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A Person-Oriented Transition Analysis

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Nonlinear Effort-Time Dynamics of Student Engagement in a Web-Based Learning Platform: A Person-Oriented Transition Analysis

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Abstract

Behavioural engagement as a predictor of academic success hinges on the interplay between effort and time. Exploring the longitudinal development of engagement is vital for understanding adaptations in learning behaviour and informing educational interventions. However, person-oriented longitudinal studies on student engagement are scarce. Moreover, online engagement metrics are rarely grounded in theory and often result in simplified descriptions overlooking the complexity of engagement processes. This study applies a theory-based operationalization of behavioural engagement to examine the log data of 236 students in a web-based learning platform. We explored 1) whether weekly profiles based on distinct engagement patterns can be identified and 2) how students transition across profiles over time. Hierarchical clustering yielded one Inactive and six active profiles (Fast-Learners, Regular-Learners, Average-Engagement, Minimalists, Struggling-Learners, and Procrastinators). Results suggest heterogeneity in profile emergence, with effective engagement characterized by alignment with the course deadlines. Process mining revealed changes in profile membership across weeks. Profile transitions revealed relative stability among effective groups and greater fluctuation among low-time profiles. By investigating the complexity and temporality of engagement in online learning, our findings provide insights for developing personalized learning support through training artificial intelligence applications and informing learning analytics dashboards.

Notes for Practice

- Understanding behavioural engagement as a multidimensional, dynamic, and context-specific process allows for a more nuanced analysis of how students interact with online learning over time.
- This study applies a person-oriented, theory-based approach to identify weekly engagement profiles from log data, highlighting how patterns of compliance and regularity shape effective study behaviour.
- Transitions between weekly engagement profiles show evolution of student engagement over time, offering insights into stable, fluctuating, and inactive engagement patterns.
- The study contributes to learning and curriculum analytics by informing instructional approaches and curriculum interventions, while also supporting diverse student groups in online learning environments.

Keywords: Student engagement, temporal learning analytics, online learning, person-oriented analysis, transition analysis, higher education

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1. Introduction

With the increasing digitalization of higher education, web-based platforms that offer a flexible learning environment and allow for exploring self-paced learning experiences are commonly adopted (Heil & Ifenthaler, 2023). In blended undergraduate

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courses, web-based platforms can be used to complement the instruction by providing learning materials for practice to help students reinforce important skills and reach course learning goals (Ipinnaiye & Risquez, 2024). Practice platforms are designed to support teaching and learning through the adaptive use of educational resources, such as open educational resources or licensed content, and interactive environments that provide immediate feedback and promote active learning (Ipinnaiye & Risquez, 2024). For example, teachers may provide online take-home practices via web-based platforms to give students the opportunity to review and consolidate the lecture material and prepare for the upcoming lectures (Magalhães et al., 2020). How students engage in practice is a critical learning component for improving academic achievement (Dorko, 2021). In this study, we define engagement as students' productive involvement with the learning materials (Ben-Eliyahu et al., 2018). In the particular context of web-based practice, this productive involvement can be operationalized as student investment of effort and time to complete their assigned practice (Flunger et al., 2015). Online practice environments offer significant autonomy, such as the choice of when and where to engage with the learning materials but often lack direct and real-time instructor support (Wong, Baars, et al., 2019). While empowering, this autonomy challenges students to independently manage many learning tasks and assignments, leading to struggles with consistent engagement (Wong, Khalil, et al., 2019). Moreover, engagement patterns in online learning vary widely (Saqr & López-Pernas, 2021). Some students start highly engaged but lose momentum, while others remain consistently disengaged (Marple et al., 2019; Muir, 2014). This heterogeneity highlights the need for timely, adaptive support to maintain engagement and ensure success (Rienties et al., 2019).

The field of learning analytics (LA) offers tools and techniques for processing fine-grained temporal engagement data to support real-time and personalized student support (Lim et al., 2023). Despite the LA advances in capturing online learning processes, ensuring the transparency and clarity of engagement investigations in the field remains a challenge (Bond et al., 2023; Vytasek et al., 2020). Student engagement is a complex, multidimensional construct comprising various components (Reschly & Christenson, 2022). Theory can provide a framework for selecting and interpreting the appropriate online indicators (Er et al., 2021). Moreover, engagement components interact, creating patterns that change dynamically over time (Symonds et al., 2024). Consequently, theory-based examinations of engagement patterns are essential for identifying the evolution of meaningful and complex learning processes (López-Pernas & Saqr, 2024). Prior work has employed theory-based investigations by mapping engagement data into different phases of self-regulated learning (SRL) in various learning contexts, such as learning management systems, problem-solving, and collaborative peer feedback (e.g., Er et al., 2021; He et al., 2024; Zhang et al., 2022). We build on this work to examine the longitudinal evolution of online practice patterns based on the synergy of engagement components, given that longitudinal investigations of online engagement are still limited (e.g., López-Pernas & Saqr, 2024; Saqr & López-Pernas, 2021).

This study explores engagement as a complex and dynamic construct using the lens of the SRL framework (Wiedbusch et al., 2023). SRL offers a robust foundation for understanding how students adapt their learning behaviour, especially in flexible, online practice settings where self-management is critical (Wong, Khalil, et al., 2019). Building on previous research (e.g., Barthakur et al., 2021; Kokoç et al., 2021), we employ a combination of person-oriented approaches and process mining techniques. Specifically, we perform a weekly clustering analysis, an approach suitable for identifying student subgroups with distinct engagement characteristics, to identify profiles that emerge in specific periods of the course. Furthermore, we use process mining to investigate transitions between these profiles, uncovering patterns of change and stability over time. These methods were selected to capture both the complex patterns that emerge and how they evolve throughout the course. This weekly analysis of online data provides educators with actionable insights, enabling the timely identification of diverse student needs and the implementation of tailored support based on meaningful engagement characteristics (Lim et al., 2023).

2. Background

2.1. Behavioural Engagement: A Key Component of Student Engagement

Student engagement represents one of the most important constructs for understanding how and why students invest and act in various educational settings (Reschly & Christenson, 2022). Engagement comprises affective (e.g., interest), behavioural (e.g., effort exertion), and cognitive (e.g., concentration) components (Fredricks et al., 2004). How these components are defined and interpreted can vary across learning contexts (Boekaerts, 2016). The process through which students become and remain engaged in learning has been studied via the lens of SRL (Cleary & Zimmerman, 2012; Wolters & Taylor, 2012). SRL describes how students consciously regulate affective, behavioural (meta)cognitive, and motivational aspects of learning (Zimmerman, 2002). During the learning task, cognitive engagement regulates the enactment of behavioural engagement, which in turn informs cognitive engagement maintenance and monitoring mechanisms (Wiedbusch et al., 2023). From an SRL perspective, engagement is sustained through self-amplifying, feedback loops that form "virtuous" or "vicious" engagement cycles and can magnify initial inter-individual differences over time (Skinner & Pitzer, 2012). Working on course assignments is an illustrative example of a learning task that requires students to engage in SRL processes since they need to initiate and carry out their assignments away from the structured and supportive classroom environment (Xu & Corno, 2022).

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As engagement in this study is examined through student interactions with the web-based practice platform, we focus on the behavioural component of the construct (Wiedbusch et al., 2023). Behavioural engagement in studying can be understood via two aspects: time and effort (Wolters & Brady, 2021). Time spent studying has been positively associated with effective time management and achievement (Wolters & Brady, 2021). Effort refers to the degree to which students seriously work on their tasks, even if they don't solve all the tasks correctly (Flunger et al., 2015). Effort exertion in studying take-home assignments entails three aspects:

1. *Compliance*: Student effort to complete the assignment by working on this as well as they can. Compliance requires engagement in effective planning and time management to meet the assigned deadlines (Wang et al., 2023). It also requires monitoring the ongoing learning progress until completing the task (Järvelä et al., 2016).
2. *Persistence*: Willingness to continue investing time and adapting one's behaviour in response to challenging tasks. Persistent students might adapt their behaviour until they reach their learning goal (Chen et al., 2018).
3. *Regularity*: Frequency of working on tasks. Scheduling regular sessions for studying has been associated with setting effective time-related goals, where students determine when and for how long they will study, and selecting effective strategies, such as spaced practice (Wolters & Brady, 2021).

Prior research in behavioural engagement in traditional (offline) assignment formats emphasizes the importance of examining effort and time in conjunction to better understand the various configurations of study behaviour (e.g., Flunger et al., 2015; Shin & Sohn, 2019; Valle et al., 2019; Xu, 2022). For example, Flunger et al. (2015) found five types of engagement in which effort and time were positively associated with three types, i.e., high-effort, average-learners, and minimalists, and negatively associated with two types, i.e., fast-learners and struggling-learners.

2.2. Examining Behavioural Engagement in Online Learning

In online settings, engagement with course materials has been generally operationalized with various indicators, such as the number of assignment views, the number of completed assignments, and practice session duration (e.g., Chen et al., 2018; Kokoç et al., 2021). Research indicates that combining online indicators can effectively measure aspects of behavioural engagement in studying. For example, Yang et al. (2020) examined procrastination based on the timing at which the homework started and the practice duration before submission. In another example, Prat and Code (2021) investigated time and persistence based on the number of correct and incorrect problem attempts, log-in timestamps, and inactive time. While researchers should explain how the selected online indicators align with theory when operationalizing engagement, to date, there are limited studies using theory-driven approaches in investigations of engagement (e.g., Er et al., 2021; He et al., 2024; Zhang et al., 2022). An example of theory-based operationalization is provided by He et al. (2024), where engagement with various formative assessment activities, such as quizzes and assignments, was examined as an SRL process. In particular, the authors conceptualized engagement as the performance phase of SRL that contains processes during the learning task. The alignment between online actions and theorized engagement processes, such as the use and adaptation of study strategies, as illustrated in this research, is a useful approach for conducting transparent measurement of online engagement.

Various indicators of online behavioural engagement have been used in studies employing person-oriented analysis. Studies adopting clustering analyses have investigated student profiles that demonstrate different engagement patterns in undergraduate online studying environments. Evidence shows that students can adopt high, medium, or low engagement levels when they work on assignments. In Yang et al. (2020), procrastination-related behaviours included low active time, high inactive time, and submissions close to the deadline. The authors found three profiles: non-procrastinators, procrastinator-candidates, and procrastinators. Kokoç et al. (2021) examined engagement in four assignments. Clustering analysis for each assignment yielded three clusters of low, medium, and high engagement. The low-engagement profile was characterized by low effort and time. The medium-engagement profile also started their assignment submission near the deadline, but they spent more time completing the assignment than the low-engagement profile. The high-engagement profile was characterized by starting earlier, completing the assignment submission on the last day, and making much more effort.

In less structured learning settings (e.g., online practice), prior work has employed the lens of SRL to examine complex and heterogeneous engagement profiles. This line of research has assumed that effective engagement can be understood using both the intensity and timing indicators (e.g., Rienties et al., 2019). For example, Chen et al. (2018) identified two clusters of engagement. The most effective cluster started and submitted the assignments early, checked answers multiple times, continued until answering correctly, and worked on the assignment regularly with shorter intervals between problem-solving sessions. H. Li et al. (2018) found four profiles based on two indicators: timing and completed exercises. Both Early-Completers and Late-Completers completed the required online materials, but Early-Completers started earlier. Early-Dropouts accessed the material early but then dropped out of the course. Late-Dropouts started late but failed to complete the required online materials. Rienties et al. (2019) and Tempelaar et al. (2023) clustered students based on the intensity of attempts in three learning phases. Four (Rienties et al., 2019) and five (Tempelaar et al., 2023) profiles were found that differed in when and how much students engaged in the platform. The most effective profiles started practising and completed the exercises early in the course (Early-Mastery) or studied quite hard to prepare for the middle and the end of the course (Strategic). Taken together, engagement in online practice is characterized by vast heterogeneity, suggesting the benefits of person-oriented analyses in detecting the various engagement patterns (Tempelaar et al., 2023). Furthermore, the lens of SRL can offer valuable insights on the examination of effective and ineffective engagement patterns in flexible learning settings (Rienties et al., 2019). However, to capture engagement complexity, operationalization of the construct requires a critical, theory-anchored combination of various relevant components, such as compliance, persistence, timing, and regularity (Vytasek et al., 2020).

2.3. Examining the Temporal Changes of Engagement

Engagement unfolds over time following trajectories that can be shaped by various factors, including motivation, task characteristics, and prior learning experiences (Fredricks et al., 2004; Wang & Degol, 2014). Prior research has identified that engagement declines across weeks or years (e.g., Liborius et al., 2019; Martin et al., 2015; Ziegler & Opdenakker, 2018). Evidence suggests that there is a vast variability in engagement evolution when accounting for intra-individual differences. Results from longitudinal studies in face-to-face settings showed that some student groups can maintain stable levels of high or low engagement, while others show variations, ascending to higher engagement levels or declining to disengagement (e.g., Archambault & Dupéré, 2017; Y. Li & Lerner, 2011; Upadyaya & Salmela-Aro, 2013; Zhen et al., 2020). These findings underscore the heterogeneity in engagement change patterns, reflecting the diverse ways in which students respond to learning environments over time. Despite the extensive research on engagement evolution in face-to-face settings, such research is still limited in online settings (López-Pernas & Saqr, 2024).

Results on engagement transitions in online settings are still inconclusive. Studies have combined person-oriented with transition analyses to examine whether and how students change their engagement patterns over time. Some studies show that students tend to maintain their level of engagement, especially in highly engaged groups, when they transition across courses (Saqr & López-Pernas, 2021) or assignments (Conde et al., 2024; Kokoç et al., 2021). Other studies examined the consistency of engagement strategies across weeks based on engagement in various learning activities (Barthakur et al., 2021; Pardo et al., 2019). For example, Barthakur et al. (2021) found three types of transitions between weekly learning strategies. In the first transition, students either maintained their engaged strategy or moved to disengagement after achieving their goal, indicating robust self-regulation and performance goal orientation. In the second transition, learners who adopted the disengaged strategy either kept this strategy or moved to the assessment-oriented strategy, indicating poor regulation and attempts to "catch-up." In the third transition, learners who adopted the selective strategy transitioned to all other strategies equally, suggesting strong SRL skills and adaptivity in following their learning goals. Poquet et al. (2023) found that steep changes in learning behaviour at the beginning of the course resulted in transitions to less effective study strategies, suggesting the critical role of the early adoption of effective study behaviour. Focusing on webinar attendance, Getman et al. (2024) found that adaptivity rather than stability indicates effective regulation of behaviour. Given that the evolution of engagement might depend on the learning activity type (Skinner & Pitzer, 2012), more research is needed to understand transition patterns in different online activities. To conclude, literature indicates that understanding how students engage in online practice environments requires not only the investigation of complex patterns but also how these patterns change over time.

2.4. The Current Study

Despite the convergence in the roles of compliance, persistence, regularity, and time spent as critical components of effective online study behavioural patterns (e.g., Prat & Code, 2021; Yang et al., 2020), the reviewed literature has mainly focused on some of these aspects and neglected a combined investigation that can provide insights into more complex engagement patterns (e.g., H. Li et al., 2018; Rienties et al., 2019). Moreover, while prior studies agree that engagement profiles are malleable, relevant research in online learning is still underdeveloped (López-Pernas & Saqr, 2024). Existing evidence suggests that students can change their engagement patterns often during a course (e.g., Barthakur et al., 2021; Poquet et al., 2023). However, most studies have used a single coherent clustering approach throughout the study period. A few studies constitute an exception. Lust et al. (2013) conducted a clustering analysis in two learning phases separately. In the first phase, three clusters were identified, whereas an additional cluster emerged in the second phase. Pardo et al. (2019) identified eight distinct clusters by performing one clustering for each week in the semester. One cluster appeared only in weeks 11 and 12 and reflected a unique pattern of engagement. These findings support the view of engagement as a complex and dynamically changing construct (Symonds et al., 2024).

The current study adopts this perspective by exploring behavioural engagement profiles in a web-based practice platform used in a blended higher education context. The practice platform integrates open educational resources in an interactive learning environment designed to supplement in-class instruction. These environments are particularly beneficial to support learning in blended higher education settings as instructors can leverage adaptable learning materials to better align teaching content with learning objectives and diversify assessment strategies. For students, web-based practice platforms provide enriched, self-paced learning opportunities outside class time, enabling them to revisit and reinforce concepts introduced during lectures (Brahimi & Sarirete, 2015). Importantly, the interactivity afforded by these platforms promotes active participation and supports mastery-oriented learning, requiring students to solve problems, receive immediate feedback, and reflect on their responses (Nipa & Kermanshachi, 2020). However, since these benefits rely on student ability to maintain consistent and meaningful engagement with the material, examining the evolution of behavioural engagement patterns in this type of online learning environment is essential to gain insights into potential differences in engagement across diverse student groups (Kim et al., 2020).

Given the scarcity of theory-based investigations of engagement (He et al., 2024), our indicators are developed based on theoretical views of effort (e.g., compliance and persistence) and time investment in studying. Engagement is perceived as a complex construct, as effort and time interact to produce states of more or less effective self-regulation (Flunger et al., 2015). Moreover, engagement is perceived as dynamic since the interplay between the indicators over time can lead to new states (López-Pernas & Saqr, 2024; Wiedbusch et al., 2023). Using a weekly temporal analysis, we examine longitudinal transitions in engagement profiles within blended undergraduate mathematics courses. We address the following research questions:

RQ1: To what extent can we identify distinct, weekly-based profiles of online behavioural engagement based on diverse patterns of effort and time?

RQ2: How do the identified profiles change across the eight-week course, and how do students transition from one profile to another across weeks?

3. Methods

3.1. Participants

Participants of this study were 236 students enrolled in three Linear Algebra courses at a Dutch university from February to April 2023. Before the study, students provided their informed consent and completed the demographics questionnaire. Of the 236 students, 78% identified as male, 18.2% as female, 2.1% as non-binary, and 1.6% preferred not to respond. Most students (80%) were younger than 20 years old, while 19% were between 20 and 25 years old, and 1% were between 25 and 30 years old. Three engineering programs were represented: Mechanical Engineering (46%), Computer Science and Engineering (29%), and Civil Engineering (25%).

3.2. Study Context

The study is part of a research program evaluating the redesign of mathematics courses for engineering students. Mathematics is fundamental in various engineering programs (Pepin & Kock, 2021). However, non-mathematics majors often struggle to sustain their engagement in mathematics courses due to low motivation or perceived difficulty (Hochmuth, 2020). At the same time, in undergraduate mathematics, the development and strengthening of conceptual understanding and fluency with mathematical techniques requires students to spend a significant amount of time practising (Dorko et al., 2023; Faitelson et al., 2024). The Linear Algebra courses were service mathematics courses taught in the first academic year of various undergraduate engineering programs. The eight-week courses consisted of two lectures per week for the Mechanical and Civil Engineering programs and three lectures per week for the Computer Science Engineering program. Common learning goals and learning materials were used across all three courses. The courses were developed based on a blended learning format where students were expected to: 1) prepare for the lecture with pre-lecture videos and exercises, 2) participate in the lecture through interactive quizzes and individual/group problem-solving, and 3) practice the taught material as a homework assignment. Students accessed course information and materials and monitored their progress via the Brightspace Learning Management System (https://www.d2l.com/brightspace/). The online mathematics and statistics platform, Grasple (www.grasple.com), was integrated into the LMS as an external learning tool and used for delivering and practising the assignments.

3.2.1. Online Practice Platform

Take-home practice was assigned in the online practice platform (i.e., Grasple) after each lecture and was expected to be completed before the next lecture. Each week, students had to work on a set of exercises, named subjects (see Figure 1). The subjects differed in terms of difficulty level to target a range of learning goals. For instance, basic exercises were the easiest ones and aimed at consolidating the learning material. Theory exercises were more challenging and aimed at a deeper understanding of the concepts and procedures. Optional exercises were advanced and aimed at application. The number of assigned exercises, as well as the proportion of basic, challenging, and advanced exercises, varied across weeks.

There are two types of exercises in Grasple: 1) fixed-order exercises, which are considered completed when students attempt a predefined number of questions even when the questions are not correctly solved, and 2) adaptive-order exercises, which are considered completed only when students attempt a predefined number of questions and all questions are correctly solved.

Each exercise consists of several multiple-choice or open-ended questions. Students had a maximum of three attempts per question, and after three attempts, students had the option to restart the question. At each incorrect attempt for a question in both exercise types, pre-determined feedback was provided to guide students in their next attempt. Teachers designed feedback for specific incorrect answers, allowing the platform to recognize common mistakes and provide relevant explanations. Moreover, students could skip a question and move to the next one.

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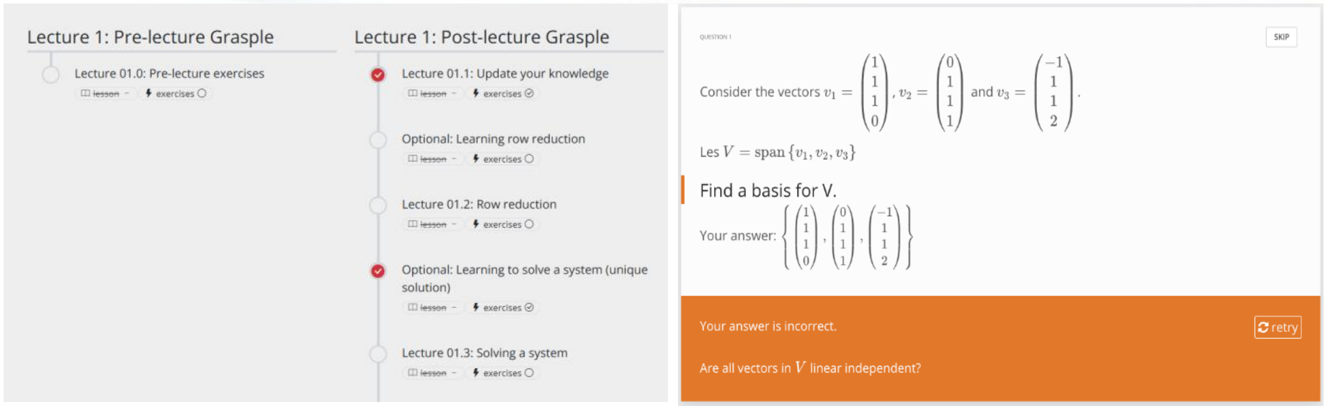

Figure 1. Screenshots from the Grasple environment: overview of the assigned subjects in Lecture 1 (left) and an open-ended exercise with feedback provided after an incorrect attempt (right).

3.3. Behavioural Engagement Operationalization

Following the approach of similar studies, one week was selected as the unit of analysis as it was aligned with the course design and schedule (e.g., Pardo et al., 2019). The development of the indicators was based on a combination of theory, learning context, and prior LA research. Drawing from the definition of effort components (i.e., compliance, persistence, and regularity) and time invested in studying, as employed in prior research (e.g., Flunger et al., 2015) and our conceptualization of engagement (see section 2.1.1.), we identified relevant processes of behavioural engagement in studying using Grasple. The alignment between these processes and the theorized aspects is shown in Table 1. To assess these processes, we used a combination of measures identified in our literature review and prior LA research on engagement (e.g., Saqr et al., 2023). After identifying the relevant measures, the calculation of each indicator was further adjusted to the affordances and constraints of the learning environment.

Table 1. The Six Indicators of Online Behavioural Engagement

Engagement Aspect	Indicator	Operationalization
Effort		
Compliance	Attempt rate	The extent to which students attempted to complete the subjects they worked on in a particular week (H. Li et al., 2018). The mean value of the percentage of unique exercises attempted in each subject per week.
Compliance	On-time rate	The extent to which students worked on the subjects before the weekly deadline assigned by the teacher (e.g., Yang et al., 2020). The mean value for the number of exercises was derived for each subject followed by a mean score for all subjects in a given week.
Persistence	Reattempt rate	The extent to which students keep working on (i.e., reattempted) exercises that were previously solved incorrectly during a particular week (e.g., Prat & Code, 2021). The total number of incorrect reattempts was divided by the total number of attempts across all subjects in a given week.
Regularity	Regularity	The extent to which students regularly worked on their assignments during a particular week. Regularity was calculated as the entropy of daily exercise attempts (Jovanović et al., 2017) using the number of unique exercises attempted during a day with at least one exercise attempt divided by the total count of unique exercises that were attempted in a given week. The obtained proportions were considered as probabilities of exercise attempts during the days when these attempts were probable and calculated using Shannon's entropy algorithm (1948) as follows: $$H(X) = -\sum_{i=1}^{n} p_i log_2 p_i$$
Time		
Time invested	Practice duration	Duration of the online practice sessions in a week. Practice duration is calculated by taking the difference between the total time spent and the total duration of the practice breaks at the given period. The time difference between two action-timestamps larger or equal to 45 minutes was considered a practice break (Maldonado-Mahauad et al., 2018).
Time invested	Active days	The number of days of a particular week at which the students have at least a single log record of an online attempt to solve an exercise (Saqr & López-Pernas, 2021).

3.4. Data Processing

The six indicators were developed based on log data from student interactions with Grasple. The online interactions were exported in CSV files in the form of event data in eight weekly batches. Each event was represented by a row and consisted of 12 items, such as subject name and exercise timestamp (see Supplementary Data). After removing the data from the students who did not participate in the study, the raw weekly datasets were prepared for processing using R programming language (R Core Team, 2024). On average, 112,627 events were obtained each week. First, after pseudonymizing the data, we tidied up the main dataset and formatted the date and time variables. Next, variables related to the course schedule (i.e., *course name*, *deadline*) were added to the main dataset.

To compute the indicators, variables from different categories were combined. For example, the *attempt rate* indicator was computed based on the first *exercise timestamp* of a given *exercise id* for which the action result was 1 or 0 for the *correct* variable and 0 for the *skipped* variable. During this process, distinct data tables for the six student engagement indicators were created. NA records were converted to null, indicating that the given student was not active on the platform during the given week. After de-identifying the data, the data tables were connected to create the final dataset on the engagement indicators across the eight weeks. For transparency, the code used in data processing is publicly available.[1]

3.5. Data Analysis

3.5.1. Clustering

Agglomerative hierarchical clustering (AHC) was applied to the six indicators to identify distinct profiles of student engagement. This clustering method has been proposed as suitable for detecting profiles of student behaviour based on log data (e.g., Araka et al., 2022). AHC is a bottom-up approach where each data point starts as a cluster by itself, and the two closest clusters begin to merge into one progressively until there is only one cluster. During the merging process, the linkage criteria determine how cluster distances are calculated to identify the closest clusters (Gore, 2000). We performed Ward's linkage method, which merges clusters in a way that minimizes within-cluster variance, with squared Euclidean distance (Gore, 2000). For conducting each weekly clustering, the variables were z-score normalized to facilitate the comparison between the indicators (Riestra-González et al., 2021). Cluster analysis was conducted with the NbClust R package (Charrad et al., 2014). To determine the number of clusters, we followed the evaluation method provided by the NbClust R function. This function allows simultaneous evaluation of algorithms based on 30 validation indices to provide the best clustering solution.

We conducted cluster analysis separately for each of the eight weeks. Since the content and the level of difficulty of the material changed every week, we expected that students would demonstrate different engagement levels each week to adapt their behaviour to the new context (Pardo et al., 2019). A few outliers (5–9) were detected each week across all eight analyses. Comparing cluster solutions with and without outliers, we found only slight differences in distance matrices. For instance, in Week 1, the mean distance changed minimally from 3.17 (with outliers) to 3.23 (without outliers), with similar trends across weeks (see Supplementary Data). The number of clusters remained the same for five weeks, while Weeks 1, 3, and 8 showed differences of one or two clusters. Since removing the outliers does not significantly alter the clustering solutions, we decided to retain the outliers in the analytical process. Following prior work (Mirriahi et al., 2018; Pardo et al., 2019), we labelled each student profile based on common and distinctive patterns between clusters. Each week, the indicator (e.g., compliance) was characterized as high or low for each cluster by considering the maximum value that could be obtained in the given indicator, as shown in Table 2. Since we were interested in determining what could be defined as high and low in each indicator, the maximum value was considered the most appropriate value of reference, as it showed the highest possible value that could be obtained for the given indicator. The half of the maximum value was determined as the cut-off. Outliers were not included in the cut-off calculation because their extreme values could skew the determination of "high" or "low" levels for each indicator. Therefore, the variable was considered "high" when it was equal to or above the cut-off value and "low" when it was below the cut-off value. For example, if a cluster's reattempt rate value in Week 1 is .22, it will be considered that a cluster has a low reattempt rate based on the cut-off value of .28 in Week 1 (see Table 2). Effort and time indicator combinations were examined to explore the various potential patterns: high-effort/high-time, high-effort/low-time, low-effort/high-time, and low-effort/low-time. These patterns guided the interpretation of the clusters. Thus, a profile label corresponded to a pattern and was applied to all the clusters that bore this pattern (Pardo et al., 2019). Students who were inactive during a particular week were grouped and formed the "inactive" group for that week.

[1] Code repository available at: https://osf.io/v5tus/?view_only=22a8bf0b1df342d0b9671baba7f2e7ed

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Table 2. Maximum and Cut-off Values for Each Engagement Indicator Per Week

Week	Attempt rate		On-time rate		Reattempt rate		Regularity		Practice duration		Active days	
	Maximum	Cut-off	Maximum	Cut-off	Maximum	Cut-off	Maximum	Cut-off	Maximum	Cut-off	Maximum	Cut-off
WK1	1.00	0.50	1.00	0.50	0.56	0.28	2.47	1.24	493.00	246.50	6.00	3.00
WK2	1.00	0.50	1.00	0.50	0.66	0.33	2.56	1.28	546.00	273.00	7.00	3.50
WK3	1.00	0.50	1.00	0.50	0.67	0.34	2.35	1.18	439.00	219.50	6.00	3.00
WK4	1.00	0.50	1.00	0.50	0.67	0.34	2.47	1.24	439.00	219.50	7.00	3.50
WK5	1.00	0.50	1.00	0.50	0.50	0.25	2.48	1.24	433.00	216.50	6.00	3.00
WK6	1.00	0.50	1.00	0.50	0.67	0.34	2.44	1.22	533.00	266.50	6.00	3.00
WK7	1.00	0.50	1.00	0.50	0.67	0.34	2.32	1.16	484.00	242.00	6.00	3.00
WK8	0.95	0.48	1.00	0.50	0.28	0.14	2.63	1.32	522.00	261.00	7.00	3.50

3.5.2. Statistical Analysis

To assess the differences between the emergent profiles, we conducted a multivariate analysis of variance (MANOVA). For each of the eight weeks, we tested a MANOVA model with profile assignment as an independent variable and the six engagement indicators as dependent variables (Kovanović et al., 2015). Assumptions of homogeneity of covariance and homogeneity of variances were assessed using Box's M and Levene's test, respectively. When assumptions were violated, a robust method using Pillai's trace statistics was applied following Kovanović et al.'s (2015) work. MANOVA results were compared to the results of the robust rank-based variation of the MANOVA analysis (Nath & Pavur, 1985). Significant MANOVA results were followed by univariate one-way analyses of variance (ANOVA) with Benjamini-Hochberg correction (Benjamini & Hochberg, 1995) to further examine the indicators of difference. In the case of homogeneity of variance violation, the Mann-Whitney U test (for two profiles) and the Kruskal-Wallis test were conducted with Dunn–Bonferroni's test for pairwise comparison.

3.5.3. Transition Analysis

We used a combination of heatmap, flow visualization, and process mining (PM) to investigate the longitudinal development of the identified profiles across the eight-course weeks. The heatmap was used to provide an overall (i.e., macro-level) visualization of the emergence and submergence of profile groups. The Process Mining PM^2 method (van Eck et al., 2015) was selected to identify paths between common and different profiles (i.e., micro-level) from one week to the other. PM^2 encompasses four stages: 1) data extraction, 2) event log generation, where the concepts of cases, activities, and temporal order of activities are defined, 3) model discovery, and 4) process model analysis (van Eck et al., 2015). For the model discovery, we used the Disco algorithm, based on the Fuzzy algorithm concept, to transform complex data into process-map models (Günther & van der Aalst, 2007). Using the Disco software (van der Aalst, 2016), we explored the most and least prominent variants of student transitions from one profile to another. We used student_ID as case_ID and profile membership in a given week (e.g., Profile1_Week1) as activity variable. Two consecutive events for a student (e.g., Profile1_Week1 -> Profile2_Week2) were analyzed as paths from one profile to another for the given student. Case analysis was used to track all types of transitions and their frequencies (Figure 2).

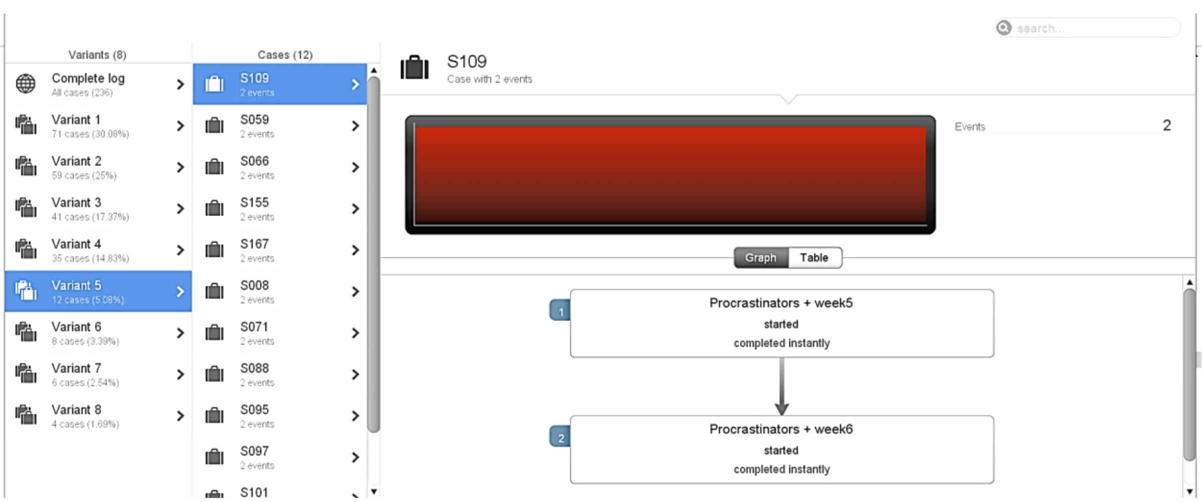

Figure 2. Example list of the 112 transitions across profiles obtained using Disco software. Variant 1 shows the transition of 12 students from the Procrastinators profile in week 5 to the Procrastinators profile in week 6.

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4. Results

4.1. Engagement Profiles in Online Practice

4.1.1. Weekly Identified Engagement Profiles

In the first research question, we focused on identifying distinct profiles of behavioural engagement based on six log-type indicators that represented different aspects of behavioural engagement. Figure 3 shows the cluster solution implemented each week (a detailed analysis of cluster solutions is available in the Supplementary Data). According to the majority rule of the validation indices in NbClust, two to four clusters of active students were proposed as the optimal solution. In the seventh week, a 10-cluster solution was proposed by seven indices, whereas a 3-cluster solution was proposed by six indices. After testing both solutions, we opted for the 3-cluster solution as it demonstrated a more interpretive categorization.

We explored whether similar patterns could be identified among clusters throughout the weeks and whether these patterns represented similar configurations of effort and time (see Tables 2 and 3). The effort–time configurations guided the cluster interpretation. For example, Cluster 1 of Week 5 (WK5/C1), which demonstrated high attempt rate, on-time rate, and reattempt rate, differed slightly in reattempt rate scores from another group of clusters (WK1/C1, WK4/C1, WK6/C2, WK8/C2). Therefore, these five clusters were merged into one group with a common active pattern (high attempt rate and on-time rate).

Six active patterns were detected in total. These six active patterns, along with the inactive group, were perceived as seven distinct profiles of behavioural engagement (see Figure 4 and Table 3). A description of these profiles is provided below. Moreover, labels were given to each cluster based on the similarities with engagement profiles identified in the literature (Flunger et al., 2015; Yang et al., 2020).

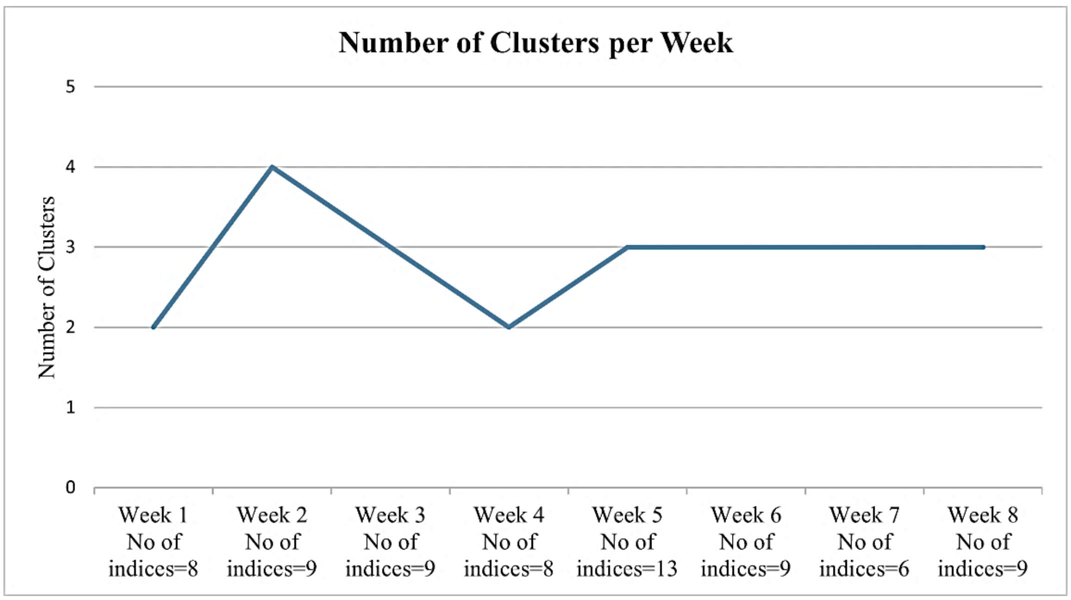

Figure 3. Optimal cluster solution per week suggested by most NbClust validation indices.

Profile 1. Fast-Learners (FL): In five weeks' analyses, clusters associated with this profile were identified. These students had high scores at both compliance indicators, i.e., the attempt rate and on-time rate, moderate at reattempt rate, and low scores at the remaining indicators. Students in this group managed to work on many exercises following the course schedule, spent less time on their assignments, and had fewer regular practice sessions.

Profile 2. Regular-Learners (REG): This profile is associated with clusters that emerged in four different weeks' analyses. Students in this group demonstrated high levels of regularity, practice duration, and active days, while they showed moderate levels on the remaining effort indicators. This suggests that these students regularly attempted to solve many of their assignments exercises and were mostly on-time for the assignment deadline. They also tended to have longer practice sessions and active days compared to other groups.

Profile 3. Average-Engagement (AE): This profile is associated with clusters that emerged in two different weeks' analyses. Students in this profile had moderate scores at all engagement indicators.

Profile 4. Minimalists (MIN): This profile is associated with clusters that emerged in six different week's analyses. Minimalists demonstrated moderate levels of attempt and reattempt rate, and low levels at the rest of the indicators. This indicates that students in that group did their assignments in short, intensive sessions. However, they were mostly behind schedule, as only a few exercises were attempted before the assigned deadline.

Profile 5. Struggling-Learners (STR): Two different weeks' analyses yielded a cluster associated with this profile. Struggling-Learners showed low levels at all the indicators except the reattempt rate indicator, where they scored higher than any other profile. These students had short practice sessions where they worked on a few exercises. The high reattempt rate scores in conjunction with the low attempt rate scores suggest that students persisted in exercises that they solved incorrectly by giving multiple tries.

Profile 6: Procrastinators (PROC): Also, four different weeks' analyses yielded a cluster associated with this profile. Students in this profile demonstrated high levels of regularity, practice duration, and active days, while they scored moderately at the attempt rate and low at the on-time rate and reattempt rate indicators. High regularity combined with a low on-time rate indicates that students in this profile do not steadily adhere to the course schedule, but rather have a consistent activity over time, often as part of catching up with their material. This might be an indication of procrastination-related behaviour.

Profile 7. Inactive (IN): This profile is the most frequent cluster, as it was associated with clusters that emerged every week, given that there was always a group of students who had no online activity.

The first three profiles (FL, REG, AE) exhibit effective engagement patterns, with higher combined values in compliance, regularity, and time investment compared to the remaining profiles (MIN, STR, PROC).

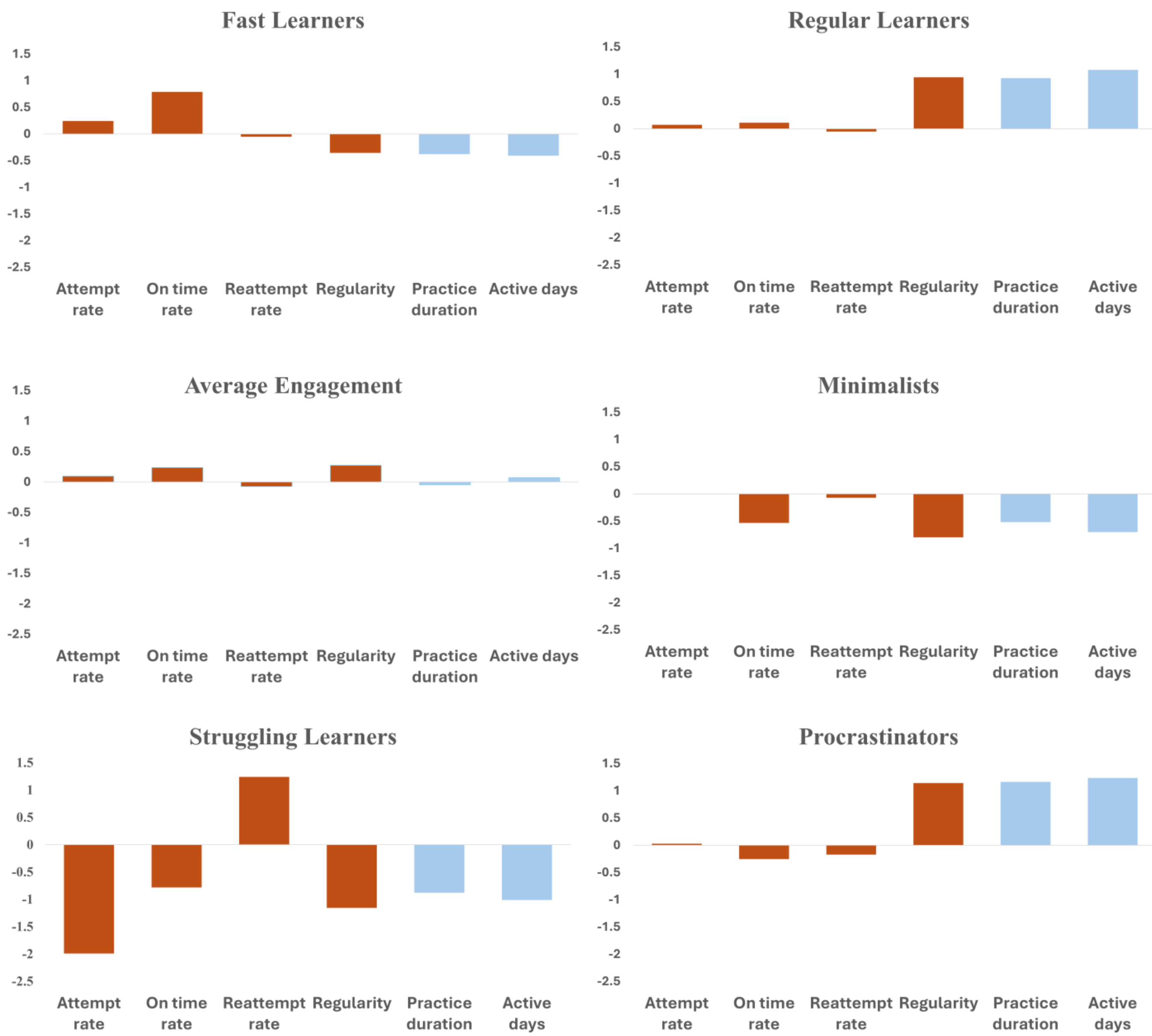

Figure 4. The six active engagement profiles (Mean scores based on z-scores for presentation).

Table 3. Weekly Clusters and Corresponding Mean Scores for Six Student Engagement Indicators per Student Profile

Profile	Week/ Cluster	Attempt rate	On-time rate	Reattempt rate	Regularity	Practice duration	Active days
Fast-Learners (FL)	WK1/C1	0.69	0.79	0.23	0.61	127.30	1.76
	WK4/C1	0.74	0.52	0.24	0.62	116.23	1.80
	WK5/C1	0.80	0.94	0.28	0.66	126.68	1.89
	WK6/C2	0.88	0.91	0.16	0.91	165.86	2.26
	WK8/C2	0.77	0.86	0.25	0.54	154.51	1.72
Regular-Learners (REG)	WK1/C2	0.70	0.80	0.20	1.60	311.58	3.60
	WK2/C4	0.68	0.70	0.23	2.04	416.46	4.84
	WK3/C3	0.75	0.50	0.17	1.67	344.73	4.08
	WK7/C2	0.74	0.55	0.29	1.34	259.75	3.06
Average-Engagement (AE)	WK2/C3	0.71	0.66	0.20	1.37	210.83	2.95
	WK3/C2	0.68	0.70	0.25	1.18	159.98	2.61
Minimalist (MIN)	WK2/C1	0.73	0.32	0.19	0.08	71.80	1.22
	WK3/C1	0.64	0.43	0.29	0.01	73.20	1.09
	WK5/C2	0.72	0.07	0.22	0.53	140.81	1.73
	WK6/C1	0.73	0.17	0.27	0.61	115.75	1.82
	WK7/C1	0.85	0.30	0.12	0.76	191.16	2.11
	WK8/C1	0.71	0.08	0.30	0.53	157.89	1.76
Struggling-Learners (STR)	WK2/C2	0.40	0.22	0.41	0.61	59.93	1.80
	WK7/C3	0.47	0.14	0.35	0.02	76.93	1.12
Procrastinators (PROC)	WK4/C2	0.78	0.48	0.22	1.69	331.74	3.82
	WK5/C3	0.74	0.10	0.17	1.66	503.96	3.90
	WK6/C3	0.79	0.46	0.23	1.61	335.34	3.70
	WK8/C3	0.73	0.15	0.27	1.89	491.28	4.76

4.1.2. Profile Difference Analysis

Figure 5 provides an overview of the results of the MANOVA conducted on the identified profiles for each week. There were significant differences in the six indicators among the weekly identified profiles. The weekly multivariate effect size (η^2) ranged from $\eta^2 = .59$ to $\eta^2 = .76$. These findings suggest a large effect size (Cohen, 1988). Post-hoc comparisons were performed to explore the differences between the profiles concerning each engagement indicator (for a detailed report, see Supplementary Data). Figure 5 shows that all the pairs of profiles differed in some of the indicators, except for REG vs. STR (week 2), MIN vs. STR (week 2), and FL vs. PRC (week 6), where the differences emerged across all indicators. Moreover, besides the cases of MIN vs. STR (week 2) and FL vs. MIN (week 8), the profiles showed differences in both effort and time indicators, suggesting that they represent distinct types of behavioural engagement.

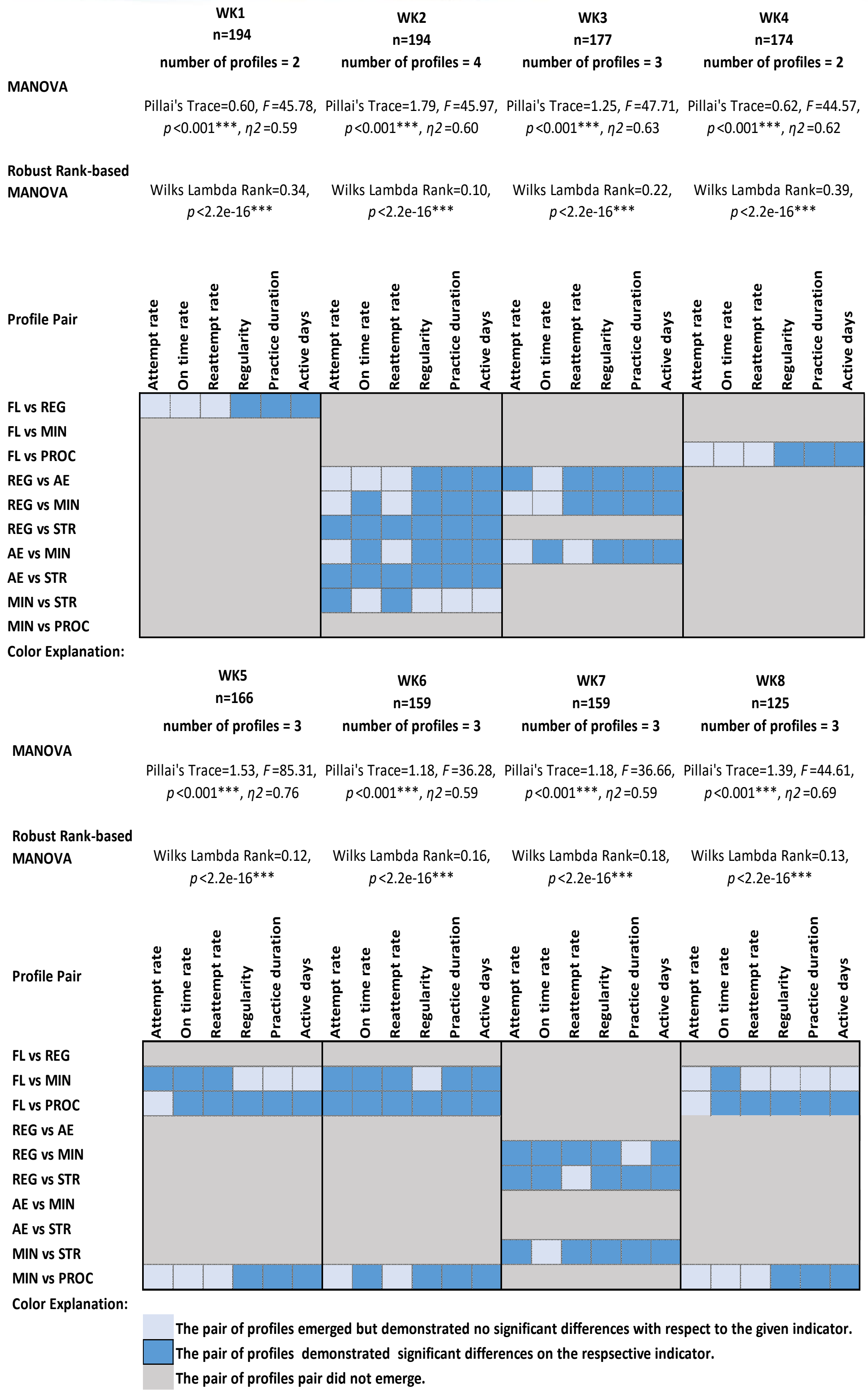

Figure 5. MANOVA results on statistically significant differences between the student profiles based on the six engagement indicators across Weeks 1–4 (top figure) and Weeks 5–8 (bottom figure).

4.2. Longitudinal Development of the Engagement Profiles

4.2.1. Size of profiles across weeks

Figure 6 shows the heatmap distribution and density of the profiles across the eight weeks. When examining how each profile changes over the weeks, three observations can be made. First, only the Inactive profile emerged every week. Second, there were differences in how the six profiles fluctuated. MIN and FL were the most consistent active profiles, with MIN emerging in 6 weeks and FL emerging in 5 weeks. This indicates that these two active profiles and the Inactive profile represented the more common types of online behavioural engagement in this course.

While REG and STR profiles emerged in the first half of the course, these two profiles "disappeared" after weeks 2 and 3 to emerge again in week 7. The remaining two profiles emerged only at a specific part of the course. AE emerged only in weeks 2 and 3, while PROC first appeared at week 4 and almost consistently emerged until the end of the course. These fluctuations indicate that certain profiles might be more typical for specific periods. For instance, while practising regularly and spending large amounts of time on assignments was a prevalent behavioural pattern across the whole course (REG, PROC), doing so by following the course schedule and working on exercises before the deadline was more common during the first three weeks (REG, AE).

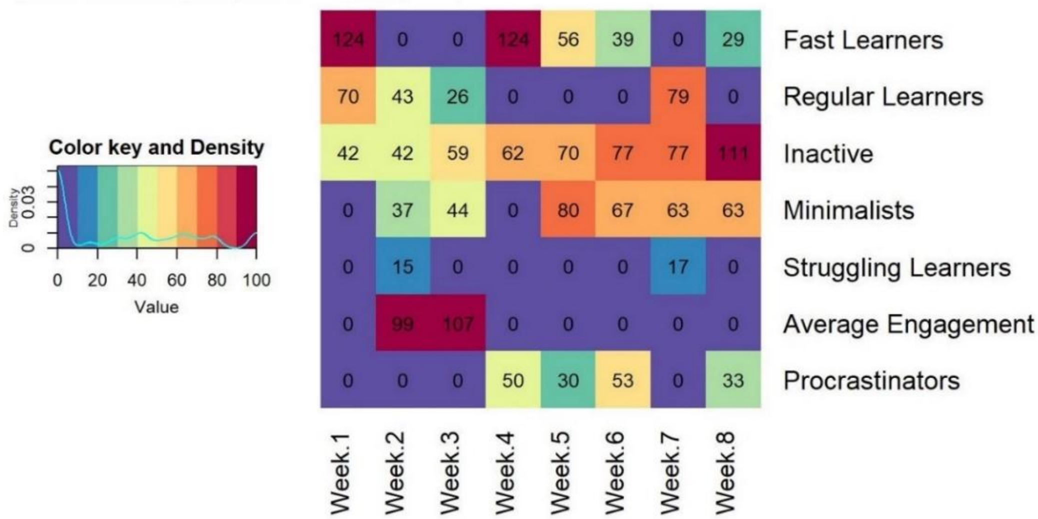

Figure 6. Heatmap profile distribution and density across the eight weeks.

Third, differences were identified regarding the size of the dominant profiles across the two halves of the course. At the two extremes were the Inactive and STR profiles. The first increased steadily over the weeks, while the second represented the smallest group of students (15 and 17 at weeks 2 and 7, respectively). In weeks 5 to 8, the MIN profile was generally the largest among the active profiles, with the number of students ranging from 63 to 80. FL profile became smaller over time. The PROC profile consists of a steadily low to moderate number of students across weeks.

These findings suggest that, during the course, active students attempted to complete a moderate number of the assigned exercises. Moreover, every week, most of the students had short practice sessions, which, after week 3, became less regular. However, in the second half of the course, students were less compliant. This pattern changed only in week 7, where REG profile was the largest active group with 79 students. In fact, REG profile had almost the same number of students in weeks 1 (n =70) and 7 (n =79), suggesting that putting high levels of regularity and spending a lot of time practising was the most common at the beginning and the end of the course.

4.2.2. Transitions of Profiles Across Weeks

Next, we explored how the profiles changed from week to week. The results of the process mining analysis revealed the various types of transitions. Figure 7 portrays these transitions during the periods from week 1 to week 4 and week 5 to week 8, respectively. Each node denotes a profile, while each flow denotes the transition of students from one profile to the other. Flows take the colour of the target profile.

From Figure 7, three transition patterns can be observed. First, most students who were in the Inactive group at a certain week remained in the Inactive group. Furthermore, the students shifting from an active group to the Inactive group were more than the students following the opposite path. Of the students who shifted to the Inactive group, most were coming from a moderate-low time profile. For instance, in weeks 1–3, from the 39 students who moved to the Inactive group from an active group, 16 came from the FL, 10 from the AE, 10 from the MIN, and 9 from the STR group. Regarding the students that left the Inactive group, a similar pattern was observed, since most of them shifted to a low time profile. A change was found in week 8, where an almost equal number of students from MIN (n = 25) and REG (n = 24) moved to the Inactive group.

Second, relatively stable transitions were observed during the intermediate weeks. For instance, most of the students who were in the REG (n = 73) and FL (n = 64) groups in week 1, moved to the REG and AE groups in week 2. Similarly, most of the students who were in the REG (n = 30) and AE (n = 58) groups in week 2, moved to the AE group in week 3. In the second part of the course, most of the students in a low-time profile (i.e., FL, MIN) transited either to the same profile or to the other low-time profile (see weeks 4, 5, and 6). Third, the patterns of transition regarding the active profiles changed when moving to weeks 4 and 7. Figure 7 shows that the flows were mainly split into two types of profiles: 1) low time with irregular practice sessions (FL in week 4 and MIN in week 7) and 2) high time with regular practice sessions (PROC in week 4 and REG in week 7).

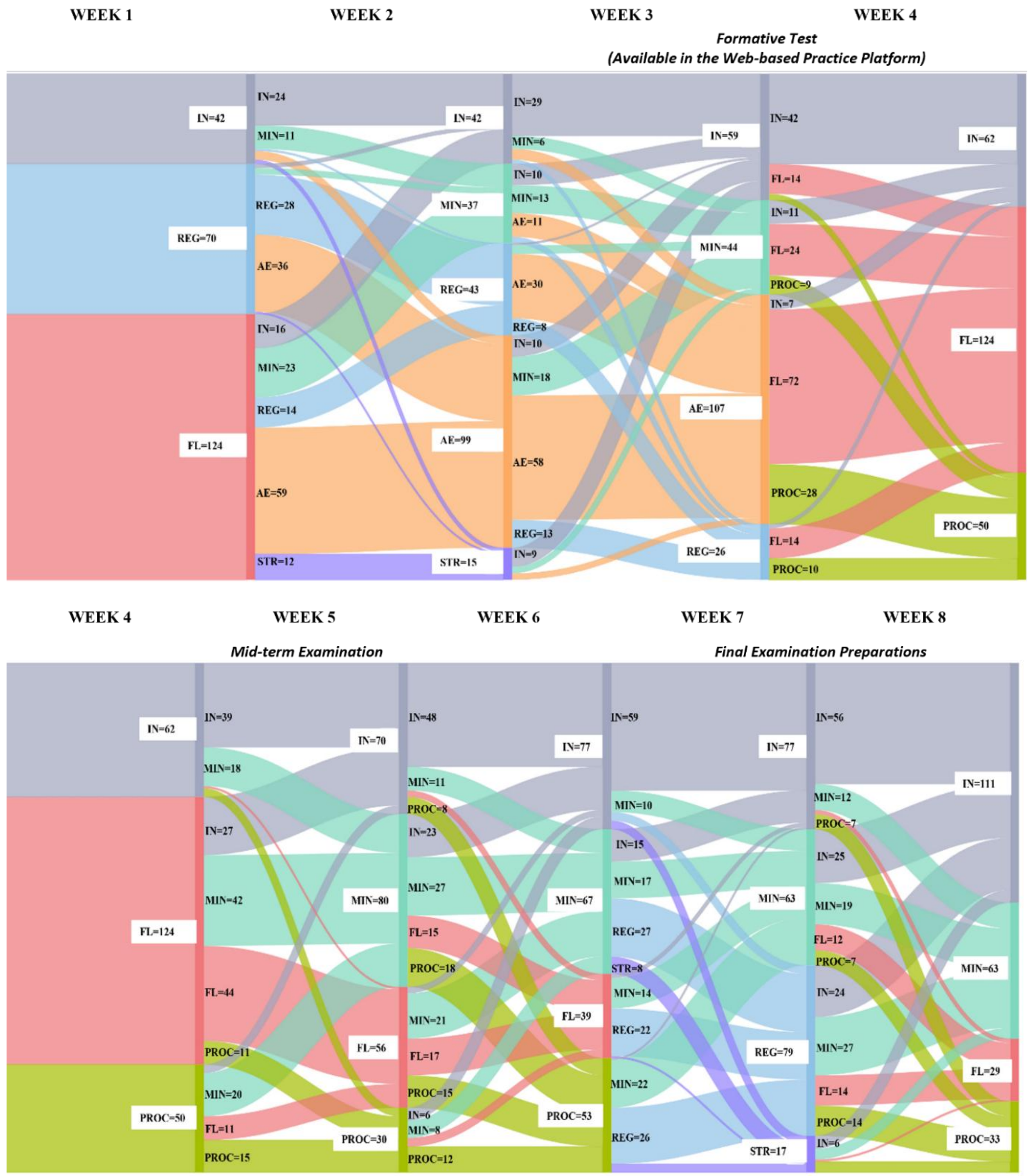

Figure 7. Profile-to-profile transitions in weeks 1–4 (top figure) and weeks 4–8 (bottom figure). General course milestones are depicted. Transitions representing more than 2% of the study population are presented (full transition analysis is included in the Supplementary Data).

5. Discussion

The study explores the longitudinal development of behavioural engagement profiles in studying online based on effort and time interaction. We operationalized effort and time using six log-type indicators obtained from a web-based learning platform. To capture the dynamic development of the engagement profiles over the course, we conducted eight separate cluster analyses, one for each week of the course, and examined the transitions of profiles across weeks.

In RQ1, we inquired what behavioural engagement profiles can be identified based on the six log-type indicators. In total, we identified six profiles that demonstrated different patterns of effort and time. Compared to prior studies that identified 2–5 distinct profiles (e.g., Chen et al., 2018; Kokoç et al., 2021), we found a larger number of profiles. We found that three profiles (Fast-Learners, Regular-Learners, and Average-Engagement) demonstrated more effective engagement patterns than the remaining three (Procrastinators, Minimalists, and Struggling-Learners). Rienties et al. (2019) found two effective and two ineffective profiles. As indicated by Tempelaar et al. (2023), fine-grained temporal analysis (i.e., a weekly time window) can result in richer solutions and a larger number of profiles.

Students in the effective profiles regulated their engagement by managing study time according to the course schedule. Regular-Learners used many practice sessions and invested much time in practising. Identified also in previous research in online learning settings (e.g., Chen et al., 2018), this engagement pattern indicates effective skills in time management and study strategies selection. Students in the other two effective profiles showed moderate (Average-Engagement) or low (Fast-Learners) regularity and time spent, suggesting that in certain weeks working sufficiently on the assigned tasks and meeting the deadlines does not necessarily relate to high regularity and time spent.

Procrastination-related behaviour was common across the ineffective engagement patterns. Even though students in the Procrastinator and Minimalist profiles tried to complete most of the subjects that they initiated, they often did not manage to practise before the assigned deadline. The Procrastinators tried to catch up with the material by using regular sessions. The high levels of regularity and time in the platform suggest that Procrastinators showed investment in their online practice. Further research using repeated student self-reports is needed to determine whether this group strategically postponed their practice or lacked the necessary self-regulation skills (Barthakur et al., 2021). On the other hand, students in the Minimalist profile used few practice sessions and spent little time. This pattern might be related to a late start of practice and subsequent cramming behaviour (Conde et al., 2024; H. Li et al., 2018). Moreover, as with Fast-Learners, Minimalists worked on a high number of exercises in a short time, suggesting that students could effectively monitor their progress until completing the task (Järvelä et al., 2016).

Students in the Struggling-Learner profile worked on a few exercises in a short amount of time and were mostly behind schedule, demonstrating poor SRL skills. Profiles with low engagement scores have been identified in prior research (Kokoç et al., 2021; H. Li et al., 2018; Pardo et al., 2019). However, the Struggling-Learner profile demonstrated very high levels of persistence (i.e., made multiple reattempts), indicating that these students might have struggled with their assignments. Chen et al. (2018) found that high persistence was associated with higher time spent, timeliness, and regularity. Future research that would include aspects such as the level of task difficulty, the completion score, or course grade is needed to further advance our understanding of the role of persistent behaviour in working with challenging tasks in online environments.

The study provides insights into configurations of engagement characterized by inconsistencies in how the various indicators were connected. Unlike previous findings in online learning, our profiles did not demonstrate patterns with purely high or low scores across the indicators, but showed that high compliance might not be connected to high regularity and high persistence or high effort might not be connected to high time, emphasizing theoretical views on dynamic relationships between effort and time (Flunger et al., 2015). As proposed also in Zhang and Gao (2024), such inconsistencies in the connection between the engagement indicators reveal the complexity and nonlinearity of the construct. This may be also related to the assignment format. For example, in Kokoç et al. (2021) and Yang et al. (2020), students were expected to submit one assignment per week. In this type of assignment, positive associations between the compliance indicators were anticipated among the groups. In the current study, students were expected to practise multiple exercises, while they had to meet two to three deadlines per week. This finding suggests that learning environments that allow flexible and repeated practice could encourage the development of more diverse types of engagement.

In RQ2, we sought to understand whether the profiles were stable and how students transitioned from one profile to another. The results indicate various patterns in student transitions across the profiles over time, supporting the view of student engagement as a fluid and dynamic construct (López-Pernas & Saqr, 2024; Wong, Khalil, et al., 2019). However, three distinct transition patterns were identified across the weeks. The first pattern was observed for the active profiles until week 4. A relatively stable pattern of transitions between Regular-Learners and Average-Engagement was found. Moreover, students starting as Fast-Learners could move to any profile in week 2, with most students moving to the Average-Engagement. These results emphasize previous findings in online learning that students in highly engaged groups tend to maintain stable engagement states (Kokoç et al., 2021; Saqr & López-Pernas, 2021). Students tend to maintain effective engagement during this period, even though they seem to adjust some aspects of their behaviour, such as increasing or reducing their regularity.

These findings are in line with previous evidence that shows students with effective engagement strategies demonstrate adaptivity and strong SRL skills (Barthakur et al., 2021; Getman et al., 2024). These findings suggest the importance of compliance and regularity components in sustaining consistent engagement. Students who showed ineffective patterns or inactivity were less likely to move to an effective pattern. Prior work has also shown that adopting ineffective engagement patterns early in the course can be associated with difficulties in improving their trajectory and can be an indication of struggling students who need targeted feedback and scaffolding (Poquet et al., 2023).

The second pattern of active profiles was observed in weeks 4–8. Transition patterns were less stable, and students moved mainly between Fast-Learners, Minimalists, and Procrastinators. In this study, the fluctuations between these profiles indicate that students might struggle to maintain consistent study patterns, while the decline in Fast-Learners reveals a drop in adhering to the course schedule. In terms of engagement patterns, the findings show that low time investment combined with low compliance could be related to irregularities and abrupt changes in studying. This aligns with previous findings of highly fluctuating transitions among less engaged states (Saqr & López-Pernas, 2021). The increase of Procrastinators in week 6 and the re-emergence of Regular-Learners in week 7 suggests that students adopted more effective patterns towards the end of the course (Pardo et al., 2019). The third pattern shows that students who adopted an ineffective profile or were inactive in a given week were more likely to transition to an ineffective or inactive profile. This pattern progressed with increasing stability throughout the course and is like the persistently disengaged trajectory found in López-Pernas and Saqr (2024). The only exception was found between weeks 3–4, where inactive students moved to the fast-learner profiles, indicating exam-oriented behaviour and poor regulation of learning (Barthakur et al., 2021).

These findings are consistent with views of engagement as a dynamic construct, positing that students can adapt their learning behaviour in response to internal and external factors (Winne & Hadwin, 2008). Various potential factors could have contributed to the identified engagement changes. For example, in weeks 3 and 4, Regular-Learners decreased and low-time profiles increased, suggesting a decline in engaged time with online practice. This change could be related to adjustments in the course requirements since, during that period, students had to submit a formative test next to their regular practice. The test, embedded in the practice platform and aimed at self-assessment, was emphasized through LMS announcements. The drop in engagement with the homework may indicate a shifted focus on the test. Additionally, exam periods could explain engagement adaptations. Midterms in week 5 could account for the prevalence of low time profiles, likely due to the increased workload. The emergence of Procrastinators in week 4 indicates student attempts to catch up with the material and benefit from the immediate feedback provided in the practice exercises. Similar engagement shifts during midterms have been reported (Pardo et al., 2019; Poquet et al., 2023). Furthermore, as the material of the last weeks is usually dedicated to exam preparation, students might have been encouraged to be more regular on the platform, suggesting a performance-oriented behaviour (Barthakur et al., 2021). Since our three Linear Algebra courses had slightly different schedules due to varying numbers of lectures per week, we did not examine the influence of specific curriculum events, such as topic introductions, on engagement. Additionally, other factors related to course participation, which couldn’t be tracked via the LMS, may have influenced profile emergence and transition patterns. For example, increased lecture participation in the initial weeks might have prompted students to align their behaviour with the course schedule, leading to higher levels of effective engagement (Liborius et al., 2019). Future research could explore the relationship between lecture participation, curriculum events, and online behavioural engagement patterns. Finally, internal factors, like motivation or skills, could be investigated to explain emerging engagement patterns. For instance, declining motivation could hinder students from maintaining consistent engagement on the platform (Skinner & Pitzer, 2012).

This study uncovers mechanisms of stability and fluctuation in student engagement during online practice through a person-oriented, longitudinal lens. As engagement evolves, current patterns are likely to shape future patterns (Getman et al., 2024). Our findings emphasize the role of compliance and regularity in maintaining adaptive learning in flexible environments. The analytical approach also supports meaningful comparisons with previous work (e.g., Pardo et al., 2019; Poquet et al., 2023), especially regarding engagement transitions during critical periods such as midterms and finals. The weekly clustering approach reveals profile membership as a fluid, context-sensitive process rather than a fixed trait, reinforcing prior work (Saqr & López-Pernas, 2021). These insights support a view of engagement as a dynamic, contextualized construct (López-Pernas & Saqr, 2024) and underscore the need for adaptive interventions that respond to fluctuations across course periods (Pogorskiy & Beckmann, 2023).

6. Limitations

There are a few limitations in the study. The first limitation is related to the generalizability of the findings since the study was conducted only in the context of three Linear Algebra courses. The courses applied the same design and targeted similar learning goals. As indicated in our Discussion, in courses with a different structure and assignment requirements, some patterns might not emerge or might emerge in different course periods. A second, relevant limitation is that we did not explore the role

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of student factors, such as age and gender, in explaining differences in profile membership and transition dynamics. These limitations suggest the need for further investigation into different contexts by considering interpersonal differences.

Nevertheless, even though our study population consists predominantly of males under the age of 20, there is a level of heterogeneity in the sample reflected in the diversity of the identified profiles. The profiles presented similarities with prior research not only in undergraduate (H. Li et al., 2018) but also in K–12 settings (e.g., Flunger et al., 2015), suggesting the contribution of the study in enhancing transferability in LA-based engagement research (Bond et al., 2023).

Second, the study examined only log-type behavioural indicators. Even though we employed a multifaceted framework for studying behaviour, we did not examine affective or cognitive aspects of engagement. Future studies can build on our findings and enhance our understanding of why students shift from one profile to another by examining cognitive and affective aspects of engagement via additional data channels, such as physiological data and self-reports.

Finally, in our analysis, we did not distinguish student activity based on whether they worked on a fixed or adaptive exercise (see Section 3.2.1.). The two categories differ in terms of the completion requirements and, consequently, student scores on attempt and reattempt rate might be affected depending on the exercise type. Therefore, further investigation is required to examine whether by controlling for the exercise type, different profile solutions would emerge.

7. Implications and Future Directions

Despite the limitations, the present study brings theoretical, methodological, and practical implications to advance our understanding of engagement in online learning. Regarding theoretical and methodological implications, the view of engagement as a complex and dynamic construct provides a useful approach to measure and examine the temporal evolution of engagement. We propose that complex behavioural engagement patterns, combining aspects such as compliance and regularity, can be studied using log-data indicators. Even though we focused only on the behavioural dimension of engagement, our profile solution highlighted the interplay between the various subcomponents that form the distinct patterns that could not be easily captured when using broad categorizations of engagement (e.g., high, moderate, and low engagement). By combining cluster with transition analyses, we were able to map how the different engagement profiles co-occur and fluctuate over time. Most of the profiles, such as Fast-Learners, Minimalists, and Procrastinators, appeared throughout the weeks, suggesting consistency in the emergent patterns. Profiles that demonstrated high levels of compliance and regularity would result in more positive transitions, while transitions between ineffective profiles and inactivity were found as a “stuck” pattern that is hard to change without substantial effort (López-Pernas & Saqr, 2024). Consequently, the study provides new insights into the mechanisms of stability and fluctuation of engagement transitions.

Regarding practical contributions, this study offers insights into the learning and curriculum analytics literature on the design of teaching practices and curriculum-based interventions to support student groups with diverse learning behaviours in online settings. One application could be in the development of behavioural engagement indicators for teacher dashboards to provide information on whether additional instructional support should be designed for certain groups of students (Redmond et al., 2018). Indicators such as attempt and reattempt rates and timing can also guide iterative improvements in workload distribution and exercise sequencing within the curriculum. Integrating theory-based operationalization and temporal LA techniques in exploring online engagement data can inform the building of enriched intelligent learning technologies that capture multidimensional learning processes. Adaptive support systems could be enhanced by recognizing process-oriented engagement patterns across multiple indicators. Moreover, transition modelling could be used to predict shifts from effective to ineffective profiles based on indications such as a decreasing on-time rate or regularity. Combining process-based with outcome-focused analytics could enrich adaptive systems to tailor learning content based on both *what* students know and *how* they engage in a given week, while also informing curriculum design decisions (De Silva et al., 2024; Wang et al., 2025). For example, high-performance Fast-Learners could be provided with optional challenging problems or enrichment activities to maintain engagement without unnecessary repetition, while low-performance Fast-Learners could receive targeted self-assessment prompts or scaffolds to encourage deeper engagement. Furthermore, high-performance Regular-Learners could benefit from recognition mechanisms (e.g., badges) that reinforce consistent engagement, while low-performance Regular-Learners could receive review exercises, scaffolded tasks, and pacing adjustments that address potential misconceptions. These differentiated support strategies illustrate how insights from engagement patterns can also contribute to broader discussions about aligning course design with the needs of diverse learners, a growing topic in curriculum-focused analytics research.

These transition patterns also offer valuable implications for personalized feedback and feedforward provision that can help students reflect on their progress each week and modify their behaviour accordingly (Kong & Lin, 2023; Lim et al., 2023). For example, students showing Minimalist behaviour can be encouraged to start earlier by highlighting the benefits of distributed practice (Brown et al., 2023). Those displaying Struggling-Learner patterns could receive cognitive-oriented feedback with scaffolding strategies to help them manage difficult tasks (Kong & Lin, 2023). Weekly engagement levels can form the basis for tailored interventions, especially for those at risk of disengagement. Inactive students, for instance, may benefit from early reminders nudging them to re-engage with the materials (Brown et al., 2023). Finally, students in Inactive or low-engagement profiles might benefit from timely prompts focused on goal setting and planning to help initiate and direct their study behaviour (Wong et al., 2021).

8. Conclusion

This study applied person-oriented, temporal LA to explore how student engagement evolves in a web-based practice platform. By adopting a theory-anchored operationalization of engagement as an effort–time interplay, we investigated weekly profiles based on multiple components of online behavioural engagement. Our findings reveal that effective engagement in online practice is not necessarily defined by uniformly high scores across all indicators but rather manifests in diverse and complex patterns. Despite the pattern complexity, students in effective engagement profiles had in common the ability to regulate their study behaviour in alignment with the course schedule. Moreover, while certain engagement profiles (e.g., Minimalists) remained consistent across weeks, others (e.g., Procrastinators) emerged primarily during specific course periods, such as near midterms. These findings underscore the temporality and context-specificity of student engagement, corroborating insights from curriculum analytics literature that highlight the influence of course structure, design elements, and milestones on engagement patterns (De Silva et al., 2024). Bridging theory-informed engagement analytics with curriculum analytics can offer a more comprehensive understanding of the mechanisms underlying student engagement. In addition, by examining weekly transitions between profiles, we observed relative stability among effective engagement patterns, while low-time profiles exhibited more dynamic fluctuations. These insights highlight the importance of personalized, timely interventions — both to reinforce effective engagement strategies and to address early signs of student inactivity. Finally, the analytical approach used in the study can be applied in various online learning environments. While the degree of adaptivity or instructional control may vary across systems, the underlying engagement indicators, such as compliance, persistence, regularity, and time investment, can be adapted to reflect the characteristics of the learning environment. For example, in Intelligent Tutoring Systems, compliance can be investigated based on the extent to which students follow the system's prompts and suggestions (Azevedo et al., 2022). These differences notwithstanding, our approach can enhance the interpretability of log data across diverse learning systems when examining student engagement.

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Appendix A. Grasple Raw Data

Table 1. Structure of raw data from Grasple

Items	Description
student_name	Student name
student_id	Student unique identifier
subject_name	Subject name
subject_id	Subject unique identifier
main_exercise_id	Main exercise unique identifier
exercise_id:	(Sub)question unique identifier
session_started_at	Timestamp of practice session beginning
session_completed_at	Timestamp of practice session completion
exercise_answered_at	Timestamp of exercise attempt
session_completed	Indicates whether a session was completed Indicates
correct	whether an answer was marked as correct or incorrect
skipped	Indicates whether an exercise was skipped

Appendix B. NbCluster validation indices

Table 1. NbCluster output for Week 1 solution

KL	CH	Hartigan	CCC	Scott	Marriot	TrCovW	TraceW	Friedman	Rubin	Cindex	DB	Silhouette
2.2253	54.4927	29.6744	-5.1283	234.3334	3.92E+12	30593.27	901.9983	12.1796	1.2838	0.2855	1.7926	0.2503
0.1607	46.0535	31.1009	-6.8687	377.4436	4.22E+12	22996.3	781.2525	19.6748	1.4822	0.3224	1.9561	0.164
1.5276	45.8274	22.5327	-6.6427	593.8198	2.46E+12	18106.75	671.8533	23.1573	1.7236	0.3213	1.701	0.2079
0.5137	43.8478	28.0747	-6.817	673.2704	2.55E+12	12999.59	600.6235	23.8321	1.928	0.3084	1.5323	0.1764
0.9618	45.661	28.0699	-4.9772	805.7268	1.86E+12	10209.36	522.9437	24.9282	2.2144	0.3049	1.2548	0.2037
1.9587	48.1529	18.1192	-2.1	937.4879	1.28E+12	8179.246	455.0074	28.7152	2.545	0.3274	1.1895	0.2223
0.8725	47.6056	18.9936	-0.924	1011.527	1.14E+12	6580.581	414.8144	29.9798	2.7916	0.3159	1.232	0.2015
1.9652	48.0232	12.6144	0.5466	1092.465	9.53E+11	5094.943	376.38	32.4343	3.0767	0.3892	1.2172	0.2117
0.709	46.7455	14.7188	1.0155	1145.901	8.93E+11	4247.016	352.3544	33.3198	3.2865	0.3822	1.2296	0.206

Duda	Pseudot2	Beale	Ratkowsky	Ball	Ptbiserial	Frey	McClain	Dunn	Hubert	SDindex	Dindex	SDbw
0.7825	36.1355	1.0613	0.2746	450.9992	0.3706	0.8215	0.5625	0.0887	0.0018	2.5518	1.9527	1.7214
0.6846	27.6422	1.7434	0.2719	260.4175	0.3738	-0.05	1.2215	0.1096	0.0021	2.7378	1.8215	1.4094
0.712	35.9965	1.5388	0.2813	167.9633	0.4299	1.6436	1.4098	0.1187	0.0024	2.5099	1.6604	1.243
0.437	38.6534	4.7972	0.2934	120.1247	0.3565	-0.1556	2.5042	0.0636	0.0023	2.4243	1.5529	1.2675
0.6368	22.2438	2.1395	0.2982	87.1573	0.3789	-0.1195	2.4793	0.0651	0.0027	2.1101	1.4748	0.4931
0.6552	26.3092	1.9847	0.2917	65.0011	0.408	0.6634	2.4629	0.0737	0.0034	2.2056	1.4094	0.4356
0.6137	17.6253	2.3383	0.2814	51.8518	0.3827	0.0709	3.0816	0.0737	0.0034	2.5438	1.3436	0.4032
0.5999	18.0087	2.4745	0.2729	41.82	0.3899	0.4383	3.2305	0.0947	0.0036	2.4616	1.2861	0.3775
0.7636	10.8373	1.1582	0.2633	35.2354	0.3816	0.1152	3.4985	0.0947	0.0037	2.4274	1.2448	0.3551

*** : The Hubert index is a graphical method of determining the number of clusters. In the plot of Hubert index, we seek a significant knee that corresponds to a significant increase of the value of the measure i.e the significant peak in Hubert index second differences plot.

*** : The D index is a graphical method of determining the number of clusters. In the plot of D index, we seek a significant knee (the significant peak in Dindex second differences plot) that corresponds to a significant increase of the value of the measure.

****

* Among all indices:
* 8 proposed 2 as the best number of clusters
* 3 proposed 3 as the best number of clusters
* 2 proposed 6 as the best number of clusters
* 3 proposed 7 as the best number of clusters
* 2 proposed 10 as the best number of clusters

***** Conclusion *****

* According to the majority rule, the best number of clusters is 2

Table 2. NbCluster output for Week 2 solution

KL	CH	Hartigan	CCC	Scott	Marriot	TrCovW	TraceW	Friedman	Rubin	Cindex	DB	Silhouette
0.972	64.8561	42.709	-4.8495	208.2902	2.61E+12	29606.91	865.6052	10.4397	1.3378	0.2938	1.5318	0.3198
0.7699	60.6783	39.5557	-5.9632	400.1781	2.19E+12	22735.21	708.0947	18.8054	1.6354	0.2598	1.6274	0.2198
1.6897	61.6903	27.0983	-4.8692	542.917	1.86E+12	12578.97	586.6092	21.9534	1.9741	0.3122	1.3418	0.2412
2.5826	59.3272	16.6779	-4.2401	669.6432	1.51E+12	9015.918	513.3884	24.2574	2.2556	0.2861	1.4868	0.2078
1.3391	54.6946	13.5361	-4.652	739.6267	1.52E+12	7147.861	471.759	25.4679	2.4546	0.2789	1.3996	0.1858
0.4611	50.8446	16.5958	-4.4938	820.0147	1.37E+12	6979.084	440.0735	28.3206	2.6314	0.2725	1.4184	0.172
0.6227	49.5532	21.2076	-3.5638	894.1694	1.22E+12	5568.662	404.2016	29.3205	2.8649	0.261	1.368	0.1833
3.0113	50.6799	11.2482	-1.7341	1016.265	8.22E+11	4465.34	362.8318	31.5087	3.1916	0.3432	1.2981	0.2005
0.7203	48.7725	12.5406	-1.4541	1070.344	7.68E+11	3888.251	342.0357	32.516	3.3856	0.3311	1.3315	0.1958

Duda	Pseudot2	Beale	Ratkowsky	Ball	Ptbiserial	Frey	McClain	Dunn	Hubert	SDindex	Dindex	SDbw
0.7345	53.1369	1.3813	0.3244	432.8026	0.5159	1.2243	0.3608	0.1069	0.0024	2.3045	1.9275	1.5977
0.5539	34.626	3.0277	0.3219	236.0316	0.5057	-0.1224	0.897	0.0913	0.0025	2.2825	1.7412	1.0758
0.7628	33.5865	1.1855	0.3444	146.6523	0.5437	1.4658	0.9437	0.1148	0.0028	1.7891	1.6196	0.7054
0.6605	27.757	1.9416	0.3299	102.6777	0.4415	1.2191	2.0206	0.0681	0.0027	2.0788	1.502	0.6894
0.7192	20.3051	1.474	0.3121	78.6265	0.407	1.2804	2.5795	0.0681	0.0027	1.9243	1.43	0.5743
0.6409	15.6903	2.0816	0.2952	62.8676	0.3672	0.0167	3.3995	0.0681	0.0027	2.0239	1.3718	0.4623
0.6744	17.8598	1.8082	0.2836	50.5252	0.3779	-0.0124	3.5038	0.0681	0.0029	2.0025	1.3258	0.4594
0.7222	12.3109	1.4353	0.2749	40.3146	0.3957	0.3146	3.5631	0.095	0.0033	2.1845	1.2775	0.4496
0.521	19.3034	3.3757	0.2644	34.2036	0.3854	0.2309	3.9701	0.095	0.0034	2.1311	1.2355	0.4182

*** : The Hubert index is a graphical method of determining the number of clusters.
In the plot of Hubert index, we seek a significant knee that corresponds to a significant increase of the value of the measure i.e the significant peak in Hubert index second differences plot.

*** : The D index is a graphical method of determining the number of clusters.
In the plot of D index, we seek a significant knee (the significant peak in Dindex second differences plot) that corresponds to a significant increase of the value of the measure.

****
* Among all indices:
* 5 proposed 2 as the best number of clusters
* 4 proposed 3 as the best number of clusters
* 9 proposed 4 as the best number of clusters
* 1 proposed 5 as the best number of clusters
* 3 proposed 9 as the best number of clusters
* 2 proposed 10 as the best number of clusters

***** Conclusion *****

* According to the majority rule, the best number of clusters is 4

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Table 3. NbCluster output for Week 3 solution

KL	CH	Hartigan	CCC	Scott	Marriot	TrCovW	TraceW	Friedman	Rubin	Cindex	DB	Silhouette
0.2834	48.6556	36.0279	-5.1971	171.8939	2.39E+12	26748.76	826.2705	7.9342	1.278	0.3527	1.8827	0.2075
1.5257	47.0796	24.4618	-6.6024	307.3199	2.5E+12	19316.47	685.2048	10.2796	1.5411	0.352	1.522	0.1934
0.4471	43.7002	29.8205	-7.4136	439.3921	2.1E+12	13579.18	600.7486	12.9685	1.7578	0.3091	1.7497	0.1856
1.2749	45.6146	24.3847	-5.9515	543.0402	1.83E+12	7664.411	512.4212	14.454	2.0608	0.3124	1.4744	0.2103
1.4909	46.2715	18.4779	-4.1272	682.1279	1.2E+12	7204.591	448.7949	19.2262	2.353	0.3756	1.3256	0.2321
1.2776	45.538	15.3635	-3.1027	774.1189	9.73E+11	5575.088	405.0284	21.042	2.6072	0.3541	1.3371	0.2014
1.5026	44.4916	11.9335	-2.4006	853.1061	8.13E+11	4559.802	371.4583	22.6705	2.8428	0.3371	1.3731	0.2118
2.0109	42.9154	8.5863	-2.0912	921.9924	6.97E+11	3961.937	346.9587	25.3605	3.0436	0.3304	1.2987	0.2145
0.3767	40.8063	12.4585	-2.6044	978.4087	6.26E+11	3611.969	330.0883	27.4755	3.1991	0.3277	1.2397	0.2069

Duda	Pseudot2	Beale	Ratkowsky	Ball	Ptbiserial	Frey	McClain	Dunn	Hubert	SDindex	Dindex	SDbw
0.6303	42.2267	2.2255	0.2536	413.1353	0.3134	-0.1223	0.745	0.1048	0.0016	2.3053	2.005	2.6418
0.8101	23.6802	0.8932	0.3228	228.4016	0.3862	0.3352	0.9531	0.1116	0.0022	2.2194	1.8267	1.198
0.288	56.8736	9.1171	0.3197	150.1872	0.4185	-0.1424	1.7756	0.1116	0.0028	2.3408	1.7042	1.1448
0.6745	18.34	1.8092	0.3191	102.4842	0.4389	0.0244	1.7966	0.1159	0.0032	1.955	1.5699	0.6156
0.7344	22.0649	1.3692	0.3072	74.7992	0.4654	0.6995	1.9437	0.1476	0.0035	1.9958	1.4863	0.521
0.7118	19.03	1.5253	0.2947	57.8612	0.4248	0.5045	2.7834	0.1444	0.0036	2.2061	1.4068	0.4817
0.5434	22.6915	3.1179	0.2831	46.4323	0.3971	0.4402	3.582	0.1216	0.0037	2.163	1.3456	0.445
0.4234	24.5101	4.9631	0.2715	38.551	0.3862	0.5242	3.9511	0.1216	0.0038	2.0891	1.2895	0.4001
0.6159	12.4709	2.2847	0.2605	33.0088	0.38	0.1205	4.1515	0.1216	0.0039	2.2047	1.2421	0.366

*** : The Hubert index is a graphical method of determining the number of clusters.
In the plot of Hubert index, we seek a significant knee that corresponds to a significant increase of the value of the measure i.e the significant peak in Hubert index second differences plot.

*** : The D index is a graphical method of determining the number of clusters.
In the plot of D index, we seek a significant knee (the significant peak in Dindex second differences plot) that corresponds to a significant increase of the value of the measure.

****

* Among all indices:
* 2 proposed 2 as the best number of clusters
* 9 proposed 3 as the best number of clusters
* 1 proposed 4 as the best number of clusters
* 1 proposed 5 as the best number of clusters
* 6 proposed 6 as the best number of clusters
* 2 proposed 9 as the best number of clusters
* 2 proposed 10 as the best number of clusters

***** Conclusion *****

* According to the majority rule, the best number of clusters is 3

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Table 4. NbCluster output for Week 4 solution

KL	CH	Hartigan	CCC	Scott	Marriot	TrCovW	TraceW	Friedman	Rubin	Cindex	DB	Silhouette
9.5802	58.7923	26.2359	-3.8238	165.5045	1.64E+12	22341.64	773.5786	10.7776	1.3418	0.3059	1.5691	0.2497
0.2747	46.7248	22.0096	-6.5475	311.3361	1.6E+12	16622.08	671.198	12.0016	1.5465	0.2849	1.7387	0.1712
0.3941	42.2472	25.7984	-8.1063	403.0868	1.68E+12	11582.81	594.6588	13.3694	1.7455	0.2729	1.5986	0.1773
1.1125	42.6908	22.5006	-7.4601	506.6765	1.45E+12	8604.87	516.3066	16.461	2.0104	0.3111	1.5419	0.1822
1.4014	42.9442	17.6442	-5.823	617.5552	1.1E+12	7060.851	455.6426	18.7895	2.2781	0.3027	1.4089	0.2009
0.9619	42.2332	17.1094	-5.6559	683.6411	1.03E+12	5065.342	412.3369	20.3824	2.5174	0.2941	1.3515	0.1944
0.6561	42.0992	22.2741	-4.3516	776.9255	7.84E+11	4829.721	374.0181	24.2703	2.7753	0.276	1.3352	0.2
8.6711	44.2954	7.7006	-2.057	921.5328	4.32E+11	4148.76	329.7692	27.7348	3.1477	0.2695	1.3128	0.2206
0.3707	41.8119	10.2527	-2.2371	987.4789	3.65E+11	3945.607	315.0651	32.1552	3.2946	0.2651	1.2885	0.2165

Duda	Pseudot2	Beale	Ratkowsky	Ball	Ptbiserial	Frey	McClain	Dunn	Hubert	SDindex	Dindex	SDbw
0.8085	28.6637	0.9039	0.278	386.7893	0.3888	1.5194	0.5198	0.081	0.0019	1.8749	1.9832	1.554
0.6798	23.0834	1.7762	0.3314	223.7327	0.3421	0.0989	1.3607	0.0796	0.0018	1.8903	1.8196	1.2511
0.756	24.5263	1.2255	0.3219	148.6647	0.364	0.2017	1.5791	0.0796	0.002	1.667	1.684	0.6093
0.5519	23.5421	3.0191	0.3139	103.2613	0.3891	-0.0087	2.3735	0.0986	0.0025	1.7927	1.564	0.6276
0.5916	31.0622	2.598	0.303	75.9404	0.409	0.8457	2.487	0.1007	0.003	1.7854	1.4775	0.5863
0.6549	22.657	1.9811	0.2919	58.9053	0.38	0.2811	3.1447	0.0968	0.003	1.7053	1.404	0.4591
0.6764	13.8728	1.7791	0.2808	46.7523	0.3677	0.0113	3.8912	0.0968	0.0032	1.6825	1.3322	0.4299
0.5819	17.2437	2.6537	0.2736	36.641	0.3913	0.5842	4.0834	0.105	0.0036	1.695	1.2602	0.4418
0.5699	12.0729	2.7322	0.2622	31.5065	0.3779	0.043	4.4917	0.105	0.0037	1.915	1.2149	0.415

*** : The Hubert index is a graphical method of determining the number of clusters.
In the plot of Hubert index, we seek a significant knee that corresponds to a significant increase of the value of the measure i.e the significant peak in Hubert index second differences plot.

*** : The D index is a graphical method of determining the number of clusters.
In the plot of D index, we seek a significant knee (the significant peak in Dindex second differences plot) that corresponds to a significant increase of the value of the measure.

****
* Among all indices:
* 8 proposed 2 as the best number of clusters
* 4 proposed 3 as the best number of clusters
* 1 proposed 4 as the best number of clusters
* 1 proposed 6 as the best number of clusters
* 6 proposed 9 as the best number of clusters
* 4 proposed 10 as the best number of clusters

***** Conclusion *****

* According to the majority rule, the best number of clusters is 2

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Table 5. NbCluster output for Week 5 solution

KL	CH	Hartigan	CCC	Scott	Marriot	TrCovW	TraceW	Friedman	Rubin	Cindex	DB	Silhouette
0.7282	57.0876	43.6945	-3.2031	180.0031	1.63E+12	17804.02	734.3695	8.4611	1.3481	0.3601	1.3068	0.3118
4.8988	57.6423	20.3851	-2.0132	538.9152	4.21E+11	14210.84	579.8738	17.7716	1.7073	0.3141	1.5232	0.2465
0.6278	49.7222	18.902	-3.7969	633.4029	4.23E+11	11858.97	515.415	21.918	1.9208	0.3388	1.6485	0.1842
0.9529	46.0821	16.9282	-3.8137	773.4282	2.85E+11	10048.1	461.5607	30.4122	2.1449	0.3235	1.5859	0.1959
0.6356	43.8534	19.7419	-3.6434	826.372	2.98E+11	7435.894	417.6475	31.4846	2.3704	0.3224	1.4735	0.2048
1.1606	44.0668	17.4417	-1.9585	988.8179	1.52E+11	6299.713	371.7752	38.71	2.6629	0.3014	1.4234	0.2203
2.2398	44.1273	10.9571	-0.5749	1053.573	1.35E+11	5104.356	335.0244	39.7293	2.955	0.365	1.3131	0.234
1.0189	42.3887	10.237	-0.2809	1090.072	1.37E+11	4118.787	313.2975	40.8044	3.1599	0.3547	1.3065	0.2224
0.7494	41.0102	11.3885	0.0228	1135.608	1.28E+11	3698.67	294.1199	41.577	3.366	0.3374	1.3557	0.2233

Duda	Pseudot2	Beale	Ratkowsky	Ball	Ptbiserial	Frey	McClain	Dunn	Hubert	SDindex	Dindex	SDbw
0.7427	46.4307	1.3232	0.308	367.1848	0.5191	1.4661	0.283	0.1367	0.0029	1.7073	2.022	1.8452
0.7769	22.3948	1.0906	0.3465	193.2913	0.4846	0.8934	1.1083	0.1277	0.0027	1.7891	1.7622	1.2769
0.6568	28.2183	1.9739	0.3271	128.8538	0.4445	0.6016	1.8484	0.0995	0.0028	1.9448	1.6503	0.8393
0.7077	17.3514	1.5525	0.3087	92.3121	0.4228	0.2991	2.4333	0.0995	0.003	1.9693	1.5333	0.701
0.6577	14.5753	1.9336	0.3016	69.6079	0.4167	0.0153	2.9331	0.1045	0.0031	1.7693	1.4503	0.5914
0.5829	16.4607	2.6387	0.29	53.1107	0.4378	-0.0175	3.0925	0.1045	0.0035	1.6116	1.3729	0.5071
0.6875	15.002	1.6976	0.2832	41.878	0.4532	0.6611	3.1351	0.1317	0.0038	1.5846	1.3241	0.4908
0.7419	11.8292	1.3003	0.2729	34.8108	0.4277	0.3917	3.7203	0.1317	0.0039	1.7219	1.2768	0.4457
0.6824	7.4464	1.6852	0.2632	29.412	0.403	0.0463	4.5337	0.1317	0.0039	1.8224	1.2346	0.4168

*** : The Hubert index is a graphical method of determining the number of clusters.
In the plot of Hubert index, we seek a significant knee that corresponds to a significant increase of the value of the measure i.e the significant peak in Hubert index second differences plot.

*** : The D index is a graphical method of determining the number of clusters.
In the plot of D index, we seek a significant knee (the significant peak in Dindex second differences plot) that corresponds to a significant increase of the value of the measure.

****

* Among all indices:
* 6 proposed 2 as the best number of clusters
* 13 proposed 3 as the best number of clusters
* 1 proposed 7 as the best number of clusters
* 1 proposed 8 as the best number of clusters
* 1 proposed 9 as the best number of clusters
* 2 proposed 10 as the best number of clusters

***** Conclusion *****

* According to the majority rule, the best number of clusters is 3

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Table 6. NbCluster output for Week 6 solution

KL	CH	Hartigan	CCC	Scott	Marriot	TrCovW	TraceW	Friedman	Rubin	Cindex	DB	Silhouette
0.1512	42.5609	33.9144	-5.045	165.0759	9.62E+11	25389.44	745.8173	5.6672	1.2711	0.3178	1.8555	0.2115
1.3391	42.5618	24.0766	-6.485	326.4114	7.85E+11	17635.47	613.3288	10.2385	1.5457	0.2845	1.6962	0.1912
0.6693	40.5179	25.0951	-6.9482	430.6029	7.24E+11	12599.9	531.3255	14.92	1.7842	0.3022	1.613	0.1967
1.4475	41.3139	19.0481	-5.9384	530.4299	6.04E+11	8163.24	457.2887	17.1252	2.0731	0.3287	1.3773	0.1938
2.611	40.6829	11.6896	-5.471	611.707	5.22E+11	6505.426	406.9531	21.8887	2.3295	0.3079	1.4502	0.1795
0.5161	38.1897	14.1596	-5.2059	648.7401	5.63E+11	5026.866	378.0676	22.4551	2.5075	0.3031	1.3605	0.1699
3.0002	37.5574	8.4682	-4.2601	734.2737	4.29E+11	4301.657	345.85	27.5478	2.7411	0.2727	1.4712	0.1764
1.3709	35.5274	7.1292	-4.2679	767.8897	4.4E+11	3656.22	327.4843	28.0175	2.8948	0.2696	1.4052	0.1618
1.038	33.6472	6.5144	-4.3909	796.6207	4.53E+11	3148.75	312.6257	28.4901	3.0324	0.2647	1.3982	0.1594

Duda	Pseudot2	Beale	Ratkowsky	Ball	Ptbiserial	Frey	McClain	Dunn	Hubert	SDindex	Dindex	SDbw
0.7119	40.4647	1.5414	0.3114	372.9086	0.3262	0.4314	0.6667	0.1121	0.0019	1.9543	2.0053	1.1344
0.7132	22.1187	1.5196	0.3197	204.4429	0.3656	0.11	1.4179	0.1034	0.0021	1.7175	1.8153	2.3835
0.5437	26.8546	3.1309	0.3193	132.8314	0.3993	-0.1315	1.7839	0.1182	0.0024	1.6808	1.6811	1.1584
0.7123	23.829	1.528	0.3189	91.4577	0.4368	0.6599	1.8395	0.1353	0.0032	1.7064	1.5848	0.5855
0.6181	21.0106	2.3096	0.3053	67.8255	0.4022	1.2047	2.6981	0.1353	0.0033	1.7134	1.4959	0.5285
0.7887	10.4503	1.0051	0.2918	54.0097	0.3777	0.1238	3.2168	0.1353	0.0033	1.7041	1.4241	0.4609
0.559	16.5649	2.8968	0.2804	43.2312	0.3856	0.6649	3.8743	0.1353	0.0038	1.8532	1.3701	0.4538
0.7028	10.1488	1.5618	0.269	36.3871	0.3755	0.4619	4.1809	0.0764	0.0039	1.7041	1.3302	0.3963
0.372	38.8275	6.2243	0.2585	31.2626	0.3646	0.415	4.589	0.0764	0.004	1.7052	1.2946	0.3663

*** : The Hubert index is a graphical method of determining the number of clusters.
In the plot of Hubert index, we seek a significant knee that corresponds to a significant increase of the value of the measure i.e the significant peak in Hubert index second differences plot.

*** : The D index is a graphical method of determining the number of clusters.
In the plot of D index, we seek a significant knee (the significant peak in Dindex second differences plot) that corresponds to a significant increase of the value of the measure.

****

* Among all indices:
* 3 proposed 2 as the best number of clusters
* 9 proposed 3 as the best number of clusters
* 1 proposed 4 as the best number of clusters
* 2 proposed 5 as the best number of clusters
* 1 proposed 7 as the best number of clusters
* 5 proposed 8 as the best number of clusters
* 2 proposed 10 as the best number of clusters

***** Conclusion *****

* According to the majority rule, the best number of clusters is 3

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Table 7. NbCluster output for Week 7 solution

KL	CH	Hartigan	CCC	Scott	Marriot	TrCovW	TraceW	Friedman	Rubin	Cindex	DB	Silhouette
0.7355	45.3071	28.4556	-4.4689	166.4608	1.2E+12	20094.43	735.6934	7.8827	1.2886	0.3483	1.7069	0.2037
0.9071	40.7261	21.9614	-6.5984	294.6831	1.2E+12	14302.14	622.8115	9.7096	1.5221	0.3445	1.7809	0.1949
0.6173	38.048	22.4508	-7.7035	391.2711	1.16E+12	11962.08	545.9533	12.6018	1.7364	0.3294	1.5984	0.1653
1.1465	38.035	19.1297	-7.3363	499.9805	9.18E+11	8828.176	476.8802	15.6007	1.9879	0.337	1.5309	0.1497
0.8776	37.7867	19.45	-6.8005	582.5522	7.86E+11	6117.485	424.188	17.0076	2.2349	0.3118	1.5011	0.1715
1.5452	38.4804	14.535	-4.9449	659.938	6.58E+11	5129.322	376.3454	18.53	2.519	0.3228	1.367	0.1798
0.8819	37.9622	15.072	-3.9222	753.7191	4.76E+11	4606.629	343.4983	21.1869	2.7598	0.3093	1.3434	0.192
0.766	38.1621	17.9628	-2.6859	816.5583	4.06E+11	3517.08	312.3239	22.9389	3.0353	0.2956	1.2186	0.2098
3.1099	39.7134	8.9287	-0.8523	882.6681	3.31E+11	2436.217	278.9224	24.0372	3.3988	0.3181	1.1452	0.2259

Duda	Pseudot2	Beale	Ratkowsky	Ball	Ptbiserial	Frey	McClain	Dunn	Hubert	SDindex	Dindex	SDbw
0.7902	27.6109	1.0117	0.2678	367.8467	0.2704	0.2761	0.6458	0.1101	0.0015	1.9052	1.9935	1.6048
0.6547	31.6401	1.9956	0.3272	207.6038	0.3346	0.5185	1.4468	0.1143	0.0018	1.7974	1.8168	1.003
0.659	21.7302	1.9443	0.3167	136.4883	0.3283	0.0261	2.0312	0.0789	0.0019	1.6381	1.6994	0.6675
0.7334	18.5413	1.3718	0.3089	95.376	0.3579	0.1973	2.3381	0.0861	0.0026	1.7667	1.6002	0.6389
0.5217	22.9196	3.3915	0.3008	70.698	0.364	0.0555	3.1012	0.0871	0.003	1.8528	1.5024	0.6117
0.5651	23.0871	2.8653	0.292	53.7636	0.3746	0.1979	3.2986	0.0943	0.0034	1.852	1.4283	0.5374
0.556	22.3562	2.9659	0.2807	42.9373	0.3721	0.2113	3.6922	0.0943	0.0036	1.7812	1.3473	0.4741
0.6131	10.0963	2.2849	0.2717	34.7027	0.3663	-0.0579	4.17	0.0943	0.0037	1.6132	1.281	0.4307
0.4845	20.2121	3.8881	0.2651	27.8922	0.3785	0.3671	4.1264	0.105	0.0042	1.719	1.2255	0.3489

*** : The Hubert index is a graphical method of determining the number of clusters.
In the plot of Hubert index, we seek a significant knee that corresponds to a significant increase of the value of the measure i.e the significant peak in Hubert index second differences plot.

*** : The D index is a graphical method of determining the number of clusters.
In the plot of D index, we seek a significant knee (the significant peak in Dindex second differences plot) that corresponds to a significant increase of the value of the measure.

****
* Among all indices:
* 5 proposed 2 as the best number of clusters
* 6 proposed 3 as the best number of clusters
* 2 proposed 5 as the best number of clusters
* 1 proposed 7 as the best number of clusters
* 2 proposed 9 as the best number of clusters
* 7 proposed 10 as the best number of clusters

***** Conclusion *****

* According to the majority rule, the best number of clusters is 10

Table 8. NbCluster output for Week 8 solution

KL	CH	Hartigan	CCC	Scott	Marriot	TrCovW	TraceW	Friedman	Rubin	Cindex	DB	Silhouette
2.1377	50.1009	25.9517	-1.8604	155.9848	2.25E+11	12024.86	528.6627	8.6293	1.4073	0.3909	1.566	0.2577
0.9133	42.9595	21.3664	-3.2038	246.4348	2.46E+11	7216.84	436.5544	12.5067	1.7043	0.3858	1.472	0.2147
1.3657	40.4434	16.1396	-3.2687	334.6653	2.16E+11	5014.275	371.4933	13.8345	2.0027	0.4062	1.5363	0.2086
1.3161	38.0959	12.7795	-3.1043	405.8161	1.91E+11	3531.269	327.7731	15.6568	2.2699	0.3816	1.3778	0.2243
1.1438	35.9759	10.9618	-3.2212	508.8438	1.21E+11	3023.986	296.2263	18.4675	2.5116	0.3713	1.3125	0.2118
0.7656	34.278	11.7097	-2.7403	568.5346	1.02E+11	2711.879	271.2407	19.5607	2.743	0.3643	1.273	0.2136
3.3186	33.6817	6.5985	-1.9219	640.31	7.49E+10	2241.652	246.7541	22.8199	3.0151	0.3411	1.4031	0.2144
0.3016	31.6853	10.7557	-2.0678	670.1877	7.46E+10	1993.649	233.5808	23.748	3.1852	0.3419	1.39	0.2067
1.5357	31.6956	8.1227	-1.2145	734.8625	5.49E+10	1773.732	213.7606	26.4265	3.4805	0.326	1.3073	0.2247

Duda	Pseudot2	Beale	Ratkowsky	Ball	Ptbiserial	Frey	McClain	Dunn	Hubert	SDindex	Dindex	SDbw
0.6537	29.6608	2.002	0.3439	264.3314	0.421	0.3881	0.7302	0.1472	0.0024	1.8015	1.9398	2.2887
0.7523	21.4026	1.2476	0.3553	145.5181	0.4537	0.5108	1.0729	0.1555	0.0028	1.6571	1.7536	0.9926
0.6595	15.4877	1.9221	0.3499	92.8733	0.4459	0.1194	1.9595	0.1428	0.0031	1.6592	1.614	0.606
0.5009	22.9207	3.6743	0.3319	65.5546	0.4639	0.3491	2.2268	0.1428	0.0033	1.5516	1.5092	0.5462
0.6389	18.6548	2.1109	0.3139	49.371	0.4598	1.4002	2.4558	0.1428	0.0033	1.374	1.4183	0.4358
0.7788	8.8048	1.0586	0.2999	38.7487	0.4204	0.1511	3.1256	0.1128	0.0034	1.4957	1.3488	0.4434
0.5413	17.7933	3.1117	0.2877	30.8443	0.4231	-7.1912	3.8101	0.1168	0.004	1.5856	1.2908	0.4439
0.6526	8.5178	1.9277	0.275	25.9534	0.3883	0.0596	4.5456	0.1168	0.004	1.6868	1.2344	0.3777
0.4897	12.5039	3.7005	0.2659	21.3761	0.394	0.1445	4.76	0.1168	0.0042	1.7913	1.1858	0.3674

*** : The Hubert index is a graphical method of determining the number of clusters.
In the plot of Hubert index, we seek a significant knee that corresponds to a significant increase of the value of the measure i.e the significant peak in Hubert index second differences plot.

*** : The D index is a graphical method of determining the number of clusters.
In the plot of D index, we seek a significant knee (the significant peak in Dindex second differences plot) that corresponds to a significant increase of the value of the measure.

****

* Among all indices:
* 3 proposed 2 as the best number of clusters
* 9 proposed 3 as the best number of clusters
* 1 proposed 4 as the best number of clusters
* 1 proposed 5 as the best number of clusters
* 3 proposed 6 as the best number of clusters
* 1 proposed 7 as the best number of clusters
* 2 proposed 8 as the best number of clusters
* 3 proposed 10 as the best number of clusters

***** Conclusion *****

* According to the majority rule, the best number of clusters is 3

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Table 9. Transition Analysis

Weeks 1_2			Weeks 2_3			Weeks 3_4			Weeks 4_5			Weeks 5_6			Weeks 6_7			Weeks 7_8		
n	Profile transition		n	Profile transition		n	Profile transition		n	Profile transition		n	Profile transition		n	Profile transition		n	Profile transition	
59	25%	FL AE	58	25%	AE AE	72	31%	AE FL	44	19%	FL FL	48	20%	IN IN	59	25%	IN IN	56	24%	IN IN
36	15%	REG AE	30	13%	REG AE	42	18%	IN IN	42	18%	FL MIN	27	11%	MIN MIN	27	11%	MIN REG	27	11%	REG MIN
28	12%	REG REG	29	12%	IN IN	28	12%	AE PROC	39	17%	IN IN	23	10%	MIN IN	26	11%	PROC REG	25	11%	MIN IN
24	10%	IN IN	18	8%	AE MIN	24	10%	MIN FL	27	11%	FL IN	21	9%	FL MIN	22	9%	PROC MIN	24	10%	REG IN
23	10%	FL MIN	13	6%	MIN MIN	14	6%	IN FL	20	8%	PROC MIN	18	8%	MIN PROC	22	9%	FL REG	19	8%	MIN MIN
16	7%	FL IN	13	6%	AE REG	14	6%	REG FL	18	8%	IN MIN	17	7%	FL FL	17	7%	MIN MIN	14	6%	REG FL
14	6%	FL REG	11	5%	MIN AE	11	5%	MIN IN	15	6%	PROC PROC	15	6%	MIN FL	15	6%	MIN IN	14	6%	REG PROC
12	5%	FL STR	10	4%	AE IN	10	4%	REG PROC	11	5%	FL PROC	15	6%	FL PROC	14	6%	FL MIN	12	5%	IN MIN
11	5% 0%	IN MIN	10	4% 0%	MIN IN	9	4% 0%	MIN PROC	11	5% 0%	PROC FL	12	5% 0%	PROC PROC	10	4% 0%	IN MIN	12	5% 0%	MIN FL
	0%			0%			0%			0%			0%			0%		7	3%	7 MIN PROC
4	2%	IN AE	9	4%	STR IN	7	3%	AE IN	4	2%	IN PROC	11	5%	IN MIN	8	3%	MIN STR			
2	1%	REG MIN	8	3%	REG REG	3	1%	IN IN	4	2%	PROC IN	8	3%	IN PROC	4	2%	IN STR	7	3%	IN PROC
2	1%	REG IN	6	3%	IN MIN	2	1%	REG IN	1	0%	IN FL	8	3%	PROC-MIN	4	2%	PROC STR	6	3%	STR IN
2	1%	IN STR	5	2%	IN AE							6	3%	PROC IN	4	2%	IN REG	5	2%	STR MIN
1	0%	REG STR	4	2%	REG MIN							4	2%	PROC FL	2	1%	FL IN	5	2%	STR PROC
1	0%	IN REG	3	1%	FLB REG							3	1%	IN FL	1	0%	FL STR	2	1%	IN FL
1	0%	IN STR	3	1%	STR AE										1	0%	PROC IN	1	0%	STR FL
			3	1%	STR MIN															
			2	1%	IN_REG															
			1	0%	REG IN															

Table 10. Cluster Solution Comparison With and Without Outliers

Week	Outliers	Number of Outliers	Number Of Clusters	Distance Calculation Comparison					
				Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1	**Included**	9	2	0.000321	2.174722	2.994283	3.174214	3.930680	9.685456
	Excluded		4	0.1388	2.3136	3.1311	3.2330	4.0021	9.4289
2	**Included**	5	4	0.116	2.180	3.018	3.189	3.989	10.282
	Excluded		4	0.1194	2.2092	3.0441	3.2011	4.0139	9.6959
3	**Included**	5	3	0.05545	2.29892	3.08224	3.21580	3.91956	9.97118
	Excluded		2	0.05519	2.28838	3.07261	3.21127	3.91831	10.03023
4	**Included**	6	2	0.1355	2.2855	3.0430	3.2039	3.9186	10.6856
	Excluded		2	0.1409	2.3409	3.0975	3.2265	3.9412	9.8937
5	**Included**	9	3	0.1273	2.3935	3.0945	3.2350	3.9376	9.0072
	Excluded		3	0.137	2.440	3.146	3.252	3.956	8.870
6	**Included**	5	3	0.307	2.329	3.075	3.223	3.926	10.663
	Excluded		3	0.414	2.346	3.092	3.230	3.932	9.617
7	**Included**	7	3	0.01118	2.29802	3.00451	3.19635	3.84474	10.04711
	Excluded		3	0.01377	2.36213	3.06088	3.22047	3.89330	9.82771
8	**Included**	5	3	0.09404	2.35440	3.15304	3.24159	4.01179	8.07620
	Excluded		2	0.1338	2.3034	3.0863	3.2152	3.9719	9.5482

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Appendix C. Descriptive Statistics, Levene's test for equality of variances, and Post-hoc Profile Comparisons

Table 1. Descriptive statistics for the six engagement indicators across the eight weeks

	Attempt _rate_week1	on_time_rate _week1	reattempt_rate _week1	Regularity _week1	practice_duration _week1	active_days _week1
Valid	236	236	236	236	236	236
Missing	0	0	0	0	0	0
Median	0.675	0.938	0.187	0.931	131,433	2,000
Mean	0.569	0.652	0.179	0.796	159,305	1,992
Std. Deviation	0.288	0.420	0.136	0.699	159,459	1,411
Skewness	-1,196	-0.662	0.329	0.165	2,052	0.427
Std. Error of Skewness	0.158	0.158	0.158	0.158	0.158	0.158
Kurtosis	0.056	-1,310	-0.614	-1,228	7,079	-0.096
Std. Error of Kurtosis	0.316	0.316	0.316	0.316	0.316	0.316
Shapiro-Wilk	0.763	0.733	0.944	0.873	0.826	0.926
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001
Minimum	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	1,000	1,000	0.560	2,466	1`,030,000	6,000

	attempt_rate _week2	on_time_rate _week2	reattempt_rate _week2	Regularity _week2	practice_duration _week2	active_days _week2
Valid	236	236	236	236	236	236
Missing	0	0	0	0	0	0
Mean	0.560	0.470	0.181	0.996	179,387	2,424
Std. Deviation	0.285	0.412	0.134	0.802	168,989	1,688
Skewness	-1,145	0.099	0.413	-0.066	1,744	0.197
Std. Error of Skewness	0.158	0.158	0.158	0.158	0.158	0.158
Kurtosis	-0.033	-1,646	0.191	-1,420	6,017	-0.662
Std. Error of Kurtosis	0.316	0.316	0.316	0.316	0.316	0.316
Shapiro-Wilk	0.783	0.822	0.941	0.874	0.864	0.937
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001
Minimum	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	1,000	1,000	0.656	2,556	1,196,833	7,000

	attempt rate week3	on_time rate week3	reattempt rate _week3	Regularity week3	practice duration _week3	active days week3
Valid	236	236	236	236	236	236
Missing	0	0	0	0	0	0
Mean	0.511	0.454	0.185	0.719	124,158	1,835
Std. Deviation	0.332	0.439	0.160	0.701	128,161	1,448
Shapiro-Wilk	0.838	0.769	0.921	0.840	0.859	0.907
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001
Minimum	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	1,000	1,000	0.667	2,355	707,250	6,000

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	attempt rate week4	on time_rate _week4	reattempt rate _week4	Regularity week4	Practice duration week4	active days week4
Valid	236	236	236	236	236	236
Missing	0	0	0	0	0	0
Mean	0.551	0.377	0.171	0.684	131,355	1,754
Std. Deviation	0.356	0.425	0.147	0.713	152,675	1,467
Skewness	-0.699	0.509	0.442	0.477	2,065	0.604
Std. Error of Skewness	0.158	0.158	0.158	0.158	0.158	0.158
Kurtosis	-1,133	-1,486	-0.367	-1,119	6,233	0.031
Std. Error of Kurtosis	0.316	0.316	0.316	0.316	0.316	0.316
Shapiro-Wilk	0.803	0.750	0.910	0.835	0.797	0.905
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001
Minimum	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	1,000	1,000	0.667	2,470	944,567	7,000

	attempt rate week5	on time_rate _week5	reattempt rate _week5	Regularity week5	practice duration _week5	active days _week5
Valid	236	236	236	236	236	236
Missing	0	0	0	0	0	0
Mean	0.528	0.259	0.161	0.547	141,854	1,530
Std. Deviation	0.362	0.403	0.146	0.655	188,206	1,403
Skewness	-0.632	1,118	0.384	0.759	2,095	0.871
Std. Error of Skewness	0.158	0.158	0.158	0.158	0.158	0.158
Kurtosis	-1,343	-0.562	-1,102	-0.669	4,912	0.550
Std. Error of Kurtosis	0.316	0.316	0.316	0.316	0.316	0.316
Shapiro-Wilk	0.780	0.630	0.894	0.792	0.746	0.878
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001
Minimum	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	1,008	1,000	0.500	2,478	1,078,283	6,000

	attempt rate week6	on time rate week6	reattempt rate week6	Regularity week6	practice duration week6	active days week6
Valid	236	236	236	236	236	236
Missing	0	0	0	0	0	0
Mean	0.528	0.303	0.155	0.686	135,579	1,720
Std. Deviation	0.385	0.402	0.145	0.724	148,889	1,562
Skewness	-0.522	0.822	0.628	0.391	1,310	0.514
Std. Error of Skewness	0.158	0.158	0.158	0.158	0.158	0.158
Kurtosis	-1,534	-1,051	-0.094	-1,339	2,240	-0.565
Std. Error of Kurtosis	0.316	0.316	0.316	0.316	0.316	0.316
Shapiro-Wilk	0.769	0.710	0.892	0.812	0.847	0.882
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001
Minimum	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	1,000	1,000	0.667	2,437	877,667	6,000

	attempt rate _week7	on time_rate _week7	reattempt rate _week7	Regularity week7	practice duration _week7	active days _week7
Valid	236	236	236	236	236	236
Missing	0	0	0	0	0	0
Mean	0.510	0.275	0.156	0.655	143,521	1,669
Std. Deviation	0.379	0.393	0.158	0.698	175,540	1,494
Skewness	-0.472	0.990	0.726	0.444	2,174	0.456
Std. Error of Skewness	0.158	0.158	0.158	0.158	0.158	0.158
Kurtosis	-1,548	-0.731	-0.350	-1,284	7,627	-0.702
Std. Error of Kurtosis	0.316	0.316	0.316	0.316	0.316	0.316
Shapiro-Wilk	0.783	0.683	0.873	0.816	0.777	0.885
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001
Minimum	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	1,000	1,000	0.667	2,318	1,129,567	6,000

	attempt rate week8	on time rate week8	reattempt rate week8	Regularity week8	practice duration week8	active days week8
Valid	236	236	236	236	236	236
Missing	0	0	0	0	0	0
Mean	0.387	0.148	0.150	0.472	129,831	1,347
Std. Deviation	0.380	0.310	0.180	0.750	198,944	1,750
Skewness	0.087	1,928	0.981	1,290	2,073	1,360
Std. Error of Skewness	0.158	0.158	0.158	0.158	0.158	0.158
Kurtosis	-1,804	2,226	0.200	0.252	4,961	1,130
Std. Error of Kurtosis	0.316	0.316	0.316	0.316	0.316	0.316
Shapiro-Wilk	0.772	0.528	0.810	0.671	0.708	0.775
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001
Minimum	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	0.994	1,000	0.833	2,626	1,158,350	7,000

Table 2. Levene's test for equality of variances

Indicators Week 1	Levene Statistic	df1	df2	Sig.	Indicators Week 2	Levene Statistic	df1	df2	Sig.
attempt_rate_week1	26.21	2.00	233.00	0.00	attempt_rate_week2	8.62	3.00	190.00	<,001
on_time_rate_week1	51.88	2.00	233.00	0.00	on_time_rate_week2	2.75	3.00	190.00	0.04
reattempt_rate_week1	41.57	2.00	233.00	0.00	reattempt_rate_week2	2.40	3.00	190.00	0.07
regularity_week1	109.27	2.00	233.00	0.00	regularity_week2	14.37	3.00	190.00	<,001
practice_duration_week1	34.09	2.00	233.00	0.00	practice_duration_week2	17.74	3.00	190.00	<,001
active_days_week1	53.91	2.00	233.00	0.00	active_days_week2	2.75	3.00	190.00	0.04

Indicators Week 3	Levene Statistic	df1	df2	Sig.	Indicators Week 4	Levene Statistic	df1	df2	Sig.
attempt_rate_week3	19.76	2.00	174.00	0.00	attempt_rate_week4	0.23	1.00	172.00	0.63
on_time_rate_week3	20.77	2.00	174.00	0.00	on_time_rate_week4	0.15	1.00	172.00	0.70
reattempt_rate_week3	5.45	2.00	174.00	0.01	reattempt_rate_week4	0.71	1.00	172.00	0.40
regularity_week3	44.43	2.00	174.00	0.00	regularity_week4	41.21	1.00	172.00	0.00
practice_duration_week3	20.59	2.00	174.00	0.00	practice_duration_week4	30.10	1.00	172.00	0.00
active_days_week3	31.87	2.00	174.00	0.00	active_days_week4	4.15	1.00	172.00	0.04

Indicators Week 5	Levene Statistic	df1	df2	Sig.	Indicators Week 6	Levene Statistic	df1	df2	Sig.
attempt_rate_week5	4.81	2.00	163.00	0.01	attempt_rate_week6	12.55	2.00	156.00	0.00
on_time_rate_week5	0.86	2.00	163.00	0.42	on_time_rate_week6	10.64	2.00	156.00	0.00
reattempt_rate_week5	0.12	2.00	163.00	0.89	reattempt_rate_week6	6.77	2.00	156.00	0.00
regularity_week5	12.80	2.00	163.00	0.00	regularity_week6	21.62	2.00	156.00	0.00
practice_duration_week5	37.46	2.00	163.00	0.00	practice_duration_week6	7.80	2.00	156.00	0.00
active_days_week5	4.46	2.00	163.00	0.01	active_days_week6	1.29	2.00	156.00	0.28

Indicators Week 7	Levene Statistic	df1	df2	Sig.	Indicators Week 8	Levene Statistic	df1	df2	Sig.
attempt_rate_week7	16.73	2.00	156.00	0.00	attempt_rate_week8	4.35	2.00	122.00	0.01
on_time_rate_week7	3.05	2.00	156.00	0.05	on_time_rate_week8	2.26	2.00	122.00	0.11
reattempt_rate_week7	9.20	2.00	156.00	0.00	reattempt_rate_week8	5.06	2.00	122.00	0.01
regularity_week7	17.67	2.00	156.00	0.00	regularity_week8	6.20	2.00	122.00	0.00
practice_duration_week7	4.12	2.00	156.00	0.02	practice_duration_week8	8.54	2.00	122.00	0.00
active_days_week7	7.50	2.00	156.00	0.00	active_days_week8	2.47	2.00	122.00	0.09

Table 3. Post-hoc pairwise comparisons using Mann-Whitney U test, and Kruskal-Wallis H test

Week	n	Indicators	Profiles	Pairwise Comparison	
				U Test	**Asymptotic Sig.(2-sided test)**
1	194	**Regularity**	Fast Learners - Regular Learners	8381.00	>0,001***
		Practice duration	Fast Learners - Regular Learners	7588.00	>0,001***
		Active days	Fast Learners - Regular Learners	8261.50	>0,001***
				H Test	**Asymptotic Sig.(2-sided test)**
2	194	**Attempt rate**	Struggling Learners-Regular Learners	79.17	>0,001***
			Struggling Learners-Average Engagement	97.52	>0,001***
			Struggling Learners-Minimalists	102.70	>0,001***
			Regular Learners-Average Engagement	18.35	0.44
			Regular Learners-Minimalists	23.53	0.37
			Average Engagement-Minimalists	-5.18	1.00
				H Test	**Asymptotic Sig.(2-sided test)**
		Regularity	Minimalists-Struggling Learners	-23.21	1.00
			Minimalists-Average Engagement	79.32	>0,001***
			Minimalists-Regular Learners	-147.40	>0,001***
			Struggling Learners-Average Engagement	56.11	>0,001***
			Struggling Learners-Regular Learners	124.19	>0,001***
			Average Engagement-Regular Learners	-68.07	>0,001***
				H Test	**Asymptotic Sig.(2-sided test)**
		Practice duration	Struggling Learners-Minimalists	5980.00	1000.00
			Struggling Learners-Average Engagement	78345.00	>0,001***
			Struggling Learners-Regular Learners	134653.00	>0,001***
			Minimalists-Average Engagement	72365.00	>0,001***
			Minimalists-Regular Learners	-128673.00	>0,001***

Week	n	Indicators	Profiles	Pairwise Comparison	
			Average Engagement-Regular Learners	-68.07	>0,001***
				H Test	**Asymptotic Sig.(2-sided test)**
		Active days	Minimalists-Struggling Learners	-23.27	0.99
			Minimalists-Average Engagement	75.14	>0,001***
			Minimalists-Regular Learners	-143.73	>0,001***
			Struggling Learners-Average Engagement	51.87	>0,001***
			Struggling Learners-Regular Learners	120.47	>0,001***
			Average Engagement-Regular Learners	-68.60	>0,001***
				H Test	**Asymptotic Sig.(2-sided test)**
3	177	**Attempt rate**	Average Engagement -Minimalists	-1.58	1.00
			Average Engagement -Regular Learners	28.50	0.03*
			Minimalists-Regular Learners	26.92	0.10
				H Test	**Asymptotic Sig.(2-sided test)**
		On time rate	Minimalists-Regular Learners	3.47	1.00
			Minimalists-Average Engagement	28.03	>0,001***
			Regular Learners-Average Engagement	-24.56	0.07
				H Test	**Asymptotic Sig.(2-sided test)**
		Reattempt rate	Regular Learners-Average Engagement	-32.41	0.01*
			Regular Learners-Minimalists	-40.71	>0,001***
			Average Engagement -Minimalists	-8.30	1.00
				H Test	**Asymptotic Sig.(2-sided test)**
		Regularity	Minimalists-Average Engagement	79.75	>0,001***
			Minimalists-Regular Learners	120.94	>0,001***
			Average Engagement -Regular Learners	41.19	>0,001***
				H Test	**Asymptotic Sig.(2-sided test)**
		Practice duration	Minimalists-Average Engagement	50.86	>0,001***
			Minimalists-Regular Learners	106.15	>0,001***
			Average Engagement -Regular Learners	55.28	>0,001***
				H Test	**Asymptotic Sig.(2-sided test)**
		Active days	Minimalists-Average Engagement	74.45	>0,001***
			Minimalists-Regular Learners	123.02	>0,001***
			Average Engagement -Regular Learners	48.57	>0,001***
				U Test	**Asymptotic Sig.(2-sided test)**
4	174	**Regularity**	Fast Learners-Procrastinators	216.00	>0,001***
		Practice duration	Fast Learners-Procrastinators	516.00	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
5	166	**Attempt rate**	Minimalists-Procrastinators	-2.90	1.00
			Minimalists-Fast Learners	26.51	>0,001***
			Procrastinators-Fast Learners	23.61	0.09
				H Test	Asymptotic Sig.(2-sided test)
		Regularity	Minimalists-Fast Learners	12.40	0.39
			Minimalists-Procrastinators	-81.68	>0,001***
			Fast Learners-Procrastinators	-69.28	>0,001***

Week	n	Indicators	Profiles	Pairwise Comparison	
				H Test	Asymptotic Sig.(2-sided test)
		Practice duration	Fast Learners-Minimalists	-1.97	1.00
			Fast Learners-Procrastinators	-71.58	>0,001***
			Minimalists-Procrastinators	-69.62	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
		Active days	Minimalists-Fast Learners	8.35	0.89
			Minimalists-Procrastinators	-73.66	>0,001***
			Fast Learners-Procrastinators	-65.31	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
6	159	**Attempt rate**	Minimalists-Procrastinators	-12.34	0.43
			Minimalists-Fast Learners	51.93	>0,001***
			Procrastinators-Fast Learners	39.59	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
		On time rate	Minimalists-Procrastinators	-33.04	>0,001***
			Minimalists-Fast Learners	80.35	>0,001***
			Procrastinators-Fast Learners	47.31	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
		Reattempt rate	Fast Learners-Procrastinators	-34.29	>0,001***
			Fast Learners-Minimalists	-43.01	>0,001***
			Procrastinators-Minimalists	8.72	0.91
				H Test	Asymptotic Sig.(2-sided test)
		Regularity	Minimalists-Fast Learners	15.83	0.26
			Minimalists-Procrastinators	-71.03	>0,001***
			Fast Learners-Procrastinators	-55.20	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
		Practice duration	Minimalists-Fast Learners	22.90	0.04
			Minimalists-Procrastinators	-71.76	>0,001***
			Fast Learners-Procrastinators	-48.87	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
7	159	**Attempt rate**	Struggling Learners-Regular Learners	51.35	>0,001***
			Struggling Learners-Minimalists	96.54	>0,001***
			Regular Learners-Minimalists	-45.20	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
		On time rate	Struggling Learners-Minimalists	19.46	0.32
			Struggling Learners-Regular Learners	46.58	>0,001***
			Regular Learners-Minimalists	27.13	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
		Reattempt rate	Minimalists-Regular Learners	59.51	>0,001***
			Minimalists-Struggling Learners	-69.86	>0,001***
			Regular Learners-Struggling Learners	-10.35	1.00
				H Test	Asymptotic Sig.(2-sided test)
		Regularity	Struggling Learners-Minimalists	43.76	>0,001***
			Struggling Learners-Regular Learners	85.51	>0,001***

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Week	n	Indicators	Profiles	Pairwise Comparison	
			Minimalists-Regular Learners	41.75	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
		Practice duration	Struggling Learners-Minimalists	43719.00	,002**
			Struggling Learners-Regular Learners	57599.00	>0,001***
			Minimalists-Regular Learners	13880.00	,223
				H Test	Asymptotic Sig.(2-sided test)
		Active days	Struggling Learners-Minimalists	43.70	>0,001***
			Struggling Learners-Regular Learners	80.52	>0,001***
			Minimalists-Regular Learners	36.82	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
8	125	**Attempt rate**	Procrastinators-Minimalists	0.43	1.00
			Procrastinators-Fast Learners	14.61	0.34
			Minimalists-Fast Learners	14.17	0.24
				H Test	Asymptotic Sig.(2-sided test)
		Reattempt rate	Fast Learners-Procrastinators	-6.75	1.00
			Fast Learners-Minimalists	-10.73	0.56
			Procrastinators-Minimalists	3.98	1.00
				H Test	Asymptotic Sig.(2-sided test)
		Regularity	Fast Learners-Minimalists	-0.06	1.00
			Fast Learners-Procrastinators	-56.45	>0,001***
			Minimalists-Procrastinators	-56.39	>0,001***
				H Test	Asymptotic Sig.(2-sided test)
		Practice duration	Minimalists-Fast Learners	0.78	1.00
			Minimalists-Procrastinators	-53.61	>0,001***
			Fast Learners-Procrastinators	-52.82	>0,001***
Symbol explanation: H= Kruskal - Wallis Test, U= Mann-Whitney Test; adjusted for ties; Adj. Sig= Significance values have been adjusted by the Dunn-Bonferroni method; * p ≤ 0.05;** p ≤ 0.01; *** p ≤ 0.001.					

Table 4. One-way ANOVA

on_time_rate_week2	Sum of Squares	df	Mean Square	F	Sig.	
Between Groups	5.69	3.00		1.90	15.68	0.00
Within Groups	22.98	190.00		0.12		
Total	28.67	193.00				

reattempt_rate_week2	Sum of Squares	df	Mean Square	F	Sig.	
Between Groups	0.60	3.00		0.20	19.84	0.00
Within Groups	1.92	190.00		0.01		
Total	2.52	193.00				

attempt_rate_week4	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	,061	1.00	,061	2562.00	,111
Within Groups	4103.00	172.00	,024		
Total	4164.00	173.00			

on_time_rate_week4	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	0.07	1.00	0.07	0.38	0.54
Within Groups	30.49	172.00	0.18		
Total	30.56	173.00			

reattempt_rate_week4	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	0.02	1.00	0.02	1.17	0.28
Within Groups	2.60	172.00	0.02		
Total	2.62	173.00			

active_days_week4	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	145.63	1.00	145.63	247.17	0.00
Within Groups	101.34	172.00	0.59		
Total	246.97	173.00			

on_time_rate_week5	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	27.91	2.00	13.96	626.57	0.00
Within Groups	3.63	163.00	0.02		
Total	31.54	165.00			

reattempt_rate_week5	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	0.25	2.00	0.13	9.43	0.00
Within Groups	2.20	163.00	0.01		
Total	2.46	165.00			

active_days_week6	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	108839.00	2.00	54420.00	67133.00	<,001
Within Groups	126456.00	156.00	,811		
Total	235296.00	158.00			

on_time_rate_week8	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	12.90	2.00	6.45	154.02	0.00
Within Groups	5.11	122.00	0.04		
Total	18.00	124.00			

active_days_week8	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	219.73	2.00	109.86	112.37	0.00
Within Groups	119.28	122.00	0.98		
Total	339.01	124.00			

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Table 5. ANOVA multiple comparisons

Indicator	(I) Profile_week2		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
on_time_rate_week2						Lower Bound	Upper Bound
	Regular Learners	Average Engagement	0.04	0.06	0.92	-0.12	0.20
		Minimalists	,37764*	0.08	0.00	0.18	0.58
		Struggling Learners	,48454*	0.10	0.00	0.22	0.75
	Average Engagement	Regular Learners	-0.04	0.06	0.92	-0.20	0.12
		Minimalists	,33740*	0.07	0.00	0.16	0.51
		Struggling Learners	,44430*	0.10	0.00	0.19	0.69
	Minimalists	Regular Learners	-,37764*	0.08	0.00	-0.58	-0.18
		Average Engagement	-,33740*	0.07	0.00	-0.51	-0.16
		Struggling Learners	0.11	0.11	0.75	-0.17	0.38
	Struggling Learners	Regular Learners	-,48454*	0.10	0.00	-0.75	-0.22
		Average Engagement	-,44430*	0.10	0.00	-0.69	-0.19
		Minimalists	-0.11	0.11	0.75	-0.38	0.17
Indicator	(I) Profile_week2		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
reattempt_rate_week2						Lower Bound	Upper Bound
	Regular Learners	Average Engagement	0.03	0.02	0.44	-0.02	0.07
		Minimalists	0.04	0.02	0.21	-0.01	0.10
		Struggling Learners	-,17723*	0.03	0.00	-0.26	-0.10
	Average Engagement	Regular Learners	-0.03	0.02	0.44	-0.07	0.02
		Minimalists	0.02	0.02	0.84	-0.03	0.07
		Struggling Learners	-,20464*	0.03	0.00	-0.28	-0.13
	Minimalists	Regular Learners	-0.04	0.02	0.21	-0.10	0.01
		Average Engagement	-0.02	0.02	0.84	-0.07	0.03
		Struggling Learners	-,22073*	0.03	0.00	-0.30	-0.14
	Struggling Learners	Regular Learners	,17723*	0.03	0.00	0.10	0.26
		Average Engagement	,20464*	0.03	0.00	0.13	0.28
		Minimalists	,22073*	0.03	0.00	0.14	0.30
Indicator	(I) Profile_week5		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
on_time_rate_week5						Lower Bound	Upper Bound
	Fast Learners	Minimalists	,87412*	0.03	0.00	0.81	0.94
		Procrastinators	,84821*	0.03	0.00	0.77	0.93
	Minimalists	Fast Learners	-,87412*	0.03	0.00	-0.94	-0.81
		Procrastinators	-0.03	0.03	0.70	-0.10	0.05
	Procrastinators	Fast Learners	-,84821*	0.03	0.00	-0.93	-0.77
		Minimalists	0.03	0.03	0.70	-0.05	0.10
Indicator	(I) Profile_week5		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
reattempt_rate_week5						Lower Bound	Upper Bound
	Fast Learners	Minimalists	,06092*	0.02	0.01	0.01	0.11
		Procrastinators	,10929*	0.03	0.00	0.05	0.17
	Minimalists	Fast Learners	-,06092*	0.02	0.01	-0.11	-0.01
		Procrastinators	0.05	0.02	0.13	-0.01	0.11
	Procrastinators	Fast Learners	-,10929*	0.03	0.00	-0.17	-0.05
		Minimalists	-0.05	0.02	0.13	-0.11	0.01
Indicator	(I) Profile_week6		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
active_days_week6						Lower Bound	Upper Bound
	Fast Learners	Minimalists	,436*	0.18	0.05	0.01	0.86
		Procrastinators	-1,442*	0.19	0.00	-1.89	-0.99
	Minimalists	Fast Learners	-,436*	0.18	0.05	-0.86	-0.01

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Indicator	(I) Profile_week2		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
		Procrastinators	-1,877*	0.17	0.00	-2.27	-1.49
	Procrastinators	Fast Learners	1,442*	0.19	0.00	0.99	1.89
		Minimalists	1,877*	0.17	0.00	1.49	2.27
Indicator	(I) Profile_week8		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
on_time_rate_week8						Lower Bound	Upper Bound
	Fast Learners	Minimalists	,78190*	0.05	0.00	0.67	0.89
		Procrastinators	,71171*	0.05	0.00	0.59	0.84
	Minimalists	Fast Learners	-,78190*	0.05	0.00	-0.89	-0.67
		Procrastinators	-0.07	0.04	0.25	-0.17	0.03
	Procrastinators	Fast Learners	-,71171*	0.05	0.00	-0.84	-0.59
		Minimalists	0.07	0.04	0.25	-0.03	0.17
Indicator	(I) Profile_week8		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
active_days_week8						Lower Bound	Upper Bound
	Fast Learners	Minimalists	-0.04	0.22	0.98	-0.56	0.49
		Procrastinators	-3,033*	0.25	0.00	-3.63	-2.44
	Minimalists	Fast Learners	0.04	0.22	0.98	-0.49	0.56
		Procrastinators	-2,996*	0.21	0.00	-3.50	-2.49
	Procrastinators	Fast Learners	3,033*	0.25	0.00	2.44	3.63
		Minimalists	2,996*	0.21	0.00	2.49	3.50

Appendix D. Benjamini-Hochberg adjustment

Week 1

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	**SE1_attempt_rate_week1**	**,001[a]**	**1**	**,001**	**,039**	**,843**	**,000**
	SE2_on_time_rate_week1	**,012[b]**	**1**	**,012**	**,120**	**,729**	**,001**
	SE3_reattempt_rate_week1	**,031[c]**	**1**	**,031**	**2,174**	**,142**	**,011**
	SE4_regularity_week1	**44,008[d]**	**1**	**44,008**	**220,494**	**<,001**	**,535**
	SE5_practice_duration_week1	**1519388,727[e]**	**1**	**1519388,727**	**92,337**	**<,001**	**,325**
	SE6_active_days_week1	**151,798[f]**	**1**	**151,798**	**256,692**	**<,001**	**,572**
Intercept	**SE1_attempt_rate_week1**	**86,012**	**1**	**86,012**	**5538,519**	**<,001**	**,966**
	SE2_on_time_rate_week1	**113,208**	**1**	**113,208**	**1105,508**	**<,001**	**,852**
	SE3_reattempt_rate_week1	**8,181**	**1**	**8,181**	**582,467**	**<,001**	**,752**
	SE4_regularity_week1	**219,199**	**1**	**219,199**	**1098,260**	**<,001**	**,851**
	SE5_practice_duration_week1	**8618163,191**	**1**	**8618163,191**	**523,745**	**<,001**	**,732**
	SE6_active_days_week1	**1284,499**	**1**	**1284,499**	**2172,095**	**<,001**	**,919**
Profile_label_week1	**SE1_attempt_rate_week1**	**,001**	**1**	**,001**	**,039**	**,843**	**,000**
	SE2_on_time_rate_week1	**,012**	**1**	**,012**	**,120**	**,729**	**,001**
	SE3_reattempt_rate_week1	**,031**	**1**	**,031**	**2,174**	**,142**	**,011**
	SE4_regularity_week1	**44,008**	**1**	**44,008**	**220,494**	**<,001**	**,535**

	SE5_practice_duration_week1	1519388,727	1	1519388,727	92,337	<,001	,325
	SE6_active_days_week1	151,798	1	151,798	256,692	<,001	,572
Error	SE1_attempt_rate_week1	2,982	192	,016			
	SE2_on_time_rate_week1	19,661	192	,102			
	SE3_reattempt_rate_week1	2,697	192	,014			
	SE4_regularity_week1	38,321	192	,200			
	SE5_practice_duration_week1	3159339,396	192	16454,893			
	SE6_active_days_week1	113,542	192	,591			
Total	SE1_attempt_rate_week1	96,080	194				
	SE2_on_time_rate_week1	141,678	194				
	SE3_reattempt_rate_week1	11,900	194				
	SE4_regularity_week1	264,364	194				
	SE5_practice_duration_week1	11964632,669	194				
	SE6_active_days_week1	1404,000	194				
Corrected Total	SE1_attempt_rate_week1	2,982	193				
	SE2_on_time_rate_week1	19,674	193				
	SE3_reattempt_rate_week1	2,727	193				
	SE4_regularity_week1	82,329	193				
	SE5_practice_duration_week1	4678728,123	193				
	SE6_active_days_week1	265,340	193				

a. R Squared = ,000 (Adjusted R Squared = -,005)

b. R Squared = ,001 (Adjusted R Squared = -,005)

c. R Squared = ,011 (Adjusted R Squared = ,006)

d. R Squared = ,535 (Adjusted R Squared = ,532)

e. R Squared = ,325 (Adjusted R Squared = ,321)

f. R Squared = ,572 (Adjusted R Squared = ,570)

1. Univariate ANOVA p-values and Adjusted p-values (Benjamini-Hochberg)

	p_values		adjusted_p_BH	
	8.430883e-01		8.430883e-01	
	7.290428e-01		8.430883e-01	
	1.419699e-01		2.129549e-01	
	1.024890e-33	***	3.074669e-33	***
	4.250003e-18	***	8.500006e-18	***
	3.084917e-37	***	1.850950e-36	***

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Week 2

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	SE1_attempt_rate_week2	1,320[a]	3	,440	46,841	<,001	,425
	SE2_on_time_rate_week2	5,670[b]	3	1,890	15,618	<,001	,198
	SE3_reattempt_rate_week2	,597[c]	3	,199	19,657	<,001	,237
	SE4_regularity_week2	84,986[d]	3	28,329	349,852	<,001	,847
	SE5_practice_duration_week2	2864294,485[e]	3	954764,828	82,364	<,001	,565
	SE6_active_days_week2	284,206[f]	3	94,735	211,071	<,001	,769
Intercept	SE1_attempt_rate_week2	49,978	1	49,978	5318,658	<,001	,966
	SE2_on_time_rate_week2	28,435	1	28,435	234,952	<,001	,553
	SE3_reattempt_rate_week2	8,221	1	8,221	812,204	<,001	,810
	SE4_regularity_week2	131,998	1	131,998	1630,132	<,001	,896
	SE5_practice_duration_week2	4534548,608	1	4534548,608	391,179	<,001	,673
	SE6_active_days_week2	918,557	1	918,557	2046,546	<,001	,915
Profile_label_week2	SE1_attempt_rate_week2	1,320	3	,440	46,841	<,001	,425
	SE2_on_time_rate_week2	5,670	3	1,890	15,618	<,001	,198
	SE3_reattempt_rate_week2	,597	3	,199	19,657	<,001	,237
	SE4_regularity_week2	84,986	3	28,329	349,852	<,001	,847
	SE5_practice_duration_week2	2864294,485	3	954764,828	82,364	<,001	,565
	SE6_active_days_week2	284,206	3	94,735	211,071	<,001	,769
Error	SE1_attempt_rate_week2	1,785	190	,009			
	SE2_on_time_rate_week2	22,995	190	,121			
	SE3_reattempt_rate_week2	1,923	190	,010			
	SE4_regularity_week2	15,385	190	,081			
	SE5_practice_duration_week2	2202478,773	190	11591,994			
	SE6_active_days_week2	85,278	190	,449			
Total	SE1_attempt_rate_week2	93,227	194				
	SE2_on_time_rate_week2	92,044	194				
	SE3_reattempt_rate_week2	11,963	194				
	SE4_regularity_week2	385,423	194				
	SE5_practice_duration_week2	14305375,916	194				
	SE6_active_days_week2	2056,000	194				
Corrected Total	SE1_attempt_rate_week2	3,106	193				
	SE2_on_time_rate_week2	28,665	193				
	SE3_reattempt_rate_week2	2,520	193				

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	SE4_regularity_week2	100,371	193				
	SE5_practice_duration_week2	5066773,258	193				
	SE6_active_days_week2	369,485	193				

a. R Squared = ,425 (Adjusted R Squared = ,416)

b. R Squared = ,198 (Adjusted R Squared = ,185)

c. R Squared = ,237 (Adjusted R Squared = ,225)

d. R Squared = ,847 (Adjusted R Squared = ,844)

e. R Squared = ,565 (Adjusted R Squared = ,558)

f. R Squared = ,769 (Adjusted R Squared = ,766)

2. Univariate ANOVA p-values and Adjusted p-values (Benjamini-Hochberg)

p_values		adjusted_p_BH	
1.041951e-22	***	1.562927e-22	***
4.037312e-09	***	4.037312e-09	***
3.845226e-11	***	4.614271e-11	***
4.252513e-77	***	2.551508e-76	***
3.532012e-34	***	7.064025e-34	***
3.123870e-60	***	9.371611e-60	***

Week 3

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	SE1_attempt_rate_week3	,209[a]	2	,105	3,473	,033	,038
	SE2_on_time_rate_week3	2,573[b]	2	1,287	8,461	<,001	,089
	SE3_reattempt_rate_week3	,219[c]	2	,110	6,222	,002	,067
	SE4_regularity_week3	57,447[d]	2	28,724	290,057	<,001	,769
	SE5_practice_duration_week3	1213322,886[e]	2	606661,443	73,616	<,001	,458
	SE6_active_days_week3	152,744[f]	2	76,372	177,191	<,001	,671
Intercept	SE1_attempt_rate_week3	60,926	1	60,926	2022,304	<,001	,921
	SE2_on_time_rate_week3	38,048	1	38,048	250,202	<,001	,590
	SE3_reattempt_rate_week3	7,092	1	7,092	402,550	<,001	,698
	SE4_regularity_week3	115,794	1	115,794	1169,312	<,001	,870
	SE5_practice_duration_week3	4734978,159	1	4734978,159	574,568	<,001	,768
	SE6_active_days_week3	857,103	1	857,103	1988,571	<,001	,920
Profile_label_week3	SE1_attempt_rate_week3	,209	2	,105	3,473	,033	,038

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	SE2_on_time_rate_week3	2,573	2	1,287	8,461	<,001	,089
	SE3_reattempt_rate_week3	,219	2	,110	6,222	,002	,067
	SE4_regularity_week3	57,447	2	28,724	290,057	<,001	,769
	SE5_practice_duration_week3	1213322,886	2	606661,443	73,616	<,001	,458
	SE6_active_days_week3	152,744	2	76,372	177,191	<,001	,671
Error	SE1_attempt_rate_week3	5,242	174	,030			
	SE2_on_time_rate_week3	26,460	174	,152			
	SE3_reattempt_rate_week3	3,066	174	,018			
	SE4_regularity_week3	17,231	174	,099			
	SE5_practice_duration_week3	1433922,202	174	8240,932			
	SE6_active_days_week3	74,997	174	,431			
Total	SE1_attempt_rate_week3	87,556	177				
	SE2_on_time_rate_week3	94,029	177				
	SE3_reattempt_rate_week3	14,063	177				
	SE4_regularity_week3	237,572	177				
	SE5_practice_duration_week3	7497906,999	177				
	SE6_active_days_week3	1287,000	177				
Corrected Total	SE1_attempt_rate_week3	5,451	176				
	SE2_on_time_rate_week3	29,033	176				
	SE3_reattempt_rate_week3	3,285	176				
	SE4_regularity_week3	74,678	176				
	SE5_practice_duration_week3	2647245,087	176				
	SE6_active_days_week3	227,740	176				

a. R Squared = ,038 (Adjusted R Squared = ,027)

b. R Squared = ,089 (Adjusted R Squared = ,078)

c. R Squared = ,067 (Adjusted R Squared = ,056)

d. R Squared = ,769 (Adjusted R Squared = ,767)

e. R Squared = ,458 (Adjusted R Squared = ,452)

f. R Squared = ,671 (Adjusted R Squared = ,667)

3. Univariate ANOVA p-values and Adjusted p-values (Benjamini-Hochberg)

p_values		adjusted_p_BH	
3.319049e-02	*	3.319049e-02	*
3.115087e-04	***	4.672630e-04	***
2.456160e-03	**	2.947391e-03	**
3.897679e-56	***	2.338607e-55	***

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p_values		adjusted_p_BH	
6.833373e-24	***	1.366675e-23	***
1.074844e-42	***	3.224533e-42	***

Week 4

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	SE1_attempt_rate_week4	,061[a]	1	,061	2,562	,111	,015
	SE2_on_time_rate_week4	,068[b]	1	,068	,385	,536	,002
	SE3_reattempt_rate_week4	,018[c]	1	,018	1,172	,280	,007
	SE4_regularity_week4	41,194[d]	1	41,194	181,374	<,001	,513
	SE5_practice_duration_week4	1654852,574[e]	1	1654852,574	119,998	<,001	,411
	SE6_active_days_week4	145,626[f]	1	145,626	247,165	<,001	,590
Intercept	SE1_attempt_rate_week4	81,511	1	81,511	3417,203	<,001	,952
	SE2_on_time_rate_week4	35,856	1	35,856	202,271	<,001	,540
	SE3_reattempt_rate_week4	7,372	1	7,372	487,686	<,001	,739
	SE4_regularity_week4	190,642	1	190,642	839,378	<,001	,830
	SE5_practice_duration_week4	7150600,122	1	7150600,122	518,511	<,001	,751
	SE6_active_days_week4	1124,775	1	1124,775	1909,038	<,001	,917
Profile_label_week4	SE1_attempt_rate_week4	,061	1	,061	2,562	,111	,015
	SE2_on_time_rate_week4	,068	1	,068	,385	,536	,002
	SE3_reattempt_rate_week4	,018	1	,018	1,172	,280	,007
	SE4_regularity_week4	41,194	1	41,194	181,374	<,001	,513
	SE5_practice_duration_week4	1654852,574	1	1654852,574	119,998	<,001	,411
	SE6_active_days_week4	145,626	1	145,626	247,165	<,001	,590
Error	SE1_attempt_rate_week4	4,103	172	,024			
	SE2_on_time_rate_week4	30,490	172	,177			
	SE3_reattempt_rate_week4	2,600	172	,015			
	SE4_regularity_week4	39,065	172	,227			
	SE5_practice_duration_week4	2371992,500	172	13790,654			
	SE6_active_days_week4	101,340	172	,589			
Total	SE1_attempt_rate_week4	101,369	174				
	SE2_on_time_rate_week4	75,970	174				
	SE3_reattempt_rate_week4	11,996	174				
	SE4_regularity_week4	230,071	174				

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	SE5_practice_duration_week4	9549756,377	174				
	SE6_active_days_week4	1232,000	174				
Corrected Total	SE1_attempt_rate_week4	4,164	173				
	SE2_on_time_rate_week4	30,558	173				
	SE3_reattempt_rate_week4	2,618	173				
	SE4_regularity_week4	80,259	173				
	SE5_practice_duration_week4	4026845,074	173				
	SE6_active_days_week4	246,966	173				

a. R Squared = ,015 (Adjusted R Squared = ,009)

b. R Squared = ,002 (Adjusted R Squared = -,004)

c. R Squared = ,007 (Adjusted R Squared = ,001)

d. R Squared = ,513 (Adjusted R Squared = ,510)

e. R Squared = ,411 (Adjusted R Squared = ,408)

f. R Squared = ,590 (Adjusted R Squared = ,587)

4. Univariate ANOVA p-values and Adjusted p-values (Benjamini-Hochberg)

p_values		adjusted_p_BH	
1.112757e-01		1.669135e-01	
5.358769e-01		5.358769e-01	
2.804411e-01		3.365293e-01	
1.079754e-28	***	3.239263e-28	***
1.606576e-21	***	3.213152e-21	***
4.234855e-35	***	2.540913e-34	***

Week 5

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	SE1_attempt_rate_week5	,227[a]	2	,114	6,777	,001	,077
	SE2_on_time_rate_week5	27,912[b]	2	13,956	626,569	<,001	,885
	SE3_reattempt_rate_week5	,255[c]	2	,127	9,434	<,001	,104
	SE4_regularity_week5	29,216[d]	2	14,608	57,052	<,001	,412
	SE5_practice_duration_week5	3352618,610[e]	2	1676309,305	92,034	<,001	,530
	SE6_active_days_week5	109,927[f]	2	54,963	74,654	<,001	,478
Intercept	SE1_attempt_rate_week5	80,334	1	80,334	4788,386	<,001	,967
	SE2_on_time_rate_week5	19,256	1	19,256	864,539	<,001	,841

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	SE3_reattempt_rate_week5	6,938	1	6,938	513,599	<,001	,759
	SE4_regularity_week5	127,691	1	127,691	498,697	<,001	,754
	SE5_practice_duration_week5	9344151,355	1	9344151,355	513,018	<,001	,759
	SE6_active_days_week5	887,388	1	887,388	1205,297	<,001	,881
Profile_label_week5	SE1_attempt_rate_week5	,227	2	,114	6,777	,001	,077
	SE2_on_time_rate_week5	27,912	2	13,956	626,569	<,001	,885
	SE3_reattempt_rate_week5	,255	2	,127	9,434	<,001	,104
	SE4_regularity_week5	29,216	2	14,608	57,052	<,001	,412
	SE5_practice_duration_week5	3352618,610	2	1676309,305	92,034	<,001	,530
	SE6_active_days_week5	109,927	2	54,963	74,654	<,001	,478
Error	SE1_attempt_rate_week5	2,735	163	,017			
	SE2_on_time_rate_week5	3,631	163	,022			
	SE3_reattempt_rate_week5	2,202	163	,014			
	SE4_regularity_week5	41,736	163	,256			
	SE5_practice_duration_week5	2968896,369	163	18214,088			
	SE6_active_days_week5	120,007	163	,736			
Total	SE1_attempt_rate_week5	96,577	166				
	SE2_on_time_rate_week5	54,110	166				
	SE3_reattempt_rate_week5	11,177	166				
	SE4_regularity_week5	171,461	166				
	SE5_practice_duration_week5	13073019,207	166				
	SE6_active_days_week5	1015,000	166				
Corrected Total	SE1_attempt_rate_week5	2,962	165				
	SE2_on_time_rate_week5	31,543	165				
	SE3_reattempt_rate_week5	2,457	165				
	SE4_regularity_week5	70,952	165				
	SE5_practice_duration_week5	6321514,979	165				
	SE6_active_days_week5	229,934	165				

a. R Squared = ,077 (Adjusted R Squared = ,065)

b. R Squared = ,885 (Adjusted R Squared = ,883)

c. R Squared = ,104 (Adjusted R Squared = ,093)

d. R Squared = ,412 (Adjusted R Squared = ,405)

e. R Squared = ,530 (Adjusted R Squared = ,525)

f. R Squared = ,478 (Adjusted R Squared = ,472)

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5. Univariate ANOVA p-values and Adjusted p-values (Benjamini-Hochberg)

p_values		adjusted_p_BH	
1.489144e-03	**	1.489144e-03	**
3.007439e-77	***	1.804463e-76	***
1.327706e-04	***	1.593247e-04	***
1.651647e-19	***	2.477471e-19	***
1.776520e-27	***	5.329561e-27	***
9.655145e-24	***	1.931029e-23	***

Week 6

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	SE1_attempt_rate_week6	,525[a]	2	,263	16,512	<,001	,175
	SE2_on_time_rate_week6	13,613[b]	2	6,806	76,417	<,001	,495
	SE3_reattempt_rate_week6	,294[c]	2	,147	12,042	<,001	,134
	SE4_regularity_week6	30,111[d]	2	15,055	59,764	<,001	,434
	SE5_practice_duration_week6	1491558,837[e]	2	745779,418	71,944	<,001	,480
	SE6_active_days_week6	108,839[f]	2	54,420	67,133	<,001	,463
Intercept	SE1_attempt_rate_week6	96,188	1	96,188	6048,442	<,001	,975
	SE2_on_time_rate_week6	40,228	1	40,228	451,648	<,001	,743
	SE3_reattempt_rate_week6	7,332	1	7,332	600,459	<,001	,794
	SE4_regularity_week6	165,287	1	165,287	656,126	<,001	,808
	SE5_practice_duration_week6	6404097,384	1	6404097,384	617,792	<,001	,798
	SE6_active_days_week6	1017,209	1	1017,209	1254,856	<,001	,889
Profile_label_week6	SE1_attempt_rate_week6	,525	2	,263	16,512	<,001	,175
	SE2_on_time_rate_week6	13,613	2	6,806	76,417	<,001	,495
	SE3_reattempt_rate_week6	,294	2	,147	12,042	<,001	,134
	SE4_regularity_week6	30,111	2	15,055	59,764	<,001	,434
	SE5_practice_duration_week6	1491558,837	2	745779,418	71,944	<,001	,480
	SE6_active_days_week6	108,839	2	54,420	67,133	<,001	,463
Error	SE1_attempt_rate_week6	2,481	156	,016			
	SE2_on_time_rate_week6	13,895	156	,089			
	SE3_reattempt_rate_week6	1,905	156	,012			
	SE4_regularity_week6	39,298	156	,252			
	SE5_practice_duration_week6	1617113,619	156	10366,113			

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	SE6_active_days_week6	126,456	156	,811			
Total	SE1_attempt_rate_week6	100,774	159				
	SE2_on_time_rate_week6	59,708	159				
	SE3_reattempt_rate_week6	10,584	159				
	SE4_regularity_week6	234,418	159				
	SE5_practice_duration_week6	9547528,716	159				
	SE6_active_days_week6	1272,000	159				
Corrected Total	SE1_attempt_rate_week6	3,006	158				
	SE2_on_time_rate_week6	27,508	158				
	SE3_reattempt_rate_week6	2,199	158				
	SE4_regularity_week6	69,409	158				
	SE5_practice_duration_week6	3108672,456	158				
	SE6_active_days_week6	235,296	158				

a. R Squared = ,175 (Adjusted R Squared = ,164)

b. R Squared = ,495 (Adjusted R Squared = ,488)

c. R Squared = ,134 (Adjusted R Squared = ,123)

d. R Squared = ,434 (Adjusted R Squared = ,427)

e. R Squared = ,480 (Adjusted R Squared = ,473)

f. R Squared = ,463 (Adjusted R Squared = ,456)

6. Univariate ANOVA p-values and Adjusted p-values (Benjamini-Hochberg)

p_values		adjusted_p_BH	
3.128548e-07	***	3.754258e-07	***
7.331448e-24	***	4.398869e-23	***
1.370281e-05	***	1.370281e-05	***
5.379516e-20	***	8.069274e-20	***
7.259629e-23	***	2.177889e-22	***
9.236804e-22	***	1.847361e-21	***

Week 7

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	SE1_attempt_rate_week7	2,003[a]	2	1,001	77,521	<,001	,498
	SE2_on_time_rate_week7	3,526[b]	2	1,763	11,398	<,001	,127
	SE3_reattempt_rate_week7	1,270[c]	2	,635	53,827	<,001	,408

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	SE4_regularity_week7	29,088[d]	2	14,544	62,304	<,001	,444
	SE5_practice_duration_week7	517453,528[e]	2	258726,764	9,237	<,001	,106
	SE6_active_days_week7	67,002[f]	2	33,501	37,688	<,001	,326
Intercept	SE1_attempt_rate_week7	48,850	1	48,850	3781,596	<,001	,960
	SE2_on_time_rate_week7	11,314	1	11,314	73,144	<,001	,319
	SE3_reattempt_rate_week7	6,751	1	6,751	572,171	<,001	,786
	SE4_regularity_week7	51,888	1	51,888	222,282	<,001	,588
	SE5_practice_duration_week7	3189453,423	1	3189453,423	113,863	<,001	,422
	SE6_active_days_week7	453,208	1	453,208	509,845	<,001	,766
Profile_label_week7	SE1_attempt_rate_week7	2,003	2	1,001	77,521	<,001	,498
	SE2_on_time_rate_week7	3,526	2	1,763	11,398	<,001	,127
	SE3_reattempt_rate_week7	1,270	2	,635	53,827	<,001	,408
	SE4_regularity_week7	29,088	2	14,544	62,304	<,001	,444
	SE5_practice_duration_week7	517453,528	2	258726,764	9,237	<,001	,106
	SE6_active_days_week7	67,002	2	33,501	37,688	<,001	,326
Error	SE1_attempt_rate_week7	2,015	156	,013			
	SE2_on_time_rate_week7	24,131	156	,155			
	SE3_reattempt_rate_week7	1,841	156	,012			
	SE4_regularity_week7	36,416	156	,233			
	SE5_practice_duration_week7	4369752,952	156	28011,237			
	SE6_active_days_week7	138,670	156	,889			
Total	SE1_attempt_rate_week7	94,997	159				
	SE2_on_time_rate_week7	54,190	159				
	SE3_reattempt_rate_week7	11,641	159				
	SE4_regularity_week7	215,814	159				
	SE5_practice_duration_week7	12102524,774	159				
	SE6_active_days_week7	1182,000	159				
Corrected Total	SE1_attempt_rate_week7	4,018	158				
	SE2_on_time_rate_week7	27,658	158				
	SE3_reattempt_rate_week7	3,111	158				
	SE4_regularity_week7	65,503	158				
	SE5_practice_duration_week7	4887206,480	158				
	SE6_active_days_week7	205,673	158				

a. R Squared = ,498 (Adjusted R Squared = ,492)

b. R Squared = ,127 (Adjusted R Squared = ,116)

c. R Squared = ,408 (Adjusted R Squared = ,401)

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d. R Squared = ,444 (Adjusted R Squared = ,437)

e. R Squared = ,106 (Adjusted R Squared = ,094)

f. R Squared = ,326 (Adjusted R Squared = ,317)

7. Univariate ANOVA p-values and Adjusted p-values (Benjamini-Hochberg)

p_values		adjusted_p_BH	
4.205759e-24	***	2.523455e-23	***
2.397359e-05	***	2.876830e-05	***
1.671587e-18	***	3.343174e-18	***
1.293972e-20	***	3.881916e-20	***
1.617720e-04	***	1.617720e-04	***
4.435380e-14	***	6.653070e-14	***

Week 8

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	SE1_attempt_rate_week8	,064[a]	2	,032	1,502	,227	,024
	SE2_on_time_rate_week8	12,896[b]	2	6,448	154,022	<,001	,716
	SE3_reattempt_rate_week8	,052[c]	2	,026	1,112	,332	,018
	SE4_regularity_week8	44,622[d]	2	22,311	66,817	<,001	,523
	SE5_practice_duration_week8	2717137,638[e]	2	1358568,819	54,319	<,001	,471
	SE6_active_days_week8	219,726[f]	2	109,863	112,366	<,001	,648
Intercept	SE1_attempt_rate_week8	60,599	1	60,599	2858,610	<,001	,959
	SE2_on_time_rate_week8	14,773	1	14,773	352,890	<,001	,743
	SE3_reattempt_rate_week8	8,513	1	8,513	362,212	<,001	,748
	SE4_regularity_week8	108,730	1	108,730	325,621	<,001	,727
	SE5_practice_duration_week8	8007903,931	1	8007903,931	320,175	<,001	,724
	SE6_active_days_week8	842,527	1	842,527	861,723	<,001	,876
Profile_label_week8	SE1_attempt_rate_week8	,064	2	,032	1,502	,227	,024
	SE2_on_time_rate_week8	12,896	2	6,448	154,022	<,001	,716
	SE3_reattempt_rate_week8	,052	2	,026	1,112	,332	,018
	SE4_regularity_week8	44,622	2	22,311	66,817	<,001	,523
	SE5_practice_duration_week8	2717137,638	2	1358568,819	54,319	<,001	,471
	SE6_active_days_week8	219,726	2	109,863	112,366	<,001	,648
Error	SE1_attempt_rate_week8	2,586	122	,021			

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	SE2_on_time_rate_week8	5,107	122	,042			
	SE3_reattempt_rate_week8	2,867	122	,024			
	SE4_regularity_week8	40,738	122	,334			
	SE5_practice_duration_week8	3051341,513	122	25010,996			
	SE6_active_days_week8	119,282	122	,978			
Total	SE1_attempt_rate_week8	69,281	125				
	SE2_on_time_rate_week8	27,786	125				
	SE3_reattempt_rate_week8	12,950	125				
	SE4_regularity_week8	184,806	125				
	SE5_practice_duration_week8	13279021,316	125				
	SE6_active_days_week8	1148,000	125				
Corrected Total	SE1_attempt_rate_week8	2,650	124				
	SE2_on_time_rate_week8	18,003	124				
	SE3_reattempt_rate_week8	2,920	124				
	SE4_regularity_week8	85,360	124				
	SE5_practice_duration_week8	5768479,151	124				
	SE6_active_days_week8	339,008	124				

a. R Squared = ,024 (Adjusted R Squared = ,008)

b. R Squared = ,716 (Adjusted R Squared = ,712)

c. R Squared = ,018 (Adjusted R Squared = ,002)

d. R Squared = ,523 (Adjusted R Squared = ,515)

e. R Squared = ,471 (Adjusted R Squared = ,462)

f. R Squared = ,648 (Adjusted R Squared = ,642)

8. Univariate ANOVA p-values and Adjusted p-values (Benjamini-Hochberg)

p_values		adjusted_p_BH	
2.267709e-01		2.721251e-01	
4.204038e-34	***	2.522423e-33	***
3.321479e-01		3.321479e-01	
2.531040e-20	***	5.062079e-20	***
1.346477e-17	***	2.019715e-17	***
2.129734e-28	***	6.389201e-28	***

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