Cluster and trajectory analysis of motivation in an emergency remote programming course

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Abstract

Emergency remote teaching is a temporary change in the way education occurs, whereby an educational system unexpectedly becomes entirely remote. This article analyses the motivation of students undertaking a university course over one semester of emergency remote teaching in the context of the COVID-19 pandemic. University students undertaking a programming course were surveyed three times during one semester, about motivation and COVID concern. This work explores which student motivation profiles existed, how motivation evolved, and whether concern about the pandemic was a factor affecting motivation throughout the course. The most adaptive profile was highly motivated, more prepared and less frustrated by the conditions of the course. However, this cluster experienced the highest levels of COVID-19 concern. The least adaptive cluster behaved as a mirror image of the most adaptive cluster. Clear differences were found between the clusters that showed the most and least concern about COVID-19.

Introduction

Motivation, or “the energization and direction of behavior” (Elliot and Covington 2001), can affect student learning and performance in class (Vu et al. 2021). Indeed, motivation has often been the subject of analysis in education, both in school (Ng, Wang, and Liu 2015) and university (Çebi and Güyer 2020), as well as in multiple delivery formats, e.g. face-to-face (Ng 2016), online (Ferrer et al. 2020), and blended (Li and Tsai 2017). The onset of the COVID-19 pandemic forced many institutions to begin *emergency remote teaching (ERT)* (Hodges et al. 2020). ERT is a temporary change in the way education occurs during exceptional crisis circumstances, whereby an educational system that was previously based on face-to-face or blended teaching becomes entirely remote. Unlike online learning, in which education is planned

from the outset to operate in this format, ERT is applied in a disruptive way, and is likely to return to its original mode once the emergency is over (Hodges et al. 2020).
In an ERT course, teachers and students face several challenges. For teachers, these challenges arise from the need to replan entire courses in a short period of time, acquire new competences and learn how to use new technologies (Jimoyiannis, Koukis, and Tsiotakis 2021). Students may face concentration-related problems, as well as difficulty in interacting directly with teachers (Shim and Lee 2020) and forming bonds with their peers (Ferri, Grifoni, and Guzzo 2020). In addition, remote working conditions may not be optimal for either group, e.g., due to cramped working spaces, unstable internet connection or having to share a computer (Oliveira et al. 2021). For example, lower access to broadband internet was found to correlate with lower engagement among students during the pandemic (Domhnaill, Mohan, and McCoy 2021).
Consequently, maintaining motivation in an ERT course may be even more difficult than in a face-to-face, online or blended course. Providing greater understanding of motivation in an ERT setting may help education authorities make improved decisions in the face of multiple and fluid motivational scenarios in a future crisis involving ERT. In the case of novice programmers in a hybrid course, students were found to need a sense of belonging and connectedness to others, to maintain motivation (Lohiniva and Isomöttönen 2021).
This research focuses on an emergency remote programming course (ERPC) in Santiago, Chile, during the second academic semester of 2020 (August-December). The research questions that guided this study were the following:

- **RQ1**: Which student motivation profiles exist in emergency remote courses during the COVID-19 pandemic?
- **RQ2**: How does motivation evolve among students undertaking an emergency remote course during the COVID-19 pandemic?
- **RQ3**: Is concern about the pandemic a factor that affects the evolution of motivation?

To answer these questions, three surveys were conducted: the first (T1) was carried out in September, the second (T2) in October and the third (T3) in November. To quantify student motivation, the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al. 1991, Credé and Phillips 2011) was applied. This questionnaire is in the public domain, and no specific permissions are required for it to be applied (Duncan and McKeachie 2005). With the collected information, motivation profiles were generated by means of clustering, and the profile of each student was evaluated across the three stages of the survey, thus enabling course-based motivation trajectories to be generated, by using process mining algorithms.

Emergency remote teaching and motivation

A decrease in student motivation was found during the period of the pandemic in which students switched to the ERT learning modality (Camacho-Zuñiga et al. 2021). Students experienced greater problems completing assignments on time, managing their time and organizing their studies, interacting with teachers and teaching assistants, (Pelikan et al. 2021), as well as more distractions and lower levels of concentration (Hussein et al. 2020). Social and peer interaction also became a challenge for students (Pelikan et al. 2021), and in some cases led to a lack of motivation to study (Kapasia et al. 2020). Accordingly, higher levels of motivation were associated with assignments that specifically promoted social interaction (Ismailov and Ono 2021). Emotional and mental health problems were also reported, with several studies finding experiences of stress, anxiety, depression, feelings of being overwhelmed (Camacho-Zuñiga et al. 2021) and worries about contracting COVID-19 (Aguilera-Hermida 2020).

Despite these difficulties, some students reported some benefits of ERT, such as saving on commute time, decreasing costs (Hussein et al. 2020), having more time for hobbies, getting more sleep, and spending more time with their families (Aguilera-Hermida 2020). Indeed, some studies have reported cases of students who have maintained or even increased their levels of motivation, e.g. due to a sense of challenge to achieve personal goals (Rahiem 2021).

Regarding computer science students, one study concluded that despite the advantages computer science students might be expected to have in an online environment, the difficulties for them are the same under the ERT modality as for other students (Toti and Alipour 2021). Furthermore, the negative impact of ERT was found to be greater for students in earlier grades, and significant differences in terms of motivation to learn were reported when comparing undergraduate and graduate students.

Measuring motivation

The Motivated Strategies for Learning Questionnaire (MSLQ) has been used to assess the motivations and learning strategies of students (Credé and Phillips 2011). The present study uses the motivation section of the instrument, which consists of six scales. Although some researchers have used a *variable-centered approach*, i.e., analyzing each variable individually, this research uses a *person-centered approach*, which involves studying the person or group as a whole and measuring how they behave under the combination of certain variables (Hayenga and Corpus 2010).

Several studies have attempted to find the most adaptive and least adaptive (or maladaptive) clusters of students, whereby the greatest academic benefits are achieved by students whose profiles consist of the best combination of motivational, learning and psychological variables (Kong and Liu 2020). Adaptive profiles are generally considered to be those that combine high levels of intrinsic goal orientation (Liu et al. 2021), self-efficacy (Kong and Liu 2020), task value (Liu et al. 2014), control of learning beliefs (Çebi and Güyer 2020) and low levels of anxiety (Liu et al. 2021), which is also found in courses associated with computer science (Çebi and Güyer 2020). There is not a consensus as to whether extrinsic goal orientation is related to more or less adaptive profiles (Çebi and Güyer 2020). More adaptive profiles tend to be associated with better results (Broadbent and Fuller-Tyszkiewicz 2018).

Taking gender into account, one study found that the cluster with more women experienced slightly better levels of self-regulation, but that they were less prepared for the online learning environment (Yukselturk and Top 2013). Conversely, another study reported that women were over-represented in a cluster associated with low self-efficacy; however, this could be due to the

context, which was a highly competitive, male-dominated business administration degree (Bråten and Olaussen 2005).
While previous research has infrequently studied student movements between clusters, some research considers the transition of students from one profile to another at two points during the period of stud. Movements by individuals from the most adaptive to the least adaptive profile, and vice versa, are very rare (Bråten and Olaussen 2005; Ng, Wang, and Liu 2015). Our research considers using exactly the same profiles at three set points in the semester, enabling studying student motivation trajectories.

Study Context

COVID-19
The COVID-19 outbreak was declared a pandemic in March 2020 (World Health Organization 2021). The pandemic seriously impacted people's lives, e.g. through the direct fear of the SARS-CoV-2 virus itself, due to the possible consequences that infection might have on people or their loved ones (Günaydın 2022). The present study was conducted before the approval and use of vaccines and drugs against COVID-19, so this type of fear may have been an important factor in shaping the emotions and decisions made by our participants.
Several instruments have been developed to measure and study fear of COVID-19, e.g. the Fear of COVID-19 Scale (FCV-19S) (Ahorsu et al. 2020). Generally, psychological distress is associated to academic burnout in higher education students (Emerson, Hair, and Smith 2022), and poorer wellbeing is correlated to decreased self-reported academic performance (Malta et al. 2022). Previous studies found a significant correlation between fear of COVID-19, depression and anxiety (Ahorsu et al. 2020), as well as anger, fear and disgust (Mailliez, Griffiths, and Carre 2021). However, fear of COVID-19 was found in one case to have a positive impact on academic motivation (Günaydın 2022).
Our study took place in Chile. Two weeks after the first case of COVID was detected in March 2020, several contingency measures were implemented, including curfews and a plan in which each geographical area of the country was assigned a set of restrictions (e.g. quarantines and the closure of non-essential establishments) (Chilean Government 2021). In the three periods in which online surveys were conducted to collect data for this article, the average number of daily cases was T1=1,770 (median weekly average per 100,000 inhabitants (MWA) = 8.98); T2=1,378 (MWA = 7.54); and T3=1,303 (MWA = 7.18) (Ministry of Science, Technology, Knowledge and Innovation (Chile) 2021).

University and course
The Pontificia Universidad Católica de Chile (UC) is a prestigious university located in Latin America, with more than 3,500 teachers and 33,000 students (QS, 2020). This study was carried out in the Introduction to Programming undergraduate course, a compulsory module at UC for engineering, economics, physics, statistics and astronomy students. It is also on a list of electives

for students from certain programs and can be taken optionally by any other student. The course teaches 1,200 students per semester, divided into between 8 and 10 groups.

Prior to the pandemic, assessments in this course consisted of coding assignments submitted through a virtual mailbox, as well as written exams. However, the course became an ERPC during the pandemic and adopted the use of online judges for all assessments, i.e., web-based applications that allow for the storage of programming problems in which, through predefined inputs and outputs, students' code can be automatically evaluated (Yera et al. 2018).

Materials & Methods

Procedure

Data was collected through 3 voluntarily completed online surveys, using the SurveyMonkey software. Eligible participants were those enrolled in the Introduction to Programming course during the second academic semester of 2020 (August to December). There were 1,085 students enrolled in the course, distributed across 8 groups. Invitations to answer the surveys were sent once per survey, through the Canvas learning management system software. Students who responded were compensated with a small number of points towards one of their grades. For this reason, as well as to filter out students who did not answer all 3 surveys, we asked students to provide an identity number. The *Comité de Ética en Ciencias Sociales, Artes y Humanidades* from the Pontificia Universidad Católica de Chile granted approval to carry out this study (Reference number 200417001).

Measures

Demographic and Descriptive Data

Demographic data, including age, gender, and ethnic background, was collected, as well as information regarding prior programming knowledge. At the end of the semester data was collected on the pass/fail status of students and their final grade (a number from 1.0 to 7.0, with 4.0 being the minimum passing grade).

MSLQ questions

Only the motivation section of the MSLQ questionnaire was used for this study. This section consists of 6 scales. To obtain a score for each scale, values were averaged for each item, which were answered on a 5-point Likert scale. Each scale is described below (Credé and Phillips 2011):

- Intrinsic goal orientation: whether the student perceives that they are participating in the course out of curiosity, to learn and master a subject (4 items).
- Extrinsic goal orientation: whether the student participates in the course for rewards, grades, competition and recognition (4 items).

- Task value: how the student evaluates the course in terms of importance, usefulness and interest (6 items).
- Control of learning beliefs: learner's belief that course results depend on their effort rather than on external factors (4 items).
- Self-efficacy for learning and performance: student's expectation that they will perform well and confidence on their skills (8 items).
- Test anxiety: negative thoughts that a student may experience during a test (5 items).

COVID concern and emergency remote conditions

Four additional questions were included to represent emergency remote conditions. Of these, "I feel frustrated because my courses are online" used a 5-point Likert scale; "How comfortable do you feel with the use of a computer in your day to day?" used a 3-point Likert Scale and "My internet connection is stable" and "I have a computer for my exclusive use" had "Yes/No" options.

A COVID concern variable, with questions on a 5-point Likert scale, that incorporated not only the fear of the risk of exposure to the virus (as previous scales such as FCV-19S) but also the concern that may be generated by the risk posed by the virus to others, was also included (Table 1). (Cronbach's alpha in T1 = 0.71; Cronbach's alpha in T2 = 0.74; Cronbach's alpha in T3 = 0.76).

Participants

There were 745 valid responses to survey 1,678 valid responses to survey 2 and 727 valid responses to survey 3. The responses used for this study were only those in which respondents had provided full answers to the 3 surveys, in addition to having signed the consent form. Responses were also removed when participants did not provide their student ID, provided an incorrect student ID (e.g. their name, or less characters than valid IDs), or answered the survey more than once (only the first answer was considered). Complete responses were collected from 481 students (318 men, 158 women, 5 others; average age = 18.94, minimum age = 18 years, age SD = 2.06), i.e., 44.3% (481/1085) of all enrolled students. Of the 481 students, 88.15% were in their first year of university, 83.58% were studying engineering, and 30.35% reported having some previous programming experience. Since each of the 481 students answered the survey 3 times, a universe of 1,443 responses was collected.

Analytic approach

Cluster analysis

Student profiles were differentiated using the k-means clustering technique (Jain 2010), using the 6 MSLQ-motivation scales as input. Two k-means techniques (elbow and silhouette method) were used to find the number of clusters, and a dendrogram was used to validate that a reasonable number of clusters had been chosen.

Subsequently, the z-scores of the clusters in each of the scales were calculated. Scores above 0.5 were categorized as high, between 0.0 and 0.5 as moderate-high, between 0.0 and −0.5 as moderate-low, and below −0.5 as low, as in previous research (Ng 2016).
Statistical tests were applied to evaluate significant differences between the profiles and variables considered in the study, in order to distinguish and categorize each of the clusters. In general, one-vs-all classifications were applied to find profiles with higher or lower values in their variables compared to the remaining clusters. The tests included: a chi-square test of independence, to determine the presence of dependence between the clusters and the categorical variables; a two proportion z-test, to compare the proportions of people trained in the categorical variables among the different profiles; a Kruskal-Wallis test, to contrast if the variable was equally distributed among the profiles; a Mann-Whitney-Wilcoxon test, to establish whether, in general, any particular cluster had a numerical variable with higher or lower values with regards to others; a Welch test, to establish whether any particular cluster differed in value from another in a numerical variable, considering situations in which the variance was not homogeneous. All tests were run at a significance level of 5%. For cases of multiple comparative tests between clusters, a Holm-Bonferroni correction was executed with an α-correction of 0.016. All the analyses were performed using python 3.8.

Trajectory Analysis

In order to visualize the trajectories of the students, we applied a process mining (van der Aalst 2016) approach. The directly-follows graph (DFG) algorithm (van der Aalst 2019) in its Disco software implementation (Günther and Rozinat 2012) was used to model, by means of absolute frequencies, the number of events in each profile and the nature of the transitions between each one, as well as to reflect their respective beginning and completion points in the course. This algorithm was used because it is easily interpretable by education experts (Mahauad et al. 2018).

Results

This section answers the research questions posed in the Introduction. Each subsection represents one research question and its respective answer.

Motivation profiles in ERT during the COVID-19 pandemic (RQ1)

We obtained four clusters. Figure 1 shows the values of each of their dimensions, after having applied a z-score normalization. Table 2 summarizes the results obtained from the z-scores of the 4 profiles. Each cluster is described below.
Cluster 1 (19.68%) is notable due to all its dimensions being low except for test anxiety, which is the highest among all groups (z-score = 1.06). This group has the lowest scores in intrinsic goal orientation (z-score = -1.40), task-value (z-score = 1.50), control of learning beliefs (z-score = -1.48) and self-efficacy for learning and performance (z-score = -1.49). This cluster was assigned the name *Passive Learner* as it represents the least adaptive profile and, in general, the lowest levels of motivation and self-efficacy.

In contrast, *Cluster 2* (25.71%) is notable due to all its dimensions being high except for test anxiety, which is low. This group has the highest scores in intrinsic goal orientation (z-score = 1.42), task value (z-score = 1.29), control of learning beliefs (z-score = 1.33) and self-efficacy for learning and performance (z-score = 1.31). This cluster was assigned the label *Active Learner*, for having, in contrast to *Passive Learner*, the highest levels of motivation and self-efficacy, and therefore represents the most adaptive profile.

Cluster 3 (25.71%), provides the lowest scores in extrinsic goal orientation (z-score = -1.21) and test anxiety (z-score = -1.12). It also shows a low-moderate task value. The remaining dimensions are moderate-high. This cluster was assigned the label *Indifferent Learner* because it yields moderate or low levels of motivation, in conjunction with the lowest anxiety.

Cluster 4 (28.89%) is notable due to having the highest score on extrinsic goal orientation (z-score = 1.23). Its scores on test anxiety are also high and on both task value and control learning beliefs, moderate-high. However, its intrinsic goal orientation and self-efficacy for learning and performance scores are moderate-low. This cluster was assigned the label *Reward-oriented Learner*, as it had the highest value in that respective dimension, in addition to high anxiety.

To evaluate the consistency of the MSLQ scales used in the clusters, Cronbach's alphas were calculated for each of the 3 periods studied during the semester. The scales with the best consistency were self-efficacy and task value, all of the values of which were equal to or greater than 0.9. These were followed by the test anxiety and intrinsic goal orientation scales, both of which had values equal to or greater than 0.75. Finally, control of learning beliefs and extrinsic goal orientation showed less satisfactory results, with the first having an alpha lower than 0.7 at T1 while the latter had alphas lower than 0.7 at T1, T2 and T3.

To characterize each of the clusters, a descriptive analysis was conducted. Table 3 shows the results of each variable in a differentiated manner, segmented by profile and total study population. Table 4 displays the statistical tests performed on each of the variables, and summarizes the main results.

Representation of trajectories (RQ2)

Individual students' motivation trajectories are shown in Figure 2. The inverted triangle at the top represents the beginning of the semester, while the outgoing arcs show the number of students who began the course in each respective profile (T1). Similarly, the rectangle towards the bottom represents the end of the academic semester (T3). Its input arcs show the number of students who completed the semester in each profile. Accordingly, the intermediate arcs represent the movements between profiles throughout the semester (T1 to T2 and T2 to T3). In addition, under the name of each profile is the absolute frequency of events in each cluster, i.e., the number of students that constitute a profile.

Beginning and end of the trajectories

Most of the students began the semester in the *Indifferent Learner* profile, with 166/481 (34.51%) cases, while only 71/481 (14.76%) began in the *Passive Learner* profile. However, the profile in which the least number of learners completed the semester was *Indifferent Learner*, with 92/481 (19.12%) cases. The rest of the clusters showed no major differences at T3. Comparing the initial and final status of each profile, the *Indifferent Learner* cluster was that with the greatest outflow of students. At the end of the academic period, it consisted of 44.57% fewer people than at the beginning. Conversely, the remaining clusters showed an increase of students. The profile that experienced the highest increase of students was *Passive Learner*, which grew by 81.69%.

Movements between profiles

Regarding movements between profiles, the largest number was from the *Indifferent Learner* cluster to the *Reward-oriented Learner* cluster with 73 cases, followed by movements from the *Reward-oriented Learner* cluster to the *Passive Learner* cluster with 55 cases, then from *Indifferent Learner* to *Passive Learner* with 45 cases, and from *Reward-oriented Learner* to *Indifferent Learner* with 43 cases.

The *Indifferent Learner* profile had the highest outflow with 158/371 cases, i.e., 42.58% of those who began the semester in the profile. Similarly, the *Reward-oriented Learner* profile also experienced a high degree of outflow, with 129/417 cases of students moving to another cluster, or 30.93%. The *Reward-oriented Learner* cluster was also the group that experienced the highest inflow, with 135/417 cases, thus representing 32.37% of its total case frequency.

Most frequent variants of the trajectories

Table 5 shows the 10 most frequent variants of the student trajectories. The Type column shows the movement patterns followed regarding the 3 periods studied during the semester.

The first 4 variants are of the AAA type, i.e., in 40.33% of cases, students remained in the same profile throughout the 3 periods in question. However, the next 6/10 most frequent variants, totalling 20.58% of all cases, are primarily of the ABB type, except for one AAB type. If all trajectories (51) are considered, in 63.61% the profile at T2 and T3 remained the same for the student. This includes the AAA and ABB patterns.

There were no cases of movements from the *Passive Learner* to the *Active Learner* profile and only 5 cases in which a student moved directly from the *Active Learner* to the *Passive Learner* profile (Fig. 2). Considering all trajectories, there was only one case of a student who began the semester in the *Passive Learner* profile and completed it in the *Active Learner* equivalent, and only three cases of students who began in the *Active Learner* and finished in the *Passive Learner* cluster.

Comparison of motivational trajectories according to COVID concern (RQ3)

A comparative study was conducted between the trajectories of students with a high COVID concern z-score (greater than 0.5) and those with a low z-score (less than −0.5), based on an average taken from across T1, T2 and T3. Figure 3 shows the trajectories of students with high z-scores, corresponding to 166/481 cases, or 34.51% of the total population. The predominant profile here was *Active Learner*, as 75/166 (45.18%) students began in this cluster while 101/166

(60.84%) completed the semester in this cluster. For the *Passive Learner* profile, 5/166 (3.01%) cases began the semester in the cluster and 3/166 (1.80%) cases ended the semester in it. Only 5/166 (3.01%) students with a high COVID concern moved towards this profile throughout the entire academic period.

Figure 4 shows the behavior of students with a low COVID concern. This segment was composed of 150/481 (31.18%) students. The *Passive Learner* profile predominated, having the highest inflow of cases. Moreover, 93/150 (62.00%) students completed the semester in this profile. In the case of the *Active Learner* cluster, only 12/150 (8.00%) students began the semester in this cluster and even fewer ended the semester in this cluster (5/150, 3.33%)

Discussion

Student profiles

Student final grades are in line with previously identified positive correlations between intrinsic goal orientation (Broadbent and Fuller-Tyszkiewicz 2018), self-efficacy (Valle et al. 2015), task value (Ng 2016) and academic performance. One of the causes that could be a contributory factor to these differences between the profiles is the learning environment and psychological preparation for the ERT scenario. The *Active Learner* profile showed lower levels of frustration due to the course being online, which could indicate that this profile was less affected from ERT conditions. In contrast to the *Passive Learner* profile, the *Active Learner* cluster had students who were more comfortable using a computer and had more previous programming experience. For the *Passive Learner* cluster, this would be a disadvantage not only for being in a programming course, but also for being in an online environment.

The *Active Learner* profile was the one that showed the highest levels of COVID concern. Although several studies have shown that fear of COVID is associated with adverse psychological outcomes, our results are in line with the findings of other research in which COVID fear had a positive impact on academic motivation (Günaydın 2021). Moreover, in this study the problem-solving skills of students was a positive and significant predictor of COVID-19 fear, which could indicate that more rational people are more realistic and may, therefore, have a greater concern about the virus.

When comparing the *Indifferent Learner* and *Reward-oriented Learner* profiles, it was difficult to determine which of the two was the more adaptive. Both had fairly similar values in terms of grades and MSLQ variables but differed significantly in extrinsic goal orientation and test anxiety. Previous studies have reported varying results regarding the role of extrinsic goal orientation (Çebi and Güyer 2020; Hayenga and Corpus 2010), however, anxiety has generally been associated with negative motivational profiles (Ng 2016). Regarding the descriptive variables, although no significant differences with the other clusters were detected, there are some differences: the *Indifferent Learner* cluster showed a slightly higher proportion of students with previous programming experience, somewhat lower levels of frustration because the courses were online, and a marginally higher proportion of students who felt comfortable using a computer. This suggests that these students were a little more adjusted to the course and modality. Given the above, we posit that *Indifferent Learner* students were more adaptive than *Reward-oriented Learner* students.

Student trajectories

Student trajectories showed a predominance of the *Indifferent Learner* profile at the beginning of the semester. However, it was the cluster with the least number of students to complete the semester and the only one which experienced a decrease over the semester. This indicates that a significant proportion of the students initially had more moderate levels of motivation, COVID concern, and anxiety, but subsequently evolved over the course of the semester towards less conservative positions. The *Passive Learner* profile was the group with the fewest students at the beginning of the course, but which experienced the highest growth. This suggests high levels of lack of motivation, increased anxiety, and a lack of COVID concern. On the other hand, the *Reward oriented Learner* profile experienced the highest absolute frequency of learners. It was the profile with the highest inflow and the second highest outflow, being a high turnover cluster. Moreover, 50.93% of all students spent at least one period of the semester in this group, while 27.02% spent two or more periods therein. This indicates that a considerable proportion of the students perceived, at some point during the semester, that their predominant motivation was extrinsic, while their test anxiety was high.

Regarding the variants of the trajectories, the most frequent were found to be those in which students remained in the same profile during the three periods. Specifically in this study, the *Active Learner* profile was the most stable in terms of case inflow/outflow during the semester. The remaining principal variants were mostly cases in which the student began in one cluster but then moved to another and remained in that cluster during the second and third periods. This may suggest that the motivation of students in the first period was subject to expectations driven by uncertainty about the new modality and the pandemic. Another phenomenon was that there was almost no direct movement from the *Passive Learner* to the *Active Learner* profile and from the *Active Learner* cluster to the *Passive Learner* cluster. This may indicate that, despite the variability of movement between profiles, moving from a more adaptive to a less adaptive profile, and vice versa, requires a far more drastic change in terms of motivation, study habits and study environment, the occurrence of which is far less likely. This effect has also been found in other research that analyzed profile changes over time (Bråten and Olaussen 2005).

Specifically in the trajectories with the highest and lowest COVID concern levels, substantial differences were obtained, especially regarding the *Passive Learner* and *Active Learner* profiles, showing that very different trajectories are possible albeit dependent on COVID concern.

Conclusions

Four learner profiles were identified among students taking an ERT university programming course. The *Passive Learner* cluster was the least adaptive, with low levels of intrinsic goal orientation, task value, control of learning beliefs and self-efficacy, and high test anxiety. This cluster had a higher proportion of women than men (51.06%), a lower proportion of students with prior programming experience, a higher proportion who felt less comfortable using a computer, lower academic results, and a lower level of COVID concern. The *Active Learner* cluster was the most adaptive, an approximate mirror image of the Passive Learner profile, with the best academic results, a significantly lower proportion of women (19.68%), and a significantly higher proportion of students with previous programming experience. However, students in this cluster had higher levels of COVID concern. The *Indifferent Learner* cluster had the lowest levels of extrinsic goal orientation and test anxiety, which suggests low concern about academic performance. Finally, the *Reward-oriented Learner* cluster had the highest level of extrinsic goal orientation, as well as high anxiety, thus having the highest levels of motivation to achieve improved grades and external recognition. The *Indifferent Learner* profile was determined to be more adaptive than the *Reward-Oriented Learner* profile.

Most of the students began the semester in the *Indifferent Learner* profile. As the semester progressed, some students migrated to alternative profiles, but most remained at the same profile or only transitioned between profiles once, so there was a certain stability in the levels of motivation and anxiety. The trajectories of the students who were most concerned about COVID-19 were dominated by the *Active Learner* profile, while the trajectories of those least concerned related primarily to the *Passive Learner* profile. This shows that the trajectories not only differ, but also are mainly composed of the most and least adaptive profiles. Differences in student motivation are not only static, as determined by the different clusters, but also dynamic, as presented by the different trajectories.

There are several limitations to this study that we would like to acknowledge. First, Cronbach's alpha revealed low consistency in the responses associated with two scales. The surveys include a non-response bias due to self-selection. Attrition bias must also be taken into account due to participants who did not answer all three surveys. Surveys answered in an erroneous way, e.g., individuals who miswrote their identity number or who did not give informed consent, were excluded, thus possibly generating a selection bias. It is also important to consider differences in motivation that may have been generated between the 8 different groups undertaking the course. Indeed, recorded classes with better quality teachers produce improved student outcomes (Clark et al. 2021). Although all teachers adhered to the same assessments and assignments, their teaching styles may have varied, potentially affecting students' performance and motivation. Regarding study participants, a large number of students passed the course, when compared to previous semesters with pen-and-paper assessments, in which the passing rate was around 75%-80%, and compared to the first post-pandemic semester that used online judges, in which the passing rate was 47%. Plagiarism detection was used during the semester in question, but it is possible that some students did not work individually and were not detected.

As future work, consideration should be given to the inclusion of the resource management strategy questions from the learning strategies subsection of the MSLQ, which may help characterize student behavior. It is also important to study the relationship between students' mental health and their motivation trajectories.

References

Aguilera-Hermida, A.P. 2020. "College students' use and acceptance of emergency online learning due to COVID-19." *International Journal of Educational Research Open* 1: 100011.

Ahorsu, Daniel, Chung-Ying Lin, Vida Imani, Mohsen Saffari, Mark Griffiths, and Amir Pakpour. 2020. "The Fear of COVID-19 Scale: Development and Initial Validation." *International Journal of Mental Health and Addiction* .

Broadbent, Jaclyn, and Matthew Fuller-Tyszkiewicz. 2018. "Profiles in self-regulated learning and their correlates for online and blended learning students." *Educational Technology Research and Development* 66.

Bråten, Ivar, and Bodil S. Olaussen. 2005. "Profiling individual differences in student motivation: A longitudinal cluster-analytic study in different academic contexts." *Contemporary Educational Psychology* 30 (3): 359–396.

Camacho-Zuñiga, Claudia, Luis Pego, Jose Escamilla, and Samira Hosseini. 2021. "The impact of the COVID-19 pandemic on students' feelings at high school, undergraduate, and postgraduate levels." *Heliyon* 7 (3): e06465.

Chilean Government. 2021. "PASO A PASO, NOS CUIDAMOS." (accessed: Jan-2023), https://www.gob.cl/coronavirus/pasoapaso/.

Clark, Andrew E., Huifu Nong, Hongjia Zhu, and Rong Zhu. 2021. "Compensating for academic loss: Online learning and student performance during the COVID-19 pandemic." *China Economic Review* 68: 101629.

Credé, Marcus, and L. Alison Phillips. 2011. "A meta-analytic review of the Motivated Strategies for Learning Questionnaire." *Learning and Individual Differences* 21 (4): 337–346.

Domhnaill, Ciarán Mac, Gretta Mohan, and Selina McCoy. 2021. "Home broadband and student engagement during COVID-19 emergency remote teaching." *Distance Education* 42 (4): 465–493.

Duncan, T. G., & McKeachie, W. J. 2005. The making of the motivated strategies for learning questionnaire. *Educational psychologist*, *40*(2), 117-128.

Elliot, A.J., and M.V. Covington. 2001. "Approach and Avoidance Motivation." *Educational Psychology Review* 13: 73–92.

Emerson, David J, Joseph F Hair, and Kenneth J Smith. 2022. "Psychological Distress, Burnout, and Business Student Turnover: The Role of Resilience as a Coping Mechanism." *Research in Higher Education* 1–32.

Ferrer, Justine, Allison Ringer, Kerrie Saville, Melissa Parris, and Kia Kashi. 2020. "Students' motivation and engagement in higher education: the importance of attitude to online learning." *Higher Education* 1–22.

Ferri, Fernando, Patrizia Grifoni, and Tiziana Guzzo. 2020. "Online Learning and Emergency Remote Teaching: Opportunities and Challenges in Emergency Situations." *Societies* 10: 86.

Günther, Christian W., and Anne Rozinat. 2012. "Disco: Discover Your Processes." In *Proceedings of the Demonstration Track of the 10th International Conference on Business Process Management (BPM 2012), Tallinn, Estonia, September 4, 2012*, edited by Niels Lohmann and Simon Moser, Vol. 940, 40–44.

Günaydın, H.D. 2021. "The impact of social problem skills on academic motivation by means of Covid-19 fear." *Curr Psychol* .

Hayenga, Amynta, and Jennifer Corpus. 2010. "Profiles of intrinsic and extrinsic motivations: A person-centered approach to motivation and achievement in middle school." *Motivation and Emotion* 34: 371–383.

Hodges, Charles B., Stephanie L. Moore, Barbara B Lockee, Torrey Trust, and Mark Aaron Bond. 2020. "The Difference Between Emergency Remote Teaching and Online Learning." *Educational Review*.

Hussein, Elham, Sumaya Daoud, Hussam Alrabaiah, and Rawand Badawi. 2020. "Exploring undergraduate students' attitudes towards emergency online learning during COVID-19: A case from the UAE." *Children and Youth Services Review* 119: 105699.

Ismailov, M., and Y Ono. 2021. "Assignment Design and its Effects on Japanese College Freshmen's Motivation in L2 Emergency Online Courses: A Qualitative Study." *Asia-Pacific Edu Res* 30: 263–278.

Jain, Anil K. 2010. “Data clustering: 50 years beyond K-means.” *Pattern Recognition Letters* 31 (8): 651–666. Award winning papers from the 19th International Conference on Pattern Recognition (ICPR).

Jimoyiannis, Athanassios, Nikolaos Koukis, and Panagiotis Tsiotakis. 2021. “Shifting to Emergency Remote Teaching Due to the COVID-19 Pandemic: An Investigation of Greek Teachers’ Beliefs and Experiences.” In *Technology and Innovation in Learning, Teaching and Education*, edited by Ars´enio Reis, Jo˜ao Barroso, J. Bernardino Lopes, Tassos Mikropoulos, and Chih-Wen Fan, Cham, 320–329. Springer International Publishing.

Kapasia, Nanigopal, Pintu Paul, Avijit Roy, Jay Saha, Ankita Zaveri, Rahul Mallick, Bikash Barman, Prabir Das, and Pradip Chouhan. 2020. “Impact of lockdown on learning status of undergraduate and postgraduate students during COVID-19 pandemic in West Bengal, India.” *Children and Youth Services Review* 116: 105194.

Kong, Lc, and Woon Liu. 2020. “Understanding Motivational Profiles of High-Ability Female Students from a Singapore Secondary School: A Self-Determination Approach.” *The AsiaPacific Education Researcher* 29: 529–539.

Li, Liang-Yi, and Chin-Chung Tsai. 2017. “Accessing online learning material: Quantitative behavior patterns and their effects on motivation and learning performance.” *Computers & Education* 114: 286–297.

Liu, W. C., John C. K. Wang, H. J. Kang, and Ying Hwa Kee. 2021. “A motivation profile analysis of Malay students in Singapore.” *Asia Pacific Journal of Education* 41 (2): 299–311.

Liu, Woon Chia, Chee Keng John Wang, Ying Hwa Kee, Caroline Koh, Boon San Coral Lim, and Lilian Chua. 2014. “College students’ motivation and learning strategies profiles and academic achievement: a self-determination theory approach.” *Educational Psychology* 34 (3): 338–353.

Lohiniva, M and Isomöttönen, V. 2021. "Novice Programming Students' Reflections on Study Motivation during COVID-19 Pandemic," *2021 IEEE Frontiers in Education Conference (FIE)*, Lincoln, NE, USA, 2021, pp. 1-9, doi: 10.1109/FIE49875.2021.9637367.

Mahauad, Jorge Javier Maldonado, Mar Pérez-Sanagustín, René F. Kizilcec, Nicolás Morales, and Jorge Munoz-Gama. 2018. “Mining theory-based patterns from Big data: Identifying self-regulated learning strategies in Massive Open Online Courses." *Comput. Hum. Behav.* 80: 179–196.

Mailliez, Mélody, Mark Griffiths, and Arnaud Carre. 2021. "Validation of the French Version of the Fear of COVID-19 Scale and Its Associations with Depression, Anxiety, and Differential Emotions." *International Journal of Mental Health and Addiction* .

Malta, Gina Di, Julian Bond, Dominic Conroy, Katy Smith, and Naomi Moller. 2022. "Distance education students' mental health, connectedness and academic performance during COVID-19: A mixed-methods study." *Distance Education* 43 (1): 97–118.

Ministry of Science, Technology, Knowledge and Innovation (Chile). 2021. "Base de Datos COVID-19." (accessed: Jan-2023), https://www.minciencia.gob.cl/covid19/.

Ng, Betsy. 2016. "Towards Lifelong Learning: Identifying Learner Profiles on Procrastination and Self-Regulation." *New Waves - Educational Research & Development* 16: 41–54.

Ng, Betsy, John Wang, and Woon Liu. 2015. "Motivational-cognitive profiles of learners: Cluster movement." *Personality and Individual Differences* 85: 128–133.

Oliveira, Luciana, Anabela Mesquita, Arminda Sequeira, and Adriana Oliveira. 2021. "Emergency Remote Learning During COVID-19: Socio-educational Impacts on Portuguese Students." In *Educating Engineers for Future Industrial Revolutions*, edited by Michael E. Auer and Tiia Ru¨u¨tmann, Cham, 303–314. Springer International Publishing.

Pelikan, E., M. Lüftenegger, J. Holzer, S. Korlat, C. Spiel, and B. Schober. 2021. "Learning during COVID-19: the role of self-regulated learning, motivation, and procrastination for perceived competence." *Zeitschrift für Erziehungswissenschaft* .

Pintrich, P.R., Smith, D.A.F., García, T., and McKeachie, W.J. 1991. "A manual for the use of the motivated strategies questionnaire (MSLQ)." Ann Arbor, MI: University of Michigan, National Center for Research to Improve Postsecondary Teaching and Learning.

QS, 2020. QS Latin America University Rankings 2020, Top Universities. URL: https://www.topuniversities.com/university-rankings/latin-american-university-rankings/2020. Last accessed: January 2023.

Rahiem, Maila D.H. 2021. “Remaining motivated despite the limitations: University students’ learning propensity during the COVID-19 pandemic.” *Children and Youth Services Review* 120: 105802.

Shim, Tae Eun, and Song Yi Lee. 2020. “College students’ experience of emergency remote teaching due to COVID-19.” *Children and Youth Services Review* 119: 105578.

Toti, G., and M.A. Alipour. 2021. “Computer Science Students’ Perceptions of Emergency Remote Teaching: An Experience Report.” *SN COMPUT. SCI.* 2.

Valle, Antonio, Bibiana Regueiro, Susana Rodríguez, Isabel Piñeiiro, Carlos Freire, Mar Ferradás, and Natalia Suárez. 2015. “Perfiles motivacionales como combinaci´on de expectativas de autoeficacia y metas acad´emicas en estudiantes universitarios.” *European Journal of Education and Psychology* 8 (1): 1–8. van der Aalst, Wil M. P. 2016. *Process Mining - Data Science in Action, Second Edition*.

Springer.

van der Aalst, Wil M. P. 2019. “A practitioner’s guide to process mining: Limitations of the directly-follows graph.” In *International Conference on ENTERprise Information Systems*, Vol. 164, 321–328. Elsevier.

Vu, Tuong-Van, Lucia Weinberg, Brenda Jansen, Nienke Atteveldt, Tieme Janssen, Nikki Lee, Han Maas, Maartje Raijmakers, Maien Sachisthal, and Martijn Meeter. 2021. “MotivationAchievement Cycles in Learning: a Literature Review and Research Agenda.” *Educational Psychology Review* 1–33.

World Health Organization. 2021. “Listings of WHO’s response to COVID-19.” (accessed: Jan-2023), https://www.who.int/news/item/29-06-2020-covidtimeline.

Yera, Raciel, Rosa M. Rodr´ıguez, Jorge Castro, and Luis Mart´ınez. 2018. “A Recommender System for Supporting Students in Programming Online Judges.” In *Smart Education and e-Learning 2017*, edited by Vladimir L. Uskov, Robert J. Howlett, and Lakhmi C. Jain, Cham, 215–224. Springer International Publishing.

Yukselturk, Erman, and Ercan Top. 2013. “Exploring the link among entry characteristics, participation behaviors and course outcomes of online learners: An examination of learner profile using cluster analysis.” *British Journal of Educational Technology* 44.

Çebi, Ayça, and Tolga Güyer. 2020. “Students’ interaction patterns in different online learning activities and their relationship with motivation, self-regulated learning strategy and learning performance.” *Education and Information Technologies* 25.

Figure 1

Z-scores of the MSLQ scales for each cluster

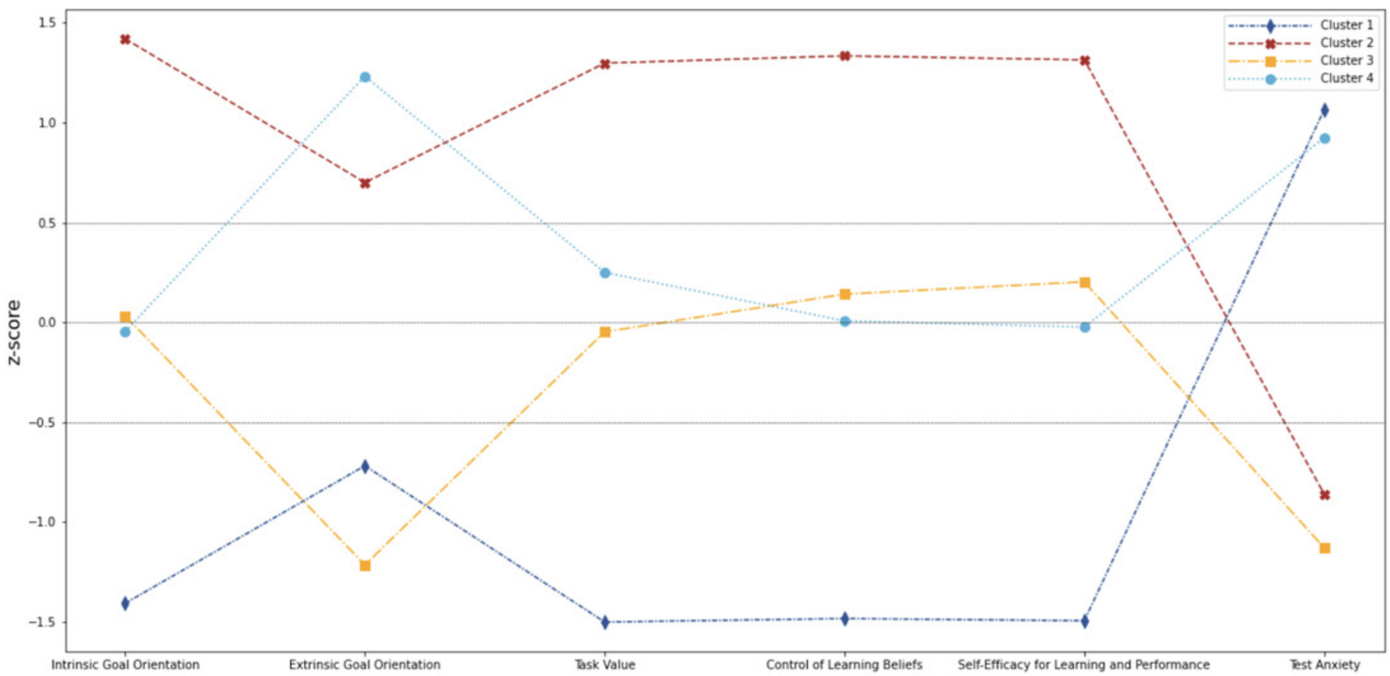

Figure 2

Individual students’ motivation trajectories

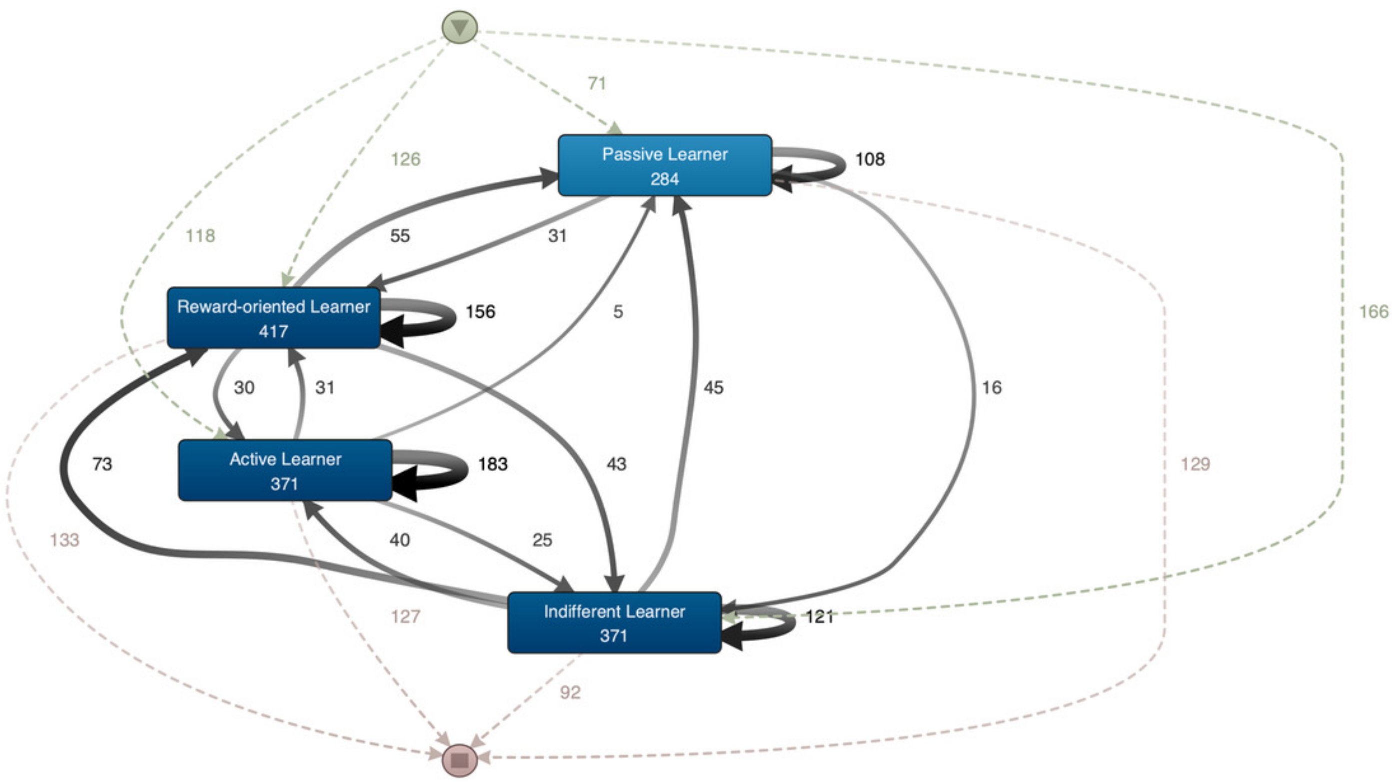

Figure 3

Trajectories for students with COVID concern z-score higher than 0.5

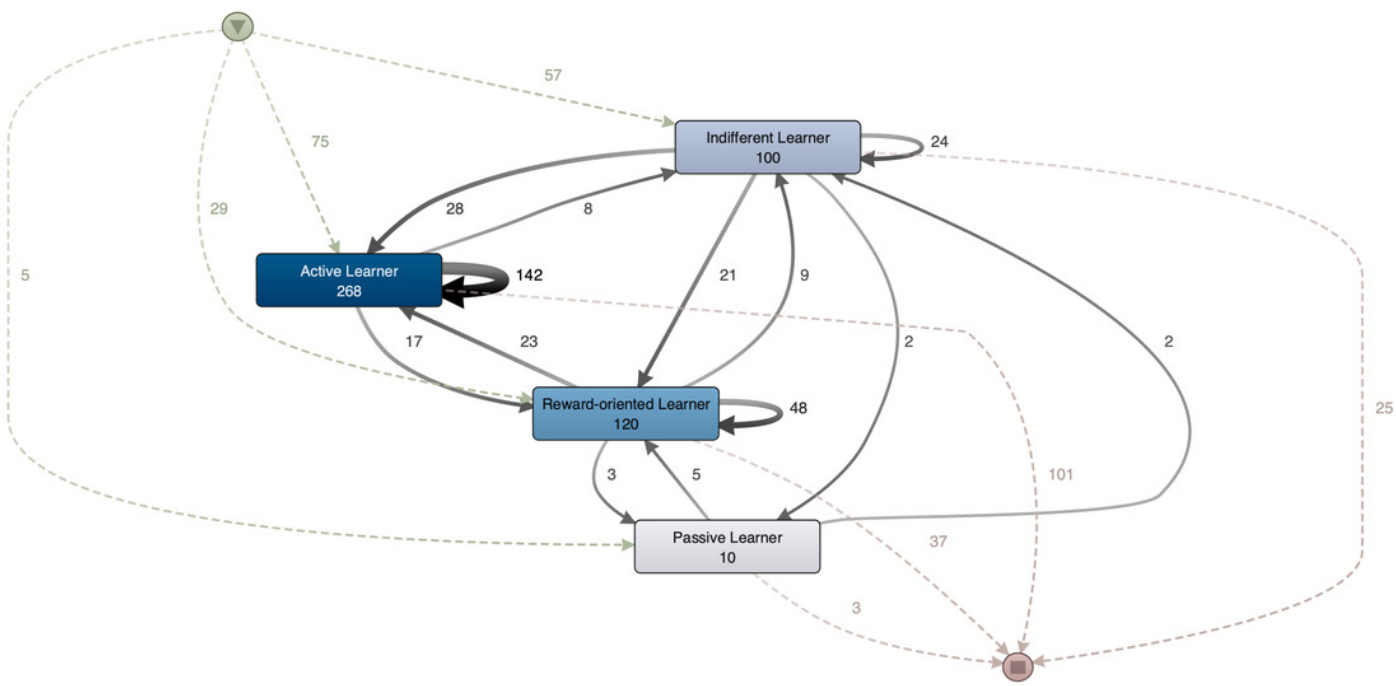

Figure 4

Trajectories for students with COVID concern z-score lower than -0.5

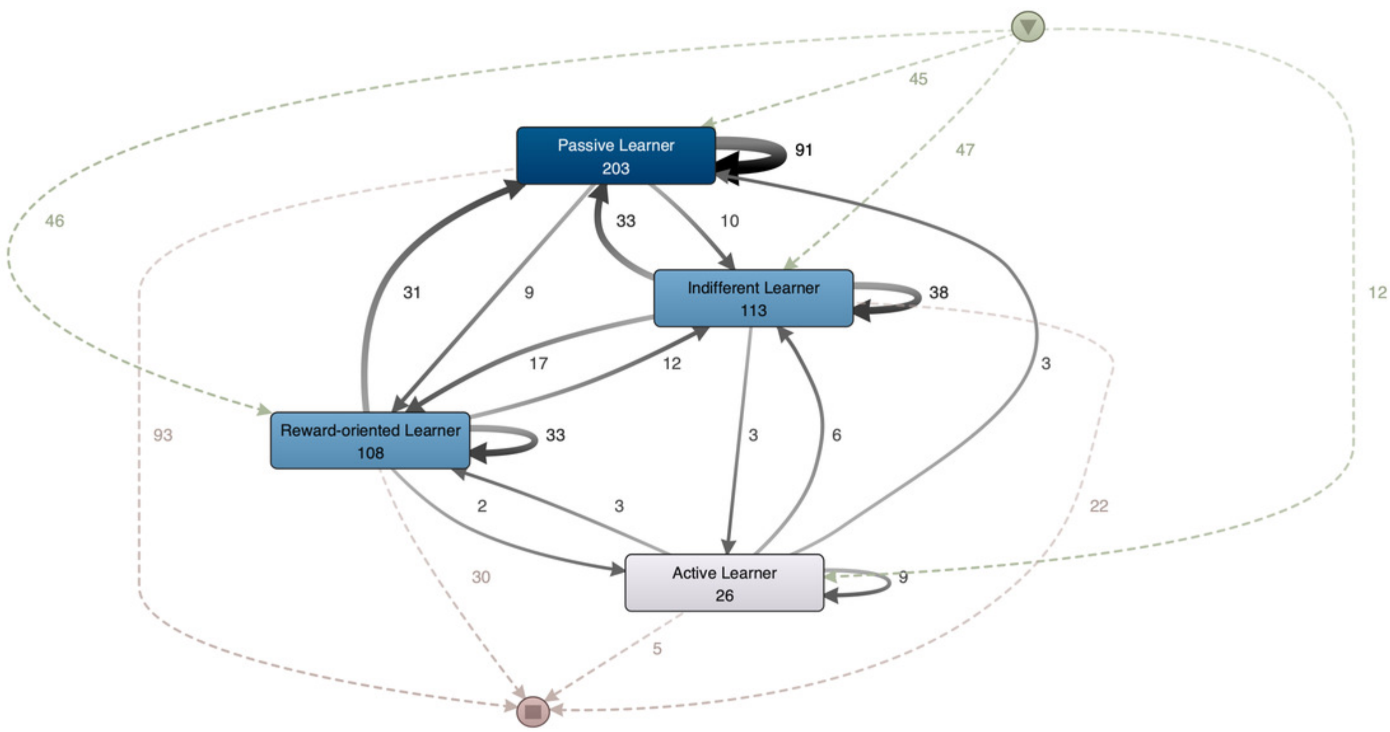

Table 1 (on next page)

COVID concern items

Variable	Items
COVID concern	I am afraid/worried of getting infected with COVID-19 I am afraid/worried that someone in my home will be infected with COVID-19 I am afraid/worried that a relative or acquaintance outside my home will be infected with COVID-19 I find it difficult to sleep because I am worried about COVID-19

Table 2
(on next page)

Interpretation of the z-scores of each profile

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Intrinsic goal orientation	Low	High	Moderate high	Moderate low
Extrinsic goal orientation	Low	High	Low	High
Task value	Low	High	Moderate low	Moderate high
Control of learning beliefs	Low	High	Moderate high	Moderate high
Self-efficacy for learning and performance	Low	High	Moderate high	Moderate low
Test anxiety	High	Low	Low	High
Label	*Passive Learner*	*Active Learner*	*Indifferent Learner*	*Reward-oriented Learner*

Table 3 (on next page)

Descriptive statistics of the variables, segmented by cluster

Variable	Passive Learner	Active Learner	Indifferent Learner	Reward-oriented Learner	Total Population
Participants	284	371	371	417	1,443
Age					
mean	18.95	18.96	19.00	18.85	18.94
SD	1.12	2.35	3.01	0.92	2.06
Gender					
m*ale*	139 (48.04%)	202 (78.71%)	265 (71.43%)	258 (61.87%)	954 (66.11%)
female	145 (51.06%)	73 (19.68%)	105 (28.30%)	151 (36.21%)	474 (32.85%)
other	0	3 (0.81%)	0	3 (0.72%)	6 (0.42%)
prefer not to say	0	3 (0.81%)	1 (0.27%)	5 (1.20%)	9 (0.62%)
Engineering students	229 (80.63%)	314 (84.64%)	316 (85.18%)	347 (83.21%)	1,206 (83.58%)
Have previous programming experience: yes	37 (13.03%)	174 (46.90%)	120 (32.35%)	107 (25.66%)	438 (30.35%)
Status					
pass	242 (85.21%)	357 (96.23%)	349 (94.07%)	393 (94.24%)	1,341 (92.93%)
fail	17 (5.99%)	6 (1.62%)	4 (1.08%)	6 (1.44%)	33 (2.29%)
plagiarism	5 (1.76%)	5 (1.35%)	10 (2.70%)	10 (2.39%)	30 (2.08%)
withdraw	20 (7.04%)	3 (0.81%)	8 (2.16%)	8 (1.92%)	39 (2.70%)
Final grade (1-7)					
mean	5.23	6.58	6.07	6.00	6.01
SD	1.29	0.95	1.28	1.21	1.27
Frustration due to online course (1-5)					
mean	3.81	2.98	3.17	3.66	3.39
SD	1.16	1.28	1.31	1.30	1.32
Exclusive computer use: yes	270 (95.07%)	365 (98.38%)	361 (97.30%)	409 (98.08%)	1,405 (97.37%)
Comfort with computer					
comfortable	44 (15.49%)	196 (52.83%)	149 (40.16%)	133 (31.89%)	522 (36.17%)
uncomfortable	78 (27.46%)	165 (44.47%)	195 (52.56%)	242 (58.03%)	764 (52.95%)
neither	162 (57.04%)	10 (2.70%)	27 (7.28%)	42 (10.07%)	157 (10.88%)
Stable connection: yes	219 (77.11%)	330 (88.95%)	332 (89.49%)	338 (81.06%)	1,219 (84.48%)
COVID concern (1-5)					
mean	2.89	4.25	3.63	3.74	3.68
SD	0.85	0.86	0.75	0.72	0.91

Table 4 (on next page)

Summary of applied statistical tests

Variable	Test	Result
Age	Kruskal-Wallis test	No significant differences between the clusters.
Gender	Two proportion z-test	Passive Learner has a higher proportion of women than the other clusters.
		Active Learner has a lower proportion of women than the other clusters.
Engineering student	Chi-square test	The proportion of engineers is independent of the cluster.
Previous programming experience	Two proportion z-test	Passive Learner has a lower proportion of students with previous programming experience than the other clusters.
		Active Learner has a higher proportion of students with previous programming experience than the other clusters.
Pass/fail status	Two proportion z-test	Passive Learner has a lower proportion of approved students than the other clusters.
Final grades	Welch test	Passive Learner has lower grades than the other clusters.
		Active Learner has higher grades than the other clusters.
Frustration because the courses are online	Mann-Whitney-Wilcoxon test	Active Learner has less frustration because the courses are online than the other clusters.
Exclusive computer	Two proportion z-test	No significant differences between the clusters.
Comfort with daily computer use	Mann-Whitney-Wilcoxon test	Passive Learner has less comfort with daily computer use than the other clusters.
		Active Learner has more comfort with daily computer use than the other clusters.
Stable connection	Two proportion z-test	No significant differences between the clusters.
COVID concern	Mann-Whitney-Wilcoxon test	Passive Learner has less concern about COVID than the other clusters.
		Active Learner has more concern about COVID than the other clusters.

Table 5(on next page)

The 10 most frequent variants of the trajectories

Type	Frecuency	T1	T2	T3
AAA	70 (14.55%)	Active Learner	Active Learner	Active Learner
AAA	43 (8.94%)	Indifferent Learner	Indifferent Learner	Indifferent Learner
AAA	42 (8.73%)	Reward-oriented Learner	Reward-oriented Learner	Reward-oriented Learner
AAA	39 (8.11%)	Passive Learner	Passive Learner	Passive Learner
ABB	23 (4.78%)	Indifferent Learner	Reward-oriented Learner	Reward-oriented Learner
ABB	22 (4.57%)	Indifferent Learner	Active Learner	Active Learner
AAB	15 (3.12%)	Reward-oriented Learner	Reward-oriented Learner	Passive Learner
ABB	14 (2.91%)	Indifferent Learner	Passive Learner	Passive Learner
ABB	14 (2.91%)	Reward-oriented Learner	Passive Learner	Passive Learner
ABB	11 (2.11%)	Active Learner	Reward-oriented Learner	Reward-oriented Learner