilizing student time series behaviour in learning management systems for early prediction of course performance. J. Learn. Anal. **7**(2), 1–17 (2020)
9. Cho, M.H., Shen, D.: Self-regulation in online learning. Distance Educ. **34**(3), 290–301 (2013)
10. Corrin, L., de Barba, P.G., Bakharia, A.: Using learning analytics to explore help-seeking learner profiles in MOOCs. In: Proceedings of the LAK, pp. 424–428 (2017)
11. Geertshuis, S., Jung, M., Cooper-Thomas, H.: Preparing students for higher education: the role of proactivity. Int. J. Teach. Learn. High. Educ. **26**(2), 157–169 (2014)
12. Jovanovic, J., Gasevic, D., Dawson, S., Pardo, A., Mirriahi, N.: Learning analytics to unveil learning strategies in a flipped classroom. Internet High. Educ. **33**, 74–85 (2017)
13. Jovanovic, J., Mirriahi, N., Gašević, D., Dawson, S., Pardo, A.: Predictive power of regularity of pre-class activities in a flipped classroom. Comput. Educ. **134**, 156–168 (2019)
14. Khalil, M., Ebner, M.: Clustering patterns of engagement in Massive Open Online Courses (MOOCs): the use of learning analytics to reveal student categories. J. Comput. High. Educ. **29**(1), 114–132 (2016). https://doi.org/10.1007/s12528-016-9126-9

15. Lallé, S., Conati, C.: A data-driven student model to provide adaptive support during video watching across MOOCs. In: Proceedings of the AIED, pp. 282–295 (2020)
16. Lee, J., Choi, H.: Rethinking the flipped learning pre-class: its influence on the success of flipped learning and related factors. Br. J. Educ. Technol. **50**, 934–945 (2019)
17. Marras, M., Vignoud, J.T.T., Käser, T.: Can feature predictive power generalize? Benchmarking early predictors of student success across flipped and online courses. In: Proceedings of the EDM, pp. 150–160 (2021)
18. McBroom, J., Yacef, K., Koprinska, I.: DETECT: a hierarchical clustering algorithm for behavioural trends in temporal educational data. In: Proceedings of the AIED, pp. 374–385 (2020)
19. Mojarad, S., Essa, A., Mojarad, S., Baker, R.S.: Data-driven learner profiling based on clustering student behaviors: learning consistency, pace and effort. In: Nkambou, R., Azevedo, R., Vassileva, J. (eds.) ITS 2018. LNCS, vol. 10858, pp. 130–139. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-91464-0_13
20. Mubarak, A.A., Cao, H., Ahmed, S.A.: Predictive learning analytics using deep learning model in MOOCs' courses videos. Educ. Inf. Technol. **26**(1), 371–392 (2021)
21. Ng, A.Y., Jordan, M.I., Weiss, Y., et al.: On spectral clustering: analysis and an algorithm. Adv. Neural. Inf. Process. Syst. **2**, 849–856 (2002)
22. O'Flaherty, J., Phillips, C.: The use of flipped classrooms in higher education: a scoping review. Internet High. Educ. **25**, 85–95 (2015)
23. Pardo, A., Gašević, D., Jovanovic, J., Dawson, S., Mirriahi, N.: Exploring student interactions with preparation activities in a flipped classroom experience. IEEE Trans. Learn. Technol. **12**(3), 333–346 (2018)
24. Rousseeuw, P.J.: Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. J. Comput. Appl. Math. **20**, 53–65 (1987)
25. Sher, V., Hatala, M., Gašević, D.: Analyzing the consistency in within-activity learning patterns in blended learning. In: Proceedings of the LAK, pp. 1–10 (2020)
26. Sletten, S.R.: Investigating flipped learning: student self-regulated learning, perceptions, and achievement in an introductory biology course. J. Sci. Educ. Technol. **26**(3), 347–358 (2017)
27. Vermunt, J.D., Donche, V.: A learning patterns perspective on student learning in higher education: state of the art and moving forward. Educ. Psychol. Rev. **29**(2), 269–299 (2017)
28. Wan, H., Liu, K., Yu, Q., Gao, X.: Pedagogical intervention practices: improving learning engagement based on early prediction. IEEE Trans. Learn. Technol. **12**(2), 278–289 (2019)