PROFILING YOUNG LEARNERS BASED ON THEIR DAILY STUDY HOURS IN A SUPPLEMENTARY E-LEARNING PLATFORM

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ABSTRACT

PROFILING YOUNG LEARNERS BASED ON THEIR DAILY STUDY HOURS IN A SUPPLEMENTARY E-LEARNING PLATFORM

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Online learning platforms (OLPs) are widely used as supplementary tools in K-12 education. Integration methods of these platforms into traditional learning environments are diverse, and they impact how students engage and learn with them. The goal of this study is to utilize cluster analysis as a learning analytics (LA) approach to reveal distinct profiles of students from grades 4 to 8 based on the hours they interact with an e-learning platform (ELP). In particular, four variables were created that indicate students' frequency of interaction with lessons and exercises in the OLP during in-school and out-of-school time. The analysis yielded three distinct profiles: low engagers (the most prevalent profile), out-school active learners, and in-school active learners. To examine how these profiles differed from each other in terms of their engagement, the Kruskal Wallis test was applied to compare using 18 evaluative variables as measurements of student engagement. The results showed that in almost all comparisons, out-of-school and in-school active learners exhibited similar engagement levels, but these were much higher than low engagers. In addition, the implications of the findings for the enhancement and effective integration of OLPs were presented.

Keywords: Learning Analytics, Online Learning Platforms, K-Means Clustering, Young Learners

ÖZ

ÖĞRETİME YARDIMCI BİR E-ÖĞRENME PLATFORMUNDA GENÇ ÖĞRENCİLERİN GÜNLÜK ÇALIŞMA SAATLERİNE GÖRE PROFİLLENDİRİLMESİ

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Çevrimiçi öğrenme platformları (ÇÖP), K-12 eğitiminde tamamlayıcı araçlar olarak yaygın şekilde kullanılmaktadır. Bu sistemlerin geleneksel öğrenme ortamlarına entegrasyonu farklılık gösterir ve entegrasyon yöntemi öğrencilerin bu platformlarla etkileşim biçimini ve öğrenmelerini etkiler. Bu çalışmanın amacı, 4. sınıftan 8. sınıfa kadar ki öğrencilerin belirli bir ÇÖP ile etkileşime girdikleri saatlere dayalı olarak profillerini ortaya çıkarmak. Bu amaç için öğrenme analitiği (ÖA) yaklaşımı ve kümeleme analizini kullanılmıştır. Kümeleme analizi için, öğrencilerin okul içi ve okul dışı zamanlarda platformlardaki dersler ve alıştırmalarla etkileşim sıklığını gösteren dört değişkene göre oluşturulmuştur. Yapılan analiz 3 farklı profil ortaya çıkarmıştır, bunlar; düşük katılım gösterenler (en yaygın profil), okul dışında aktif öğrenenler ve okul içinde aktif öğrenenlerdir. Bu profillerin ÇÖP ile etkilşimini karşılaştırmak için, 18 değerlendirme faktörü belirlenmiştir ve Kruskal Wallis testi uygulanmıştır. Sonuçlar, değerlendirme faktörlerinde okul dışı ve okul içi aktif öğrenci gruplarının neredeyse benzer katılım seviyeleri sergilediğini, ancak düşük katılım gösteren öğrencilerden ise istatistiksel olarak anlamlı düzeyde yüksek olduğunu göstermiştir. Ek olarak, çevrimiçi öğrenme sistemlerinin geliştirilmesi ve etkili entegrasyonu için bulguların çıkarımları paylaşılmıştır.

Anahtar Kelimeler: Öğrenme Analitikleri, Çevrimiçi Öğrenme Platformları, K-Means Kümeleme, Genç Öğrenciler

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ABBREVIATIONS

OLP: Online Learning Platform

LA: Learning Analytics

ICT: Information and Communication Technologies

TEL: Technology Enhanced Learning

ELP: E-Learning Platform

MCQ: Multi-Choice Question

MOOC: Massive Online Open Course

CHAPTER 1

INTRODUCTION

Integral parts of instructional design and technology as a field concern analyzing learning and performance problems as well as designing and managing instructional processes and resources to facilitate learning and performance in educational settings (Reiser, 2007). According to Januszewski & Molenda (2013, p4), facilitating covers "the design of the environment," "organizing resources," and "providing tools." Thus, educational technology focuses on the elements mentioned to create effective learning environments so that learning can occur easily. In this regard, since the beginning of the Internet era, advances in information and communications technologies (ICT) have changed and enriched the possible opportunities to facilitate learning.

As learning resources are increasingly digitized, learning now occurs not only in face-to-face but also in online environments. Although teachers in K-12 contexts are unwilling to change their teaching practice in face-to-face environments (Cuban et al., 2001), teachers and school administrators leverage the improvements in technology to provide effective and more engaging learning environments (Godzicki et al., 2013) not only within the schools but also beyond the borders of traditional school environments (Watson, 2008; Powell et al., 2015; Chatti et al., 2014). Therefore, limited classroom time does not limit essential activities to support students' learning (Feng et al., 2009). It has become more common to use technology-enhanced learning (TEL) tools to support and complement face-to-face classroom learning with online activities (Thomsen et al., 2022). Thus, Gunawardena (2017) asserts, TEL tools can change how we teach and learn. In this way, students and teachers can perform online activities, including reading additional learning resources, performing some exercises, or taking quizzes and revision tests, both in and out of the classroom.

However, new instructional models aiming to provide the best and most effective integration of the aforementioned TEL tools into face-to-face instruction continue to emerge. That is why selecting and adopting appropriate technology is crucial to support learning. Tools and instructional methods should be suitable for learners and learning environments (Januszewski & Molenda, 2013) to create effective and efficient learning settings. One approach to enhance student learning in K-12 settings has been the use of e-learning platforms (ELPs) that provide animation or video-based explanations of the subjects along with opportunities for further practice and testing. Although ELP are commonly used in K-12 settings in Turkey, schools and teachers vary in the way they integrate these platforms into their instructions. For example, while some teachers integrate them into their face-to-face teaching to reinforce student learning during the class, some others use them to provide supplementary learning activities outside the classroom, such as spaced learning activities (Kang, 2016). The ways of integrating such online learning platforms into the K-12 curriculum may have different effects on student behavior, learning, and performance, and thus deserves further investigation.

Nowadays, many online learning platforms (including learning management systems and ELPs) gather trace data left by students during their interactions, and such data can be used to monitor and identify students' online learning behaviors (Du et al., 2021). According to Chatti et al. (2014), in the TEL community, it is recently highlighted that there is a promising potential of learning analytics for exploiting big educational data to understand and support distinct learning processes. Learning analytics is defined as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs." (Siemens et al., 2011, p.2). Learning analytics has a crucial role in analyzing students' trace data to shed light into how learning occurs (Johnson et al., 2011), to predict student academic performance (Huang et al., 2020; Lu et al., 2018; Ricker, 2019), to improve students' engagement and learning outcomes (Lu et al., 2017), to improve learning design (Mangaroska & Giannakos, 2019), to monitor students' learning process (Erdemci, 2019), to identify learner profiles based on their engagement patterns (Moubayed, et al., 2020; Yen, & Lee, 2011), and to achieve data-informed decisions in educational settings (Chatti et al., 2014). In this regard, the students' traces left while using a specific ELP can be analyzed using learning analytics techniques to explore how young students use and interact with this platform and to identify learner profiles based on interaction patterns.

Learning is a complex process occurring across space, time, and media (Chatti et al., 2014). One of its distinct characteristics is that it occurs over time and is highly affected by when and how frequently and regularly learners study. The trace data emerging from student interactions with OLPs are stored with timestamps, which allows the analysis of learning in the temporal space. Temporal analysis of students' learning activities has been an important topic in learning analytics (Fiel, 2018). However, it has not been studied sufficiently on its own (Rotelli, 2022).

Teachers and institutions may choose to integrate OLP into their traditional instructions at different times (school hours or after school) which may somehow determine which hours during a day students access and use OLPs. The hour when students interact with these platforms may result in different engagement characteristics. For example, teacher-guided use during class time may affect students' engagement differently than when students use them at home alone or with parents. LAs can be harnessed to identify student profiles based on the time they use these platforms and their consequent engagement characteristics. However, Du et al. (2021) explored that most of the LA research has been conducted at higher education levels, and there is a lack of LA research on the K-12 level because of privacy issues (Gunawardena, 2017) and data security (Dellinger, 2019). Despite the concerns mentioned above, Bienkowski et al. (2012) note that K-12 schools should embrace LA to improve teaching, set policies, and measure outcomes.

When engagement is defined as involvement in learning tasks and environments, it is named as behavioral engagement by Fredricks et al. (2004). Student engagement can help examine students' learning activities and give an idea regarding the effect of interventions (Baker et al., 2012), and evaluate the quality of teaching and learning (Ma et al., 2015). Data gathered from students' interaction with OLPs can be used as indicators of students' efforts which could also be considered as indicators of students' engagement (Baker et al., 2012). In this regard, comparing students' engagement within the emerging profiles could be used to evaluate the quality of the instruction for each cluster. In addition, this comparison could be used to measure the students' behavior in terms of the different integration forms of the OLP into face-to-face instruction.

1.1 Purpose of the Study

Although OLPs are used to support instruction in the K-12 context, consideration must be given to how these platforms can be integrated to meet the needs of students by utilizing LA. However, LA harnesses various methods to discover the patterns students follow as they interact with OLPs that provide more authentic data than traditional survey methods. Some usage statistics are provided by online learning tools, such as time spent online and the total number of visits (Chatti et al., 2014). This research focuses on the time students spend online, particularly during or after school, and the duration of time students engage in the OLP. The gathered data is used to uncover the temporal profile of grade 4-8 students among various schools in Turkey. Thus, the findings are expected to assist teachers and institutions design, implement, and review courses (Lockyer et al., 2013) based on emerging student profiles.

1.2 Research Questions

This study addresses the following research questions.

- What profiles emerge based on students’ daily study hours in the online learning platform?
- How do these profiles differ from each other in terms of their engagement in the online learning platform?

1.3 Significance of the Study

LA researchers mainly employ clustering as a traditional analytic method in higher education, and there needs to be more research in the K-12 context (Papamitsiou & Economides, 2014; Du et al., 2021). While researchers in non-educational fields, such as computer science, only find patterns or report analytic results (Du et al., 2021), researchers in the field of education could suggest interventions that can improve the process of teaching and learning. Finally, Rodríguez-Triana et al. (2017) pointed out that optimizing the learning environment by using tracking data from the learning tools is the minority of the LA studies. Furthermore, LA studies have mainly focused on single school subjects, such as math (Lin et al., 2016) or science (Nalça, 2021). In order to fill these gap, all the analysis and evaluations made in this study are carried out by researchers in the field of education by using data from more than one school subject. It is aimed (i) to profile young learners based on a date-time study by following temporal data from an OLP in the context of K-12, and (ii) to compare the behavioral engagement of these emerging student clusters by using LA. Thus, it aims to provide suggestions to teachers and institutions on how these platforms could be integrated into the learning and teaching process at the K-12 level to promote the quality of instruction.

1.4 Limitations of the Study

This research study has several limitations as listed below.

- The research data were gathered from the one-month online activity logs.

- The students were chosen by convenience sampling from the 4^{th}, 5^{th}, 6^{th}, 7^{th}, and 8^{th} grades.
- Data for profiling student clusters were obtained, particularly in the average number of logs for the lesson and exercise parts of the OLP during school days.
- Demographic information about the students was not available in the data. Data for profiling was further anonymized in order to protect the privacy of the students as well as prevent any student from being identified or identifiable.
- As for the students' performances, the scores of the exams in each module on the platforms on the first attempt were accepted. Besides, we assume that students answer the test on their own.
- It is assumed that the students and the teachers used the OLP as desired.

CHAPTER 2

LITERATURE REVIEW

In this section, online learning platforms, learning analytics (LA) and the current status of LA will be explained. Objectives of LA, and application of LA will be discussed. In addition, methods of LA, and challenges of LA will be mentioned. Furthermore, the related research about the study and practice in K-12 will be covered. Finally, clustering and profiling learners will be explained, and engagement will be defined with its indicators and interpretation of them in LA studies.

2.1 Online Learning Platforms

There has yet to be a consensus on the name of such systems. It is defined by different names in the literature, such as a web-based tutoring platform (Pardos et al., 2014), an educational software system, an online tutoring system (Crossley et al., 2020), the educational portals (Kırıkkaya & Yıldırım, 2019), online education platforms (Avcı et al., 2019), web-based systems (Nacu et al., 2016). In this study, we prefer to use e-learning platforms or online learning platforms hereafter for systems because learning is basically a broad definition of activities students do to learn. Tutoring is often domain-specific and limited to the context of a course (Chatti et al., 2014).

One approach to enhance student learning in K-12 realms has been using OLP that provide animations and video-based explanations of the subjects along with opportunities for further practice and assessment. Schools and teachers vary in the way they integrate OLPs into their instructions. According to Chatti et al. (2014), OLPs are often used to enhance traditional face-to-face instruction methods in formal learning settings. However, Johnson et al. (2011) added that OLPs not only support traditional face-to-face teaching content but also enable learning to take place outside of school time. Furthermore, OLPs are also used as supplementary tools to promote independent learning (Cakrawati, 2017). The ways of integrating such learning platforms in K-12 and their impacts on students’ behavior, learning, and performance need to be investigated to understand the learning process.

In this study, one of the popular ELPs was used as a supplementary tool for traditional face-to-face instruction. It consists of school subjects, each school subject is divided into units, and each unit is made of modules. A module includes (i) lessons including short video animations that introduce and explain relevant course concepts, (ii) exercises including multiple-choice questions (MCQs) that follow and cover the concepts discussed in the video; and (iii) exams/tests with multiple-choice questions (MCQs) to access the students learning as summative assessments, and (iv) games. Moreover, while working on these activities, the system records, and stores all the student's interactions with the system. The timestamped data includes many activities such as entering/exiting the system, viewing a learning material, playing a game, doing an exercise, and navigating different pages. In addition to timestamps, test scores, and test-taking frequencies are also recorded in the system. Therefore, data on how students study and learn can be recorded at a very detailed level to explain the complexity of the learning process (Siemens, 2013).

A number of studies investigating the effect of ELPs on academic achievement (Karataş, 2021) and student and teacher` attitudes (Avcı et al., 2019) were conducted in Turkish K-12 settings, but these studies did not take advantage of LA to understand how students use and learn through OLPs. These studies depended on survey-based methodologies rather than benefiting from log data provided by OLPs which provide more authentic indicators of student engagement.

2.2 Learning Analytics

Currently, it is possible to create more engaging, efficient, and success-oriented learning environments by utilizing advanced technology in educational settings

(Powell et al., 2015). Technological advances led to new instructional approaches in learning environments, especially using the internet as a delivery method. As the use of OLPs becomes widespread, it becomes challenging to observe the students' behaviors in e-learning environments to make decisions about the instructional process (Romero & Ventura, 2007). However, these platforms enable to track most of the activities students do during the learning process and can record and produce large amounts of data related to learning. In this regard, providing data alone is insufficient to support teachers in enhancing instruction (van Leeuwen et al., 2022). As Ostrow et al. (2017) highlighted that big data can be manipulated or combined to consider different perspectives, and finally, arrive at different conclusions.

Analyzing and interpreting big data exceeds organizations' ability in terms of instruction (Siemens & Long, 2011). Hence, Siemens (2013) declared that LA was a separate educational research field that enables deriving meaningful insights from big data to improve teaching and learning (Sclater et al., 2016). In other words, LA has emerged with increasing opportunities to collect and leverage data regarding learning and learning settings called trace or log data (Gasevic et al., 2017). Moreover, there has been a growing interest in LA in technology-enhanced learning (TEL) (Chatti et al., 2014) as LA emerged from technology-enhanced learning (Ferguson, 2012).

LA interpret the big data to understand how learning unfolds, assess the academic processes, and predict future performance (Johnson et al., 2011). The broader adoption of educational technologies in primary and secondary education has resulted in growing awareness of the potential of LA to support student learning and understand their learning progress and engagement. Therefore, LA must be leveraged in ways that both recognize and draw on existing K–12 education research (Monroy et al., 2014) because Phillips & Ozogul (2020) highlight that LA is currently not often studied at the K-12 level, particularly comparing to the higher education (Lowes et al., 2015).

2.2.1 Objectives of LA

The goal of LA, according to the Society of Learning Analytics, “is understanding and optimizing learning and the environments in which it occurs.” As Clow (2013a) puts it: “Learning analytics is first and foremost concerned with learning” (p. 687). The purpose of learning analytics is to enable teachers and schools to tailor instruction to student's needs and skill levels so that it could improve instruction (Johnson et al., 2011); however, LA in higher education has primarily focused on identifying at-risk students who can then gain attention to prevent failure in a particular subject (Johnson et al., 2011).

According to Chatti et al. (2014), LA might cover these objectives below,

- **Monitoring and Analysis** aim to collect student interaction data within learning environments and generate reports to support decision-making by teachers and by the educational institution.
- **Prediction and Intervention** refers to predicting learners’ future performance based on their current activities and performance so that teachers can provide proactive intervention to students who may need additional assistance.
- **Tutoring and Mentoring** have different meanings in educational settings. Tutoring is mainly focused on helping students with their learning. In contrast, Mentoring is mainly concerned with guiding learners to achieve their goals.
- **Assessment and Feedback** aim to apply the (self-) assessment to examine the efficiency and effectiveness of the learning process so that both students and teachers get intelligent feedback related to the learning process.
- **Adaptation, Personalization, and Recommendation** refer to guiding learners on what to do next by adaptively organizing learning resources and instructional activities recommended based on the needs of the individual learner.

A recent literature review (Phillips & Ozogul, 2020) has also revealed that LA studies focus on predicting student success or failure, providing information about instructional design, and applying LA systems respectively.

2.2.2 Applications of LA

The most common LA applications in the literature are identifying at-risk students (Johnson et al., 2011), tracking and predicting learners' performance within online settings (Avella et al., 2016), designing systems and approaches to measure student performance and teacher development better (Johnson et al., 2011), detecting and analyzing the patterns of students' activities (Johnson et al., 2011), and spotting potential problematic issues during the instruction (Johnson et al., 2011).

2.2.3 Methods of LA

The core emphasis of LA is transforming massive instructional data into useful actions to promote learning (Chatti et al., 2014). LA is a kind of data-driven approach because LA focuses on data regarding learners' interactions with course content, other students, and instructors (Avella et al., 2016). Although LA uses various methods to improve learning and support performance (Chatti et al., 2014), Avella et al. (2016) state that the most common LA methods include social network analysis, visual data analysis techniques, prediction, semantics, clustering, discovery with models, and relationship mining.

Social network analysis refers to the analysis of relationships between learners, and between learners and instructors (Avella et al., 2016).

Visual data analysis techniques are used to uncover patterns and trends in large, complex data (Avella et al., 2016).

Prediction refers to developing a model that makes inferences using both a predicted variable and predictor variables (Avella et al., 2016). In addition, according to Baker

(2010), decision trees, logistic regression, and support vector machine regression are three categories of classification methods.

Clustering aims to detect data points that naturally group together by dividing the entire data set into a series of clusters (Baker, 2010),

Discovery with models refers to designing a model using predication, or clustering methods (Avella et al., 2016).

Relationship mining discovers the relationships between variables in a dataset containing many variables (Baker, 2010).

2.2.4 Challenges of LA

LA also faces some challenges including,

- The data can be gathered from different sources and formats (Johnson et al., 2011).
- Ethical (Ferguson, 2012) and privacy issues (Avella et al., 2016).
- The reduction of students to numbers and information (Johnson et al., 2011).
- Lack of connection to learning sciences (Ferguson, 2012; Avella et al., 2016; Joksimović, Kovanović & Dawson, 2019).

2.3 Learning analytics studies in K-12 level

LA studies generally focus on monitoring/analysis of the factors of academic performance (Kew & Tasir, 2021). With this regard, Liu & Cavanaugh (2012) investigated the factors influencing student academic performance in online high school algebra and indicated that the time spent in OLP and teachers' feedback are indicators of academic performance. Nalça (2021) examined the effective factors of science exam scores of secondary school students supported by online practices, and it was found that the most important variables related to the exam performance of the students were the number of tests completed and the number of questions answered. Furthermore, Lin et al. (2016) integrated an OLP into traditional face-to-face instruction in 7th-grade mathematics courses. The study indicated that this integration improved course achievement and positively affected attitudes toward studying mathematics.

LA can provide teachers and institutions with information on the effectiveness of technology-enriched instruction. Monroy et al. (2014) searched to develop a strategy for incorporating LA into designing and evaluating a K–12 science curriculum. They concluded that LA data was insufficient to understand what teachers did in their classrooms with the curriculum. They recommended using data visualization tools to translate the data into information. Moreover, access to technology and lack of time to integrate technology into regular instruction were common challenges. Van Leeuwen et al. (2021) examined how teacher characteristics relate to how teachers use dashboards, a specific application of LA, and revealed that teacher characteristics were not associated with dashboard use.

In conclusion, although some issues like the ethics and privacy of LA within K-12 are mentioned, the use of digital learning platforms and benefits from LA are currently very common (Aguerrebere et al., 2022). In this context, as Beerwinkle (2021) noted, LA can help prevent further harm to students using the online academic setting. Moreover, LA can benefit students who need to be more successful within new digital environments.

There are several areas that need further consideration in LA studies. First, although LA approaches in primary and secondary school settings provide the possibility of making data-driven decisions to improve student learning (Kovanovic et al., 2021), more studies need to be carried out. Second, existing studies have mostly been done for a certain school subject, such as science or mathematics (Hillmayr et al., 2020). Third, previous studies have utilized self-reported data such as traditional survey or questionnaire data collection methods. For these reasons, this study adopts a LA approach to gain greater insight from a large amount of data automatically accumulated by an OLP. Furthermore, although OLPs are prevalently used to support traditional instruction within K-12, there has yet to be a study in the scope of LA on how to integrate these systems into face-to-face education.

2.4 Clustering and Profiling Learners

One of the integral uses of LA is to identify student learning behavior, which can be used to create interventions that promote student learning (Kew & Tasir, 2021). In the literature, diverse data obtained from the online learning platform are used to uncover students' learning activity patterns based on various purposes. For example, based on activity sequences in an OLP, Boroujeni & Dillenbourg (2019) conducted a study to understand students' study patterns. Rotelli et al. (2022) studied to discover student temporal learning behavior patterns by using whether and when students usually work in an online learning environment. The dataset includes learners' interaction with video lectures (play, pause, download, seek, change speed), assignments (submit), and discussion forums (read, write, vote a message). Sher, Hatala & Gašević (2020) attempted to identify students' consistency patterns in online work habits based on log records including session number, start time, and end time. Tang et al. (2019) investigated to define longitudinal participation patterns of learners in an OLP according to activities related to steps of process while producing a common video such as adding a new video file, chatting via private messages, deleting a file, and updating a profile. Shi et al. (2020) studied to profile the students' engagement patterns based on activities including visits, attempts, and comments. Bouchet et al. (2013) profiled learners to foster self-regulated learning by using OLP interaction data, including visiting number, time spent on the page, and time spent for taking notes. Antonenko et al. (2012) utilized cluster analysis to profile students in terms of problem-solving strategies by using time allocation for writing tasks, visiting relevant resources, and visiting irrelevant resources. Pereira et al. (2020) conducted research to profile students' behavior in introductory programming according to domain-specific variables such as keystrokes.

2.5 Engagement

Engagement is essential to learning (Bergdahl et al., 2020; Henrie et al., 2015), and it contributes to students' learning processes and performance (Fredricks et al., 2016). It can also be an indicator of students' attitudes toward learning activities (Fredricks et al, 2016). Fredricks et al. (2004) defined three kinds of engagement: behavioral, cognitive, and emotional engagement. Behavioral engagement refers to effort or involvement in learning activities, such as time-on-tasks and attendance. Emotional engagement is associated with feelings such as a sense of belonging. Cognitive engagement is related to the learning process's psychological side, such as using learning strategies (Fredricks et al., 2004). However, Appleton et al. (2008) discovered that cognitive engagement is considered less observable and has more internal indicators. On the other hand, behavioral engagement includes explicit and observable student's specific behaviors in the learning process. Therefore, this study focuses on the students’ behavioral engagement in an ELP.

Technology-enhanced learning tools are increasingly integrated into traditional education, so understanding how students interact with such technologies has become vital (Nkomo & Nat, 2021) to build effective online learning (Dixson, 2010). Engagement could be a valuable factor for adopting learning technology (Cruz-Benito et al., 2015) or an indicator of the quality of a course, learning activity, or teaching tool (Hu & Li, 2017). Even though self-reports such as surveys are mostly used to measure student engagement in the literature (Fredricks et al., 2016), big data captured by OLP can be used to measure student engagement (Saqr et al.,2017). The challenge arises about how to measure student engagement based on their behaviors in OLP. Active participation in the learning process and time spent on a task have a positive correlation with effective learning and positive outcome (Cruz-Benito et al., 2015). That is why, Wang (2017) asserts that behavior engagement takes into account the counts and times that the learners spend on each online activity. Therefore, the log data based on students' online activities can be used (Baker et al., 2012; Ma et al., 2015) to measure engagement.

In short, OLPs provide vast amounts of information related to the learning processes, which can be exploited by clustering algorithms to profile students' learning behavior. However, the studies mentioned above mostly focus on lifelong learning (e.g., MOOCs), higher education, or a specific grade level in K-12. To the best of our knowledge, no previous research examined grade 4-8 students' daily study hours in an online learning platform to identify their engagement profiles. Accordingly, this thesis research investigates the study habits of grade 4-8 students in terms of their interaction time with an online learning environment to identify students' engagement profiles based on their study patterns, thus filling a critical gap in the literature.

CHAPTER 3

METHOD

This is an exploratory quantitative research which involves the cluster analysis of students' activity logs to identify student profiles. In the following subsections, description of the data and participants, e-learning platform, and the data analysis are described.

3.1 Description of the Data and the Participants

The research data were composed of the one-month (2021 September) online activity logs from the ELP pertaining to 1,207 students from the 4^{th} to 8^{th} grades from 1054 different schools in Turkey. The data set was categorized under four groups, each of which corresponds to a specific component of the platform: lessons (around 11,000 logs from around 950 students), practices (around 6,600 logs from around 800 students), exams (around 5,100 logs from around 638 students), and games (around 2,100 logs from around 300 students).

Although the ELP used in the study is comprised of four major components as mentioned above, this research particularly aims to profile students based on the day and time of their engagement with lessons and practices on school days, assuming that the primary learning and teaching occur due to students interaction with lesson and exercise components present in the learning platform. The process entailed several filtering steps on the data. First, logs pertaining to the activities performed on weekends were excluded to keep only the data from school days (i.e., Monday to Friday). Second, some filtering was performed based on the hour of the engagement with the platform. Specifically, from 9 am to 3 pm was determined to be school time (in-school time), and from 5 pm to 12 am was considered to be after-school time (out-of- school time). Any logs pertaining to other hours were discarded. These hours were decided according to regular school hours in Turkey, which is typically from around 8-9 am to around 3-4 pm.

After the filtering process, the resulting data set contained 906 individual students from 819 schools with different distributions to the grades, as shown in Table 3.1. However, demographic information about the students was not available in the data. The resulting data is also further anonymized in order to prevent any student from being identified or being identifiable.

Table 3.1 Distribution of the Students in the Final Data Set Across Grades

Grades	4	5	6	7	8
Student count	309	208	150	102	137

As shown in Table 3.1, out of 809 participants, 309 are from grade 4, 208 are from grade 5, 150 are from grade 6, 102 are from grade 7, while 137 of them are from grade 8.

3.2 The E-Learning Platform

The e-learning platform is an OLP prepared to support primary and secondary school students and teachers. This platform teaches various school subjects with rich content in line with the Republic of Türkiye Ministry of National Education (MEB) curriculum, as shown in Figure 3.1.

Figure 3.1. Student interface of the e-learning platform

Besides lessons about school subjects, this platform provides practices, exams, educational games, and student activity reports for each one. The platform organizes online education content according to grade level and contains all school subjects except those that are skill-based, such as art and physical education. Each school subject is divided into units, and each unit is made of modules. The number of modules varies based on the content of the unit. Every module, as shown in Figure 3.2, includes (i) lessons that are made of short videos or animations that introduce and explain relevant course concepts, (ii) activities including solved problems, and printable worksheets that follow and cover the concepts discussed in the lesson, and (iii) tests include multiple-choice questions (MCQs) that serve as summative assessments. Although there is little nuance according to the subject, each module follows the same instruction pattern.

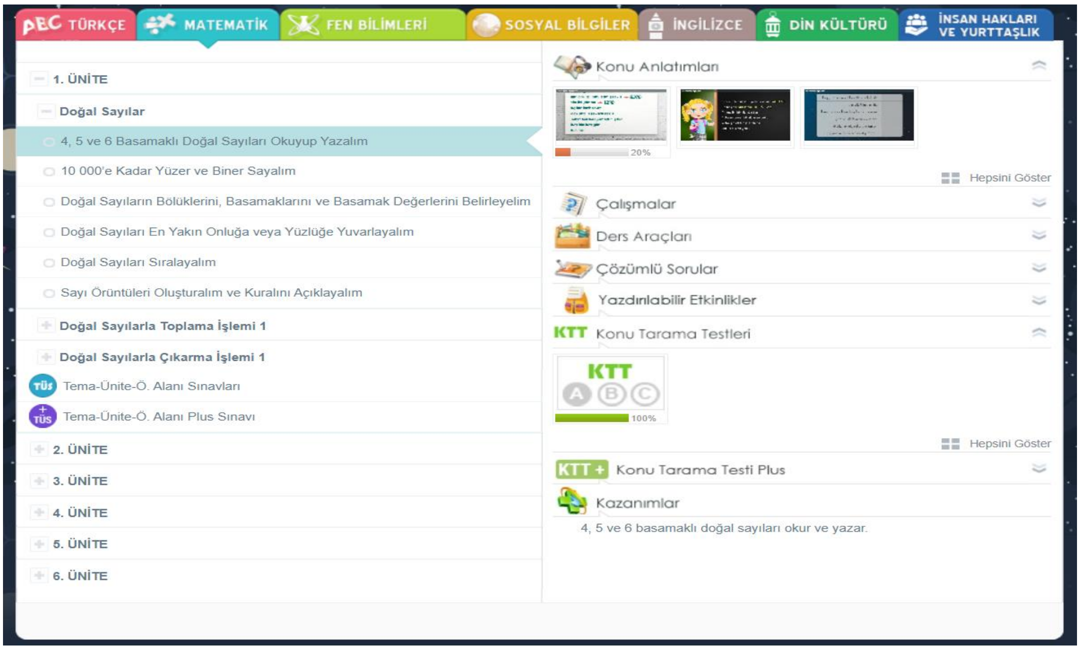

Figure 3.2. A module of math

3.2.1 Lessons

In each module, the lesson is the first step of the instruction. It is divided into some parts as videos and animations, and each one presents the distinct course objectives. During an animation-based lesson, key information appears on the screen as a note. Students can control the lessons by pausing, forwarding, and backwarding as they need. In addition, each lesson does not take more than 1.50 minutes, as shown in Figure 3.3. The format of the lesson can change according to the subject. For example, lessons can be like face-to-face classroom instruction for math or can be interactive animation to encourage active student participation in science with examples from daily life.

Figure 3.3. Screenshot of a lesson

Moreover, while taking the lessons, the system records and stores all the student's interactions with the system, as shown in Figure 3.4. The interaction information contains the entrance and exit time, completeness of the lesson, time spent for the lesson, and number of taking the lesson. Therefore, thanks to this information, students have some statistical information related to the lesson.

Figure 3.4. The screenshot of interaction information in the lesson

3.2.2 Exercises

The ELP provides exercises to reinforce the information learned through lessons. Through the exercises section, students obtain the opportunity to solve questions, which can have the following types: matching and filling the blanks, true/false. In addition, depending on the content of the lessons, experiments and documentaries were added as a part of exercise activities (Figure 3.5). In other words, this section can be defined as the formative assessment part. As shown in Figure 3.6, interaction information, including entrance and exit time, completeness of the exercise, time spent for exercise, and the number of exercises taken are stored in the system.

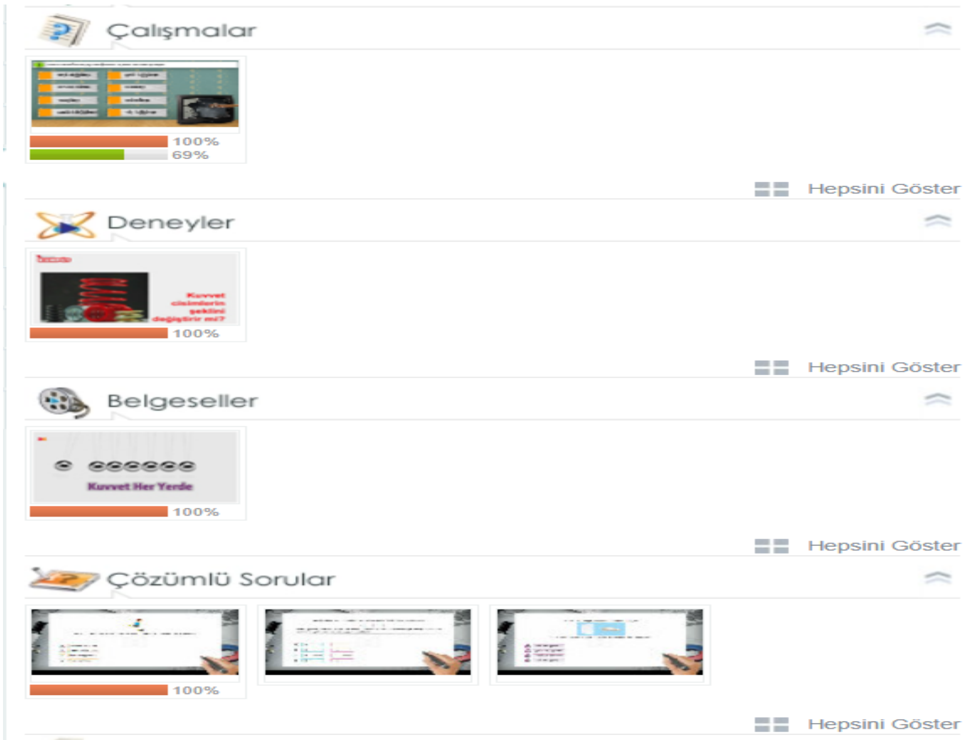

Figure 3.5. The screenshot activities section

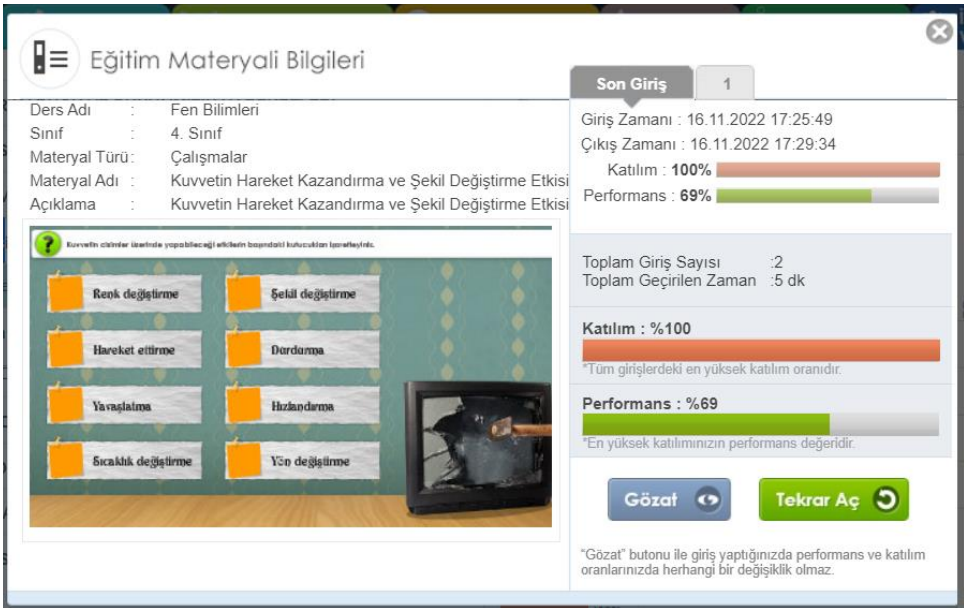

Figure 3.6. The screenshot of interaction information for activities

3.2.3 Exams

At the ELP, there are two kinds of tests students can take, one is the module review test (Figure 3.7) which has ten questions and can be taken at the end of each module. The other one is the unit review test (Figure 3.8) which covers the whole unit with 20 questions and can be taken at the end of each unit. Both tests include multiple-choice questions (MCQs) that serve as summative assessments. Students can take tests more than once, and the system saves the best score as the test score.

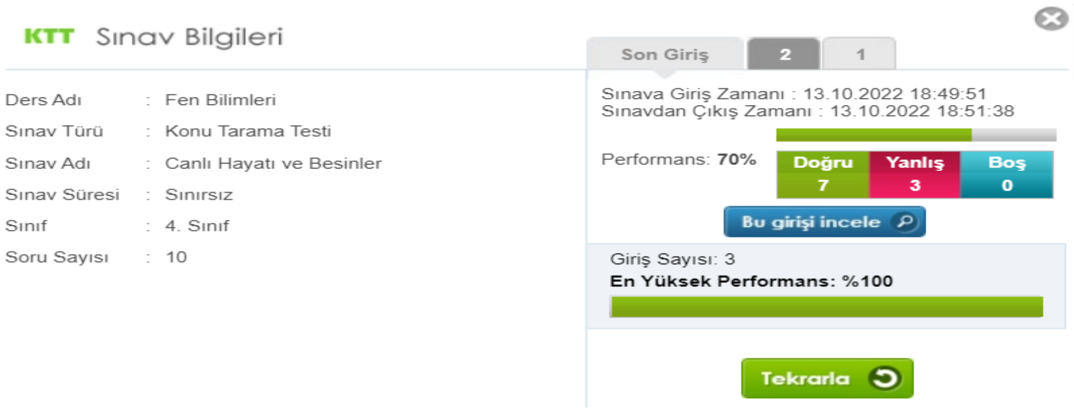

Figure 3.7. The screenshot of interaction information for the module review test

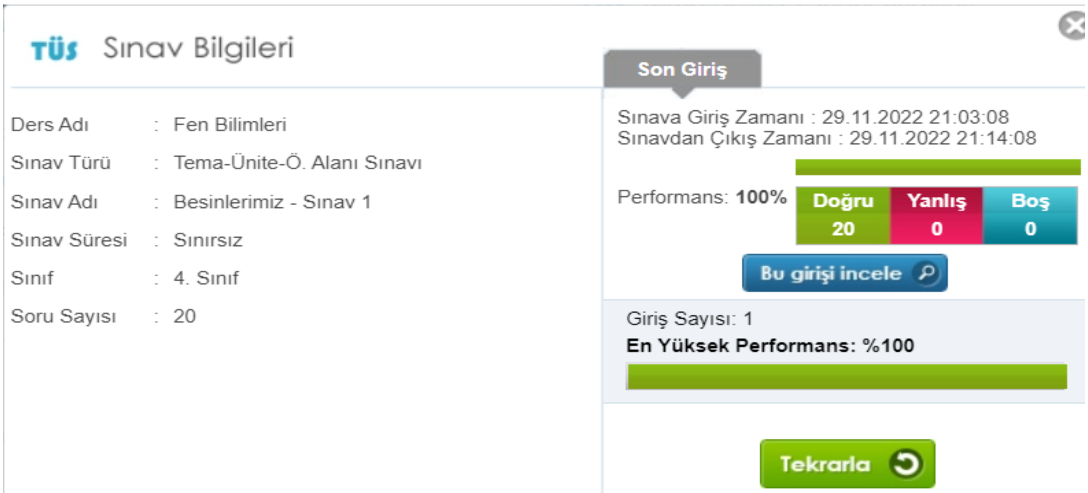

Figure 3.8. The screenshot of interaction information for a unit review test

As shown in Figure 3.7 and Figure 3.8, interaction data regarding tests are entrance and exit time, score, and the number of taken tests are saved in the system.

In conclusion, all data emerge from the students' interactions with these interfaces; this is why understanding these interfaces and possible interactions with them will help understand and interpret the emerging data.

3.3 Data Analysis

3.3.1 Cluster Analysis

Cluster analysis was performed to answer the first research question (what profiles emerge based on students' daily study hours in the online learning platform?). Cluster analysis, as a popular LA technique, helps uncover interesting patterns hidden in educational datasets (Chatti et al., 2014). User modeling as clusters is interested in understanding how users interact with the systems (Siemens, 2013) and splitting them based on their similarities so researchers can design better systems. Cluster analysis can help researchers develop profiles based on learner activities in online learning environments (Antonenko et al., 2012). A variety of clustering variables have been used in the literature, including active time online, the total number of visits, number of visits per page, distribution of visits over time, frequency of student's postings/replies, and percentage of material read, and so on. (Chatti et al., 2014). Particularly, K-Means clustering is one of the most widely used clustering methods in LA (Ning & Downing, 2015; Shi et al., 2020). K-means is a non-hierarchical (a partitioning) clustering method (Ma & Chow, 2004) that divides data into k-specific clusters based on observation similarities or dissimilarities (Lletı, et al., 2004).

Determining the optimal number of clusters is critical for the accuracy of the clustering process (Gülagiz & Sahin, 2017). The Silhouette Method is a robust approach to find the number of clusters that are well separated from each other (Rousseeuw, 1987). Therefore, in this study, Silhouette Method was used to decide on the number of clusters.

As the first research question involves profiling students based on the time of their engagement with lessons and practices on school days, the following variables were derived for clustering: 1) number of interactions with lessons in the school, 2) number of interactions with lessons outside the school, 3) number of interactions with practices in the school, and 4) number of interactions with practices outside the school. These variables were first standardized and then used in the K-Means clustering analysis to identify distinct student profiles. The interactions with lessons and practices were focused in clustering since they are the primary learning and teaching components present in the learning platform.

Preprocessing of the data was performed using Pythons' pandas and numpy libraries. The K-Means implementation of scikit-learn python library (Pedregosa et al., 2011) was used to perform the cluster analysis.

3.3.2 Statistical Comparison of the Clusters

The second research question in this thesis study involved the comparison of the emerging student profiles in terms of their engagement with different components of the learning platform. To this aim, a variety of indicators were computed from the dataset and used as the evaluative variables (Pereira et al., 2020) to identify the differences among students' engagement levels from different profiles. As presented in Table 3.2, in total 18 evaluative variables were computed to be used as indicators of student engagement with lessons, exercises, exams, and games.

Table 3.2 Evaluative Variables to Make Comparisons of the Engagement Levels between the Profiles

#	Variable name	Description	Type
Login events			
1	Average session duration	Average session duration in minutes	mean
2	Unique session count	Number of sessions per student	count
Lesson events			
3	Average time on lessons	Average time in minutes spent on lessons by each student	mean
4	Average lesson participation	The percentage of the lessons viewed by each student on average	count
5	Number of lessons viewed	Number of unique lessons viewed by each student	count
6	Number of subject areas studied	Average number of unique subject areas for which a lesson was viewed	mean
Exercise events			
7	Number of lessons exercised	Number of lessons for which an exercise was attempted	count
8	Number of subject areas exercised	Number of subject areas for which an exercise was attempted	count
9	Number of exercises intended	Number of exercises interacted by a student	count
10	Average exercise participation	The percentage of the exercises completed by each student on average	mean
11	Average time on exercises	Average time in minutes spent on exercises by each student	mean
Exam evens			
12	Number of subject areas tested	Number of subject areas for which an exam was attempted	count
13	Average time on exams	Average time in minutes spent on exams by each student	mean
14	Average exam score	The mean score of all exams taken by a student	mean
15	Number of exams taken	Number of unique exams taken by a student	count
Game events			
16	Average time on games	Average time in minutes spent on games by each student	mean
17	Number of game interactions	Number of games played by a student	count
18	Number of game sessions	Number of sessions that involved the play of any games	count

As shown in Table 3.2 evaluative variables are divided into six categories based on the components of the platform. As can be seen in the Table 3.2, each category has a number of evaluative variables with descriptions and corresponding data type.

Prior to the comparison of the profiles in terms of the evaluative variables, a normality test was performed for each cluster regarding all variables (D'Agostino, 1971). In the case of normal distribution, ANOVA was used to identify significant differences in engagement levels. For the non-normal data, Kruskal Wallis Test, as a non-parametric test, was chosen for the same analysis. The Kruskal-Wallis is a non-parametric statistical test that compares more than two independently sampled groups on a single, non-normally distributed continuous variable (McKnight & Najab, 2010; Ostertagova, Ostertag & Kováč, 2014). All statistical analysis was performed using the Scipy library in Python (Virtanen et al., 2020).

CHAPTER 4

RESULTS

This study is aimed at exploring primary school (grade 4) and middle school (grade 5-8) students' study behavior through cluster analysis. In particular, distinct student profiles were identified based on the date time of their interactions with the OLP and compared in terms of evaluative variables.

Emerging Student Profiles

The first research question concerns the identification of the student profiles based on the date time of their engagement, which involved the clustering of students based on four variables. These variables refer to the total number of lesson and exercise activities performed during the in-school time and out of school time. Descriptive statistics about these variables are shared in Table 4.1.

Table 4.1 Descriptive Statistics of the Clustering Variables

Variables	*M*	*SD*	*Max*
Lesson_inSchool	2.62	6.52	94.00
Lesson_outSchool	5.53	6.89	68.00
Exercise_inSchool	1.52	4.77	92.00
Exercise_outSchool	3.31	5.14	61.00

Before the K-Mean cluster analysis, the optimal number of clusters needs to be identified. Silhouette is a popular technique to determine the number of clusters (Shahapure & Nicholas, 2020; Shi et al., 2021). According to the Silhouette scores, 3 was found to be an ideal number to create dense yet isolated clusters. That is, three clusters (each representing a student profile) were identified as shown in Table 4.2 and Figure 4.1.

Table 4.2 Student Profiles

	Lesson_in School	Lesson_out School	Exercise_in School	Exercise_out School
Cluster #0: Low engagers	1.25	3.65	0.61	1.89
Cluster #1: After-school active learners	2.63	17.71	1.93	12.59
Cluster #2 In-school active learners	21.96	4.19	13.40	2.12

Within the scope of the first research question, Figure 4.1 indicates profile emerges based on the date-time data which the OLP captures.

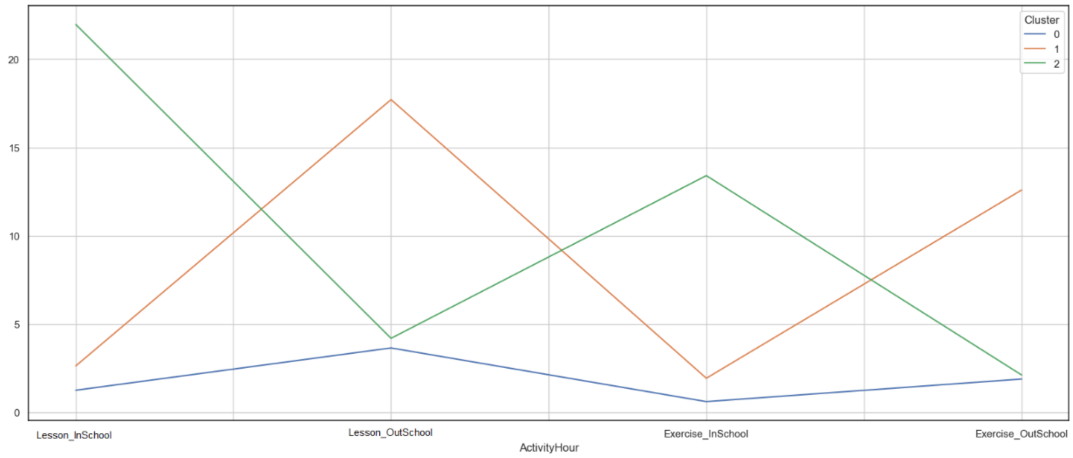

Figure 4.1. Students' behavior clusters

To answer research question 1, cluster analysis was conducted to discover learner profiles based on date-time data. The cluster analyses led to the following three clusters as shown in Table 4.2: low engagers (n=735, 81%), after-school active learners (n=119, 13%), and in-school active learners (n=55, 6%). As its profile name suggests, the low engagers were not very active during regular school hours or after-school hours. This profile was the most prevalent among the students. The other profile was after-school active learners. This group uses the system actively, mostly out of school hours; however, this group is active in the system even a little during school hours. The after-school active learners have the second biggest population. Finally, the in-school active learners were active during regular school hours, and this profile was not prevalent among students compared to the other profiles.

RQ2: How do these profiles (clusters) differ from each other in terms of various evaluative variables?

To answer research question 2, the assumption of normality was evaluated through the scipy.stats.normaltest, that combines skew and kurtosis values to test normality based on D'Agostino (1971), and D'Agostino and Pearson's (1973) test for each variable, and the results are non-normal for each evaluative variables. Histogram for each evaluative variable and all clusters are presented in Figures 4.2- 4.19.

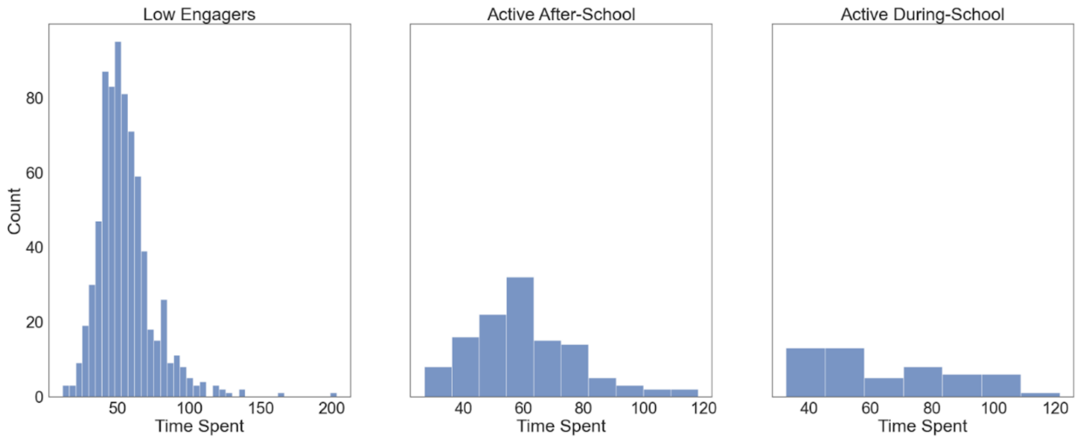

Figure 4.2. Average session duration

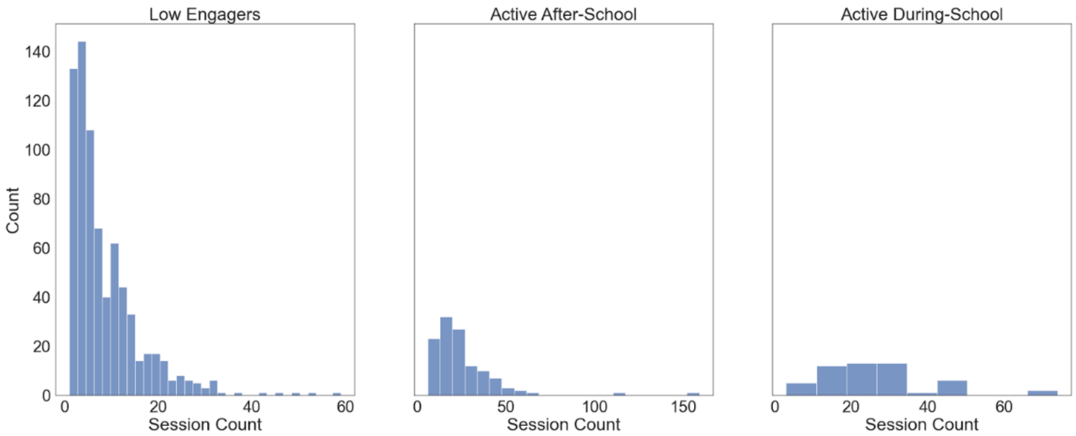

Figure 4.3. Unique session count

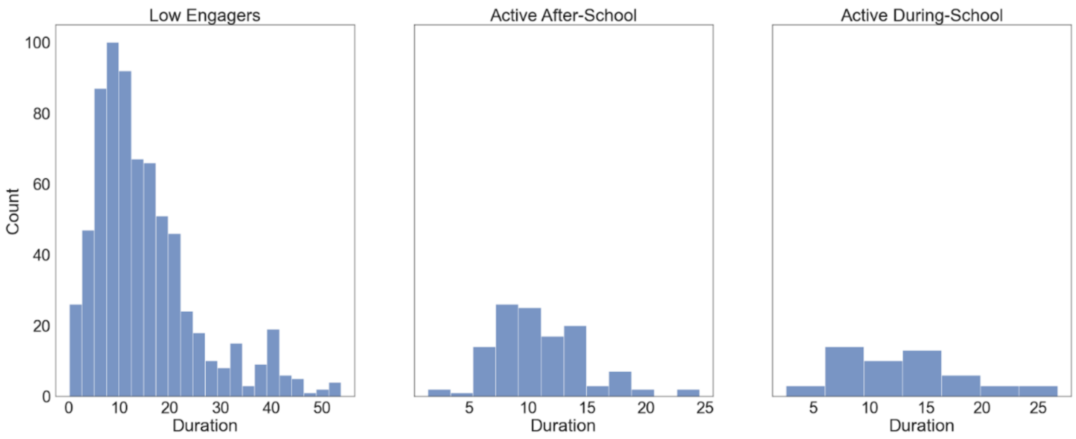

Figure 4.4. Average time on lessons

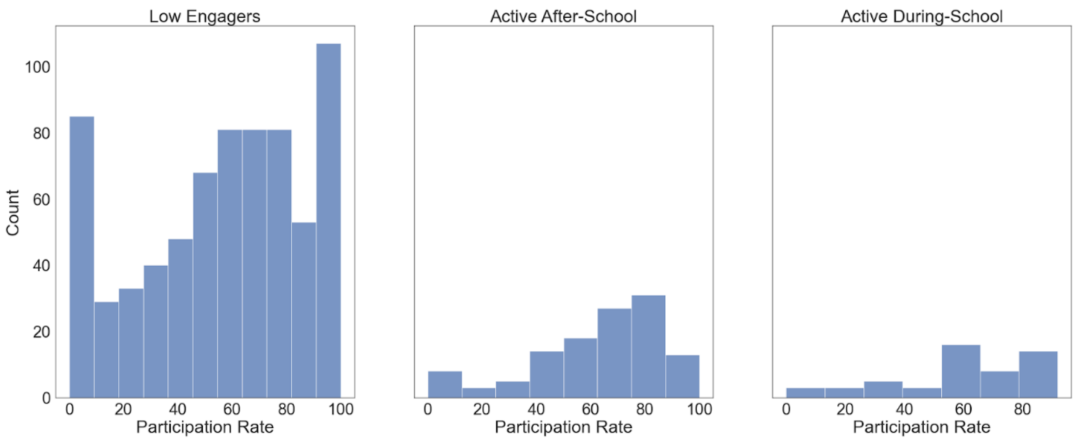

Figure 4.5. Average lesson participation

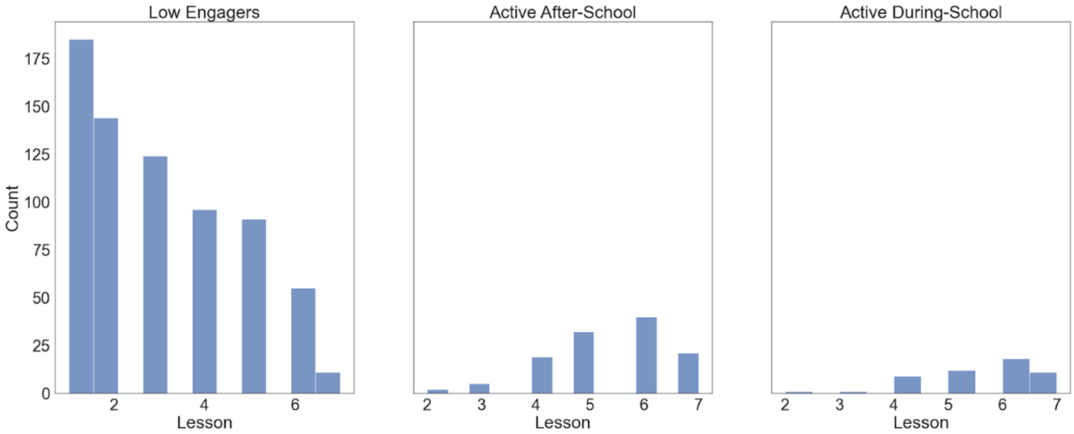

Figure 4.6. Number of lessons viewed

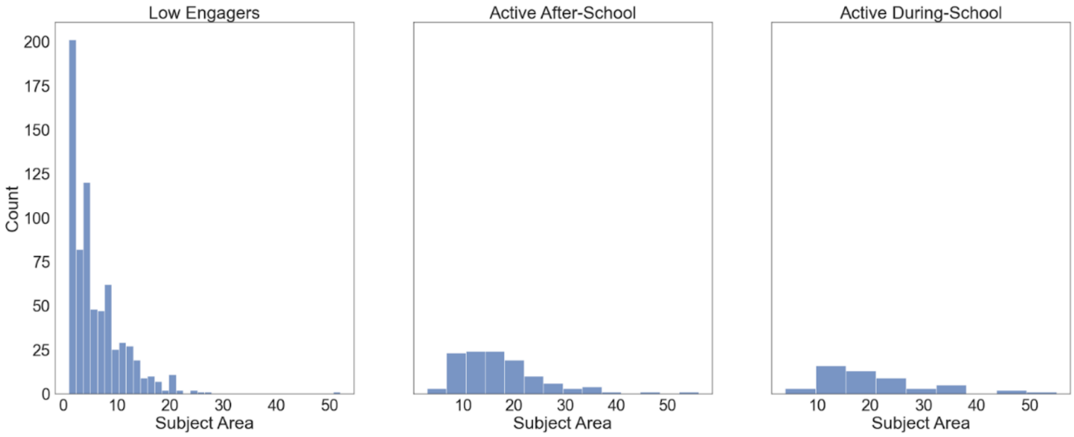

Figure 4.7. Number of subject areas studied

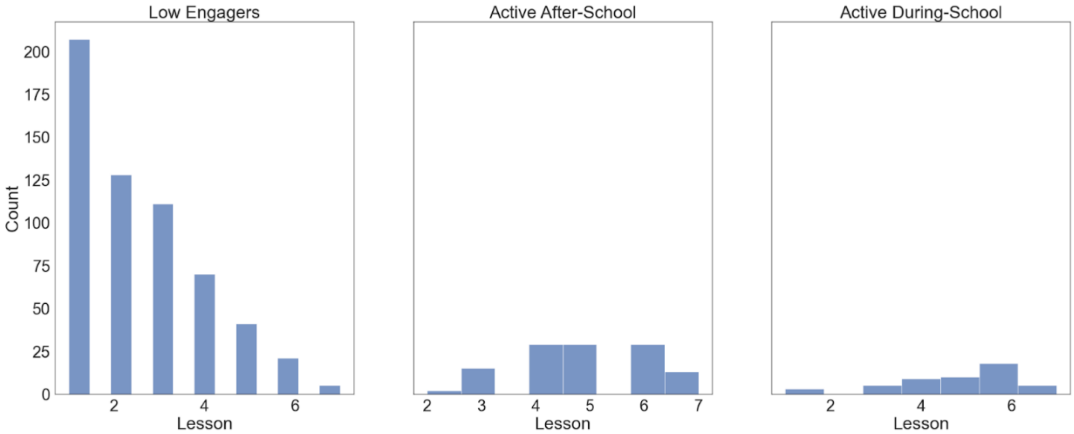

Figure 4.8. Number of lessons exercised

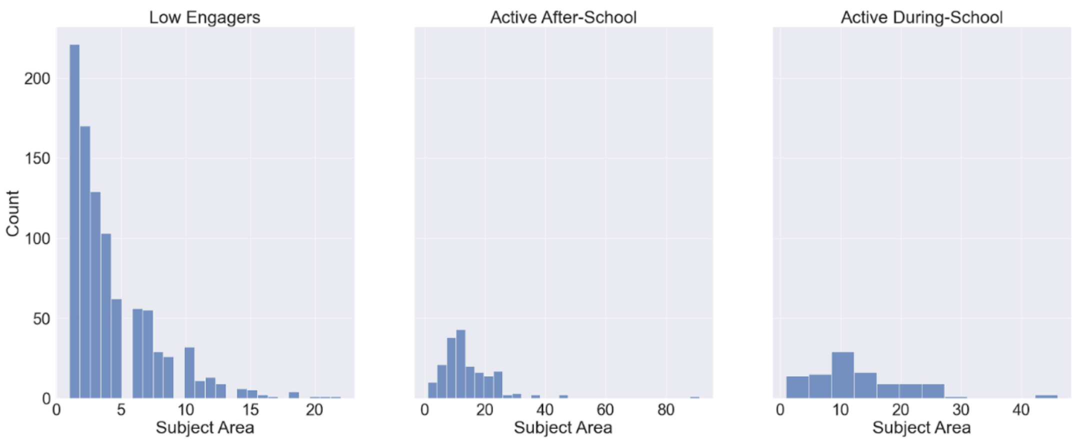

Figure 4.9. Number of subject areas exercised

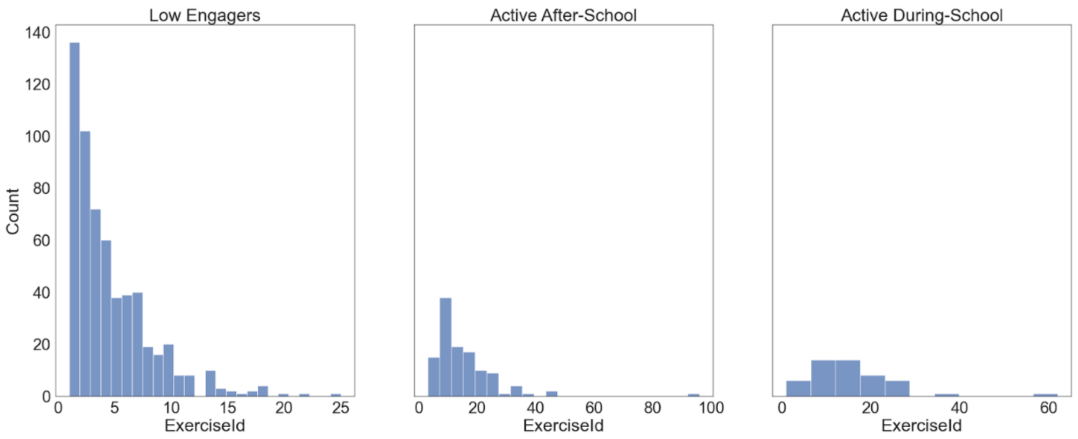

Figure 4.10. Number of exercises intended

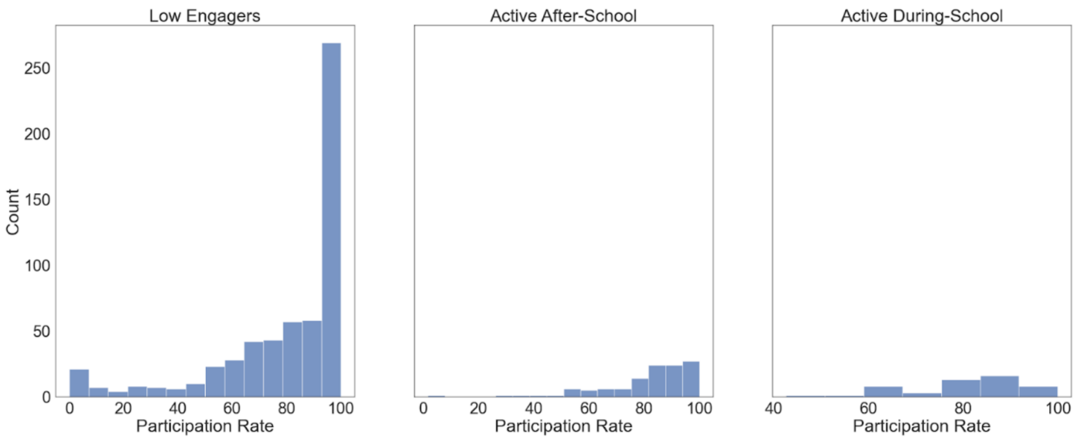

Figure 4.11. Average exercise participation

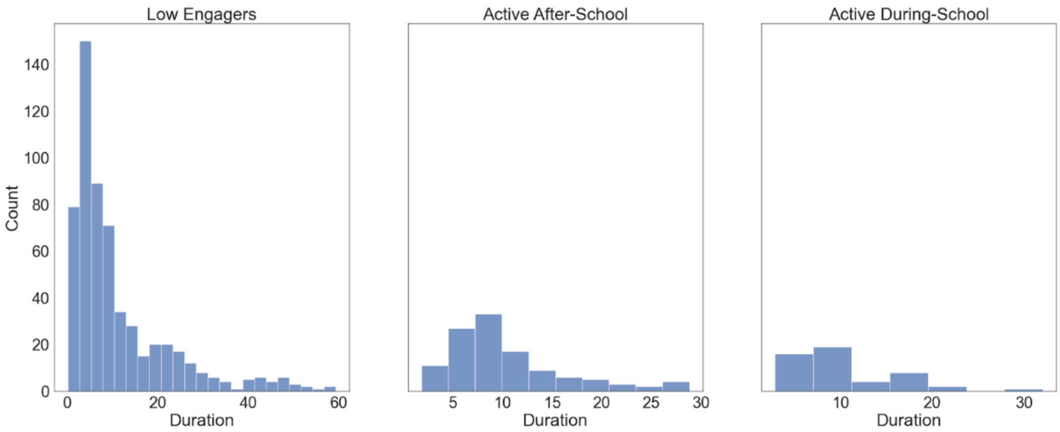

Figure 4.12. Average time on exercises

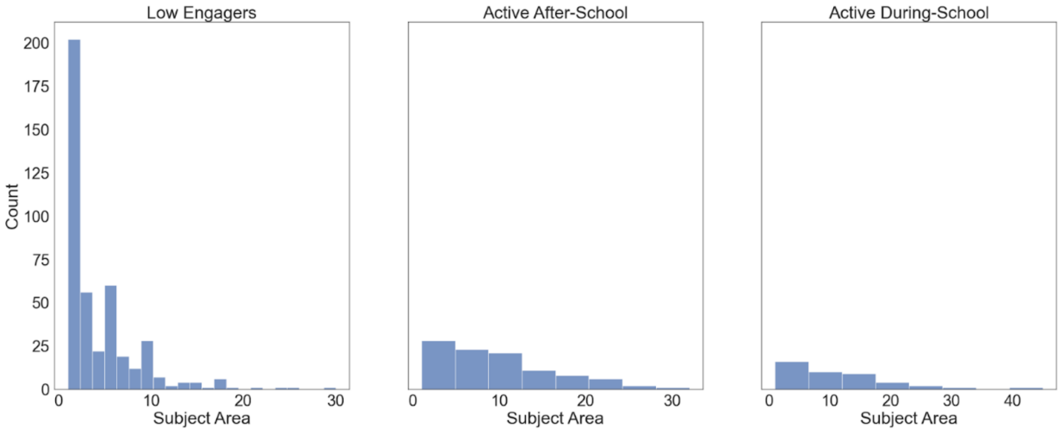

Figure 4.13. Number of subject areas tested

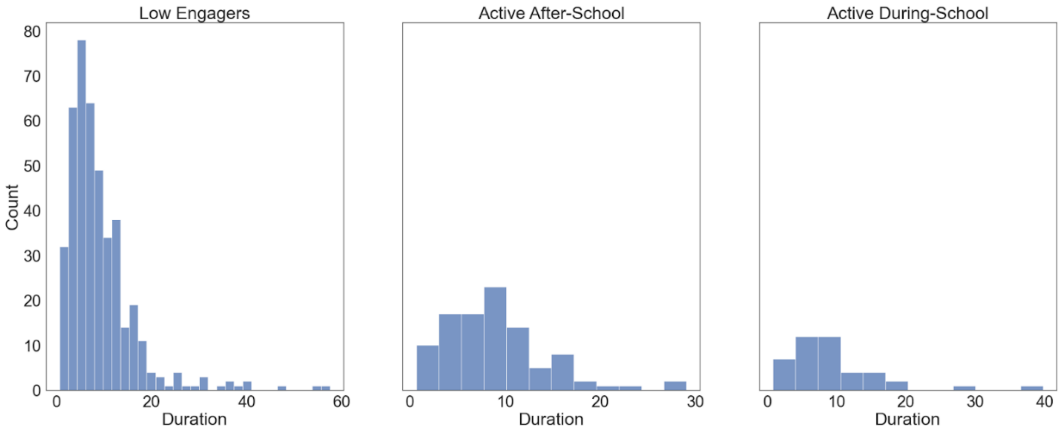

Figure 4.14. Average time on exams

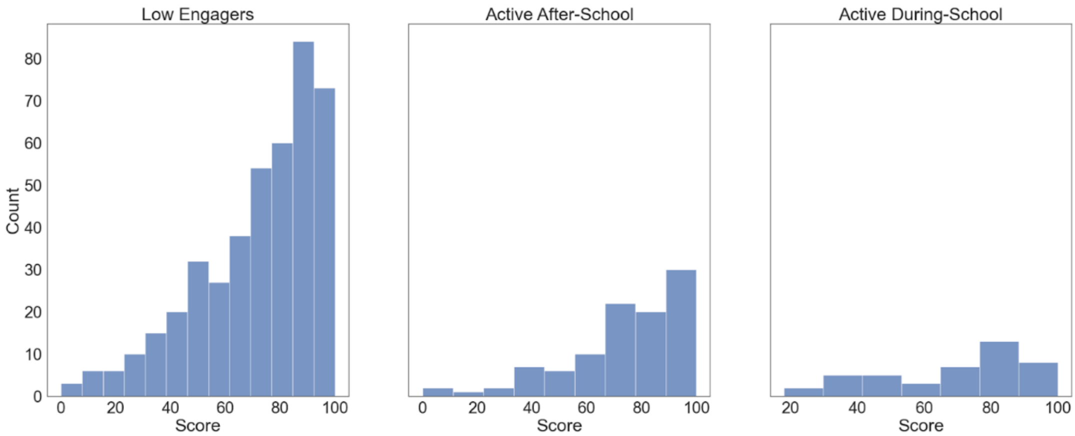

Figure 4.15. Average exam score

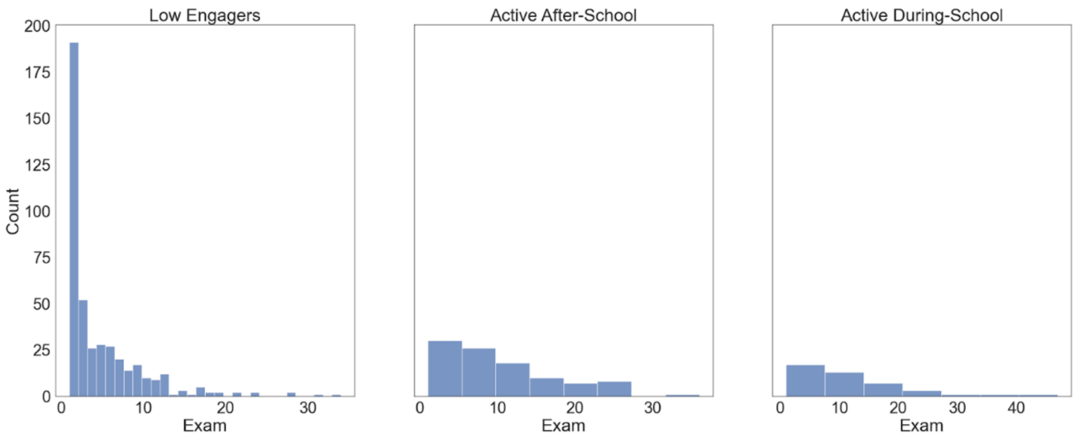

Figure 4.16. Number of exams taken

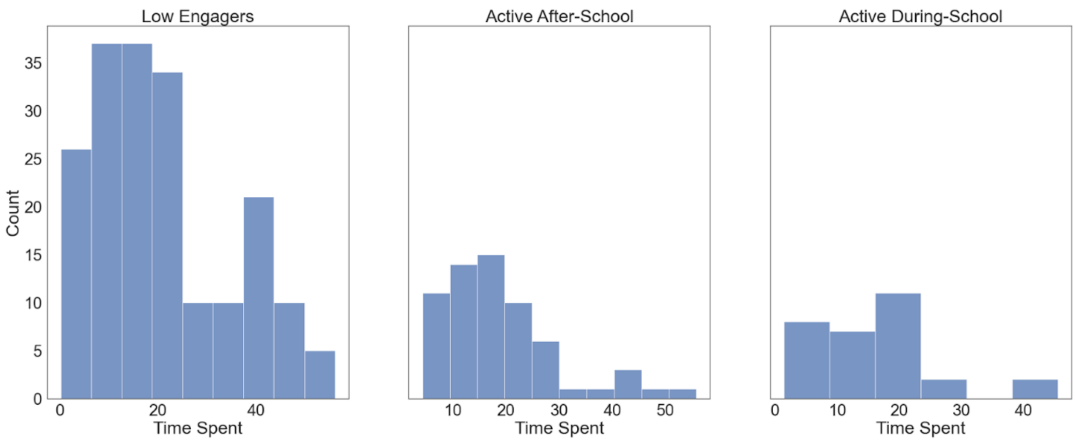

Figure 4.17. Average time on games

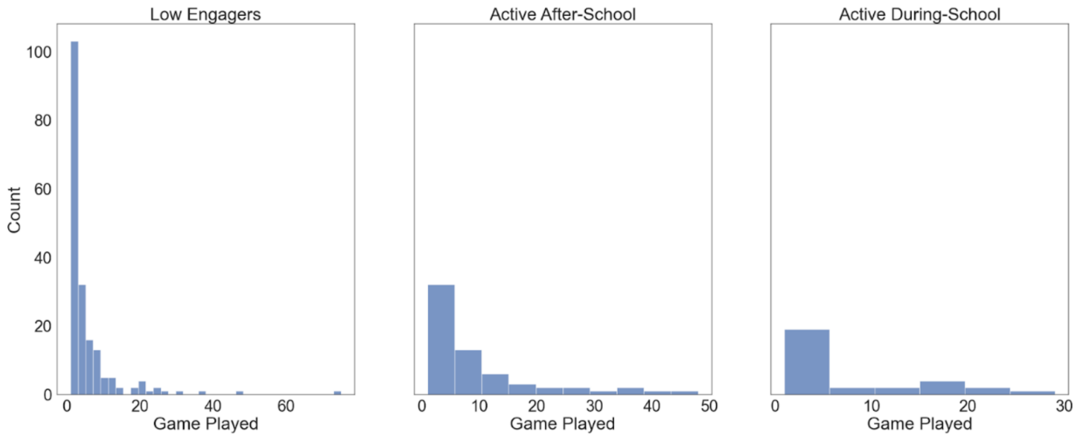

Figure 4.18. Number of game interactions

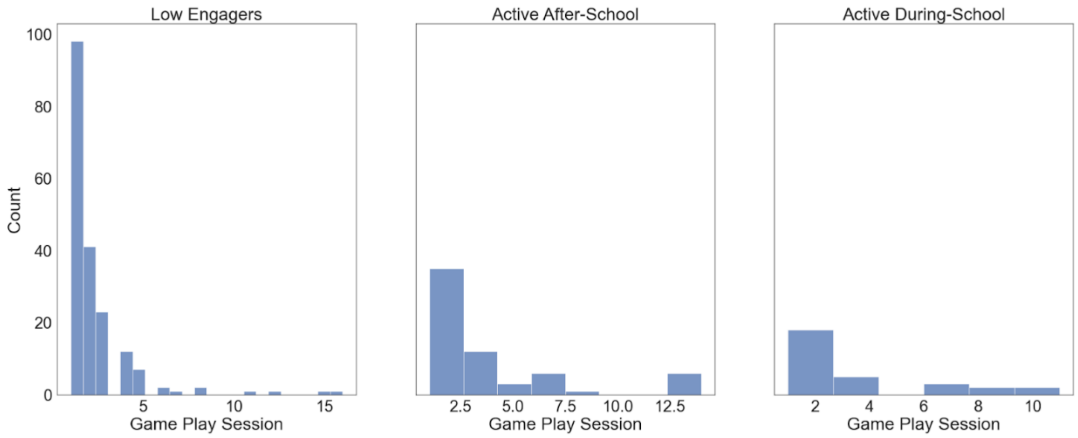

Figure 4.19. Number of game sessions

Since the normality assumption was violated, Kruskal-Wallis non-parametric test was used to compare three clusters regarding evaluative variables separately. Post hoc comparisons were conducted using Dunn's Tests with Bonferroni correction to identify which clusters differ from each other. Table 4.3 presents Kruskal-Wallis and post-hoc test results for all evaluative variables.

Table 4.3 Kruskal-Wallis and Post-hoc Test Results for All Evaluative Variables

#	Variable name	#0	#1	#2	KW Statistics	Post-hoc test results		
Login events						**#0-#1**	**#0-#2**	**#1-#2**
1	Average session duration	55.55	59.60	65.50	H=16.66, p <0.05*	p <0.05*	p <0.05*	p > 0.05
2	Unique session count	8.50	24.98	25.13	H=238.94, p<0.05*	p <0.05*	p <0.05*	p > 0.05
Lesson events								
3	Average time on lessons	15.02	10.98	13.05	H=10.94, p<0.05*	p <0.05*	p > 0.05	p > 0.05
4	Average lesson participation	55.10	62.33	59.71	H=4.18, P>0.05	p >0.05	p > 0.05	p > 0.05
5	Number of lessons viewed	2.96	5.39	5.50	H=225.84, p<0.05*	p <0.05*	p <0.05*	p > 0.05
6	Number of subject areas studied	6.04	17.29	20.83	H=283.27, p<0.05*	p <0.05*	p <0.05*	p > 0.05
Exercise events								
7	Number of lessons exercised	2.33	4.40	4.13	H=300.26, p<0.05*	p <0.05*	p <0.05*	p > 0.05
8	Number of subject areas exercised	4.18	14.24	13.12	H=427.90, p<0.05*	p <0.05*	p <0.05*	p > 0.05
9	Number of exercises intended	4.41	15.42	15.38	H=467.10, p<0.05*	p <0.05*	p <0.05*	p > 0.05
10	Average exercise participation	80.49	81.96	80.51	H=12.41, p<0.05*	p <0.05*	p <0.05*	p > 0.05
11	Average time on exercises	11.23	10.33	10.01	H=8.50, p<0.05*	p <0.05*	p >0.05	p > 0.05
Exam evens								
12	Number of subject areas tested	4.23	9.54	10.86	H=83.00, p<0.05*	p <0.05*	p <0.05*	p > 0.05
13	Average time on exams	9.17	9.06	9.50	H=1.32, p>0.05	p > 0.05	p > 0.05	p > 0.05
14	Average exam score	71.99	73.37	69.36	H=0.98, p>0.05	p > 0.05	p > 0.05	p > 0.05
15	Number of exams taken	4.75	10.26	11.44	H=75.52, p<0.05*	p <0.05*	p <0.05*	p > 0.05

Table 4.3 (cont'd)

#	Variable name	#0	#1	#2	KW Statistics	Post-hoc test results		
Game events						#0-#1	#0-#2	#1-#2
16	Average time on games	20.83	18.71	16.13	H=1.97, p>0.49	p > 0.05	p > 0.05	p > 0.05
17	Number of game interactions	5.68	9.62	7.8	H=14.04, p<0.05*	p <0.05*	p > 0.05	p > 0.05
18	Number of game sessions	2.22	3.65	3.37	H=11.31, p<0.05*	p <0.05*	p > 0.05	p > 0.05

Evaluative variable 1: Average session duration

A Kruskal-Wallis test was conducted on the average time per login of the three clusters (Cluster #0, Cluster #1, and Cluster #2). The differences between the rank totals of 55.15 (Cluster #0), 59.60 (Cluster #1) and 65.50 (Cluster #2) were significant, $H(2) = 16.66$, $p<0.05$. Post hoc comparisons were conducted using Dunn's Tests with a Bonferonni correction to examine which clusters differ from each other. Pairwise comparisons using Dunn's test indicated that Cluster #1 was significantly different from Cluster #0 ($p<0.05$). Similarly, Cluster #2 was significantly different from Cluster #0 ($p <0.05$). However, there was no significant difference between Cluster#1 and Cluster#2 ($p>0.05$). In short, post-hoc analysis shows that after-school active learners and in-school active learners significantly spend more time per login compared to low-engaged cluster.

Evaluative variable 2: Unique session count

A Kruskal-Wallis test was conducted on number of sessions per student among the three clusters (Cluster #0, Cluster #1, and Cluster #2). The differences between the rank totals of 8.50 (Cluster #0), 24.98 (Cluster #1), and 25.13 (Cluster #2) were significant, $H(2) = 238.94$, $p<0.05$. Post hoc comparisons were conducted using Dunn's Tests with a Bonferonni correction to examine which clusters differ from each other. Pairwise comparisons using Dunn's test indicated that Cluster #1 was significantly different from Cluster #0 ($p<0.05$). Similarly, Cluster #2 was significantly different from Cluster #0 ($p <0.05$). However, there was no significant difference between Cluster#1 and Cluster#2 ($p>0.05$). In short, post-hoc analysis shows that both after-school active learners and in-school active learners significantly have more login sessions comparing low-engaged cluster

Evaluative variable 3: Average time on lessons

A Kruskal-Wallis test was conducted on the duration on lessons among the three clusters (Cluster #0, Cluster #1, and Cluster #2). The differences between the rank totals of 15.02 (Cluster #0), 10.98 (Cluster #1), and 13.05 (Cluster #2) were significant, $H(2) =10.94$, $p<0.05$. Post hoc comparisons were conducted using Dunn's Tests with a Bonferonni correction to examine which clusters differ from each other. Pairwise comparisons using Dunn's test indicated that Cluster #1 was significantly different from Cluster #0 ($p <0.05$). However, there was no significant difference between Cluster #2 and Cluster #0 ($p <0.05$). Moreover, there was no significant difference between Cluster#1 and Cluster#2 ($p>0.05$). In short, the post-hoc test results indicate that the low-engaged cluster spends more time on lessons compared to the after-school active learner cluster.

Evaluative variable 4: Average lesson participation

Based on Kruskal-Wallis test result, there was no statistical significance among the clusters in terms of on average lesson participation rate among the three clusters, $H(2) =4.18$, $p>0.05$ (Table 4.3).

Evaluative variable 5: Number of lessons viewed

Based on the Kruskal-Wallis analyses, the number of unique lessons viewed by each student differed significantly among three clusters, $H(2)=225.84$, $p<0.05$. Dunn's test post hoc procedures revealed that Cluster #1 was significantly different from Cluster #0 ($p <0.05$). Similarly, Cluster #2 was significantly different from Cluster #0 ($p <0.05$), whereas there was no significant difference between Cluster#1 and Cluster#2 (p>0.05) (Table 4.3). Hence, post-hoc analysis shows that both after-school active learners and in-school active learners visit significantly more different lessons than the low-engager cluster.

Evaluative variable 6: Number of subject areas studied

Kruskal-Wallis analysis relieved that the number of unique subject areas studied by students differed significantly among groups H(2)=283.36, p<0.05 (Table 4.3). Pairwise comparisons using Dunn's test indicated that Cluster #1 was significantly different from Cluster #0 (p<0.05). Similarly, Cluster #2 was significantly different from Cluster #0 (p<0.05), whereas there was no significant difference between Cluster#1 and Cluster#2 (p>0.05) (Table 4.3). Therefore, the post-hoc test indicates that both after-school active learners and in-school active learners study significantly more unique subject areas than the low-engaged cluster.

Evaluation variable 7: Number of lessons exercised

The Kruskal-Wallis analysis on the number of lessons for which an exercise was attempted among three clusters indicated that there was statistical significance among the clusters H(2) =300,26, p<0.05 (Table 4.3). Pairwise comparisons using Dunn's test revealed significant difference between Cluster #1 and Cluster #0 (p <0.05) similarly, Cluster #2 and Cluster #0 (p<0.05), whereas there was no significant difference between Cluster#1 and Cluster#2 (p>0.05) (Table 4.3) As a result of the post-hoc test, both after-school active learners and in-school active learners do exercises regarding significantly more number of lessons than the low-engager cluster.

Evaluative variable 8: Number of subject areas exercised

Based on the Kruskal-Wallis analyses, the number of subject areas for which an exercise was attempted differed significantly among three clusters, H(2)=427.26, p<0.05 (Table 4.3). Dunn's test post hoc procedures revealed that Cluster #1 was significantly different from Cluster #0 (p<0.05). Similarly, Cluster #2 was significantly different from Cluster #0 ($p<0.05$), whereas there was no significant difference between Cluster#1 and Cluster#2 ($p>0.05$) (Table 4.3). Hence, post-hoc analysis shows that both after-school active learners and in-school active learners do exercise regarding significantly more different subjects than the low-engager cluster.

Evaluative variable 9: Number of exercises intended

Based on Kruskal-Wallis test result, there was a statistical significance among the clusters in terms of the number of exercises interacted $H(2)=267.10$, $p<0.05$ (Table 4.3). Dunn's test post hoc procedures revealed that Cluster #1 was significantly different from Cluster #0 ($p<0.05$). Similarly, Cluster #2 was significantly different from Cluster #0 ($p<0.05$), whereas there was no significant difference between Cluster#1 and Cluster#2 ($p>0.05$) (Table 4.3). In short, post-hoc analysis shows that both after-school active learners and in-school active learners interact with significantly more exercise than the low-engager cluster.

Evaluative variable 10: Average exercise participation

Kruskal-Wallis analysis relieved that the percentage of the exercises completed differed significantly among groups $H(2)=12.41$, $p<0.05$ (Table 4.3). Pairwise comparisons using Dunn's test indicated that Cluster #1 was significantly different from Cluster #0 ($p<0.05$). Similarly, Cluster #2 was significantly different from Cluster #0 ($p<0.05$), whereas there was no significant difference between Cluster#1 and Cluster#2 ($p>0.05$) (Table 4.3). Therefore, the post-hoc test indicates that both after-school active learners and in-school active learners complete significantly more percentage of exercise than the low-engager cluster.

Evaluative variable 11: Average time on exercises

After conducting the Kruskal-Wallis analysis, there was statistical significance among the clusters in terms of the average time spent on exercises $H(2)=8.50$, $p<0.05$ (Table 4.3). Pairwise comparisons using Dunn's test indicated that Cluster #1 was significantly different from Cluster #0 ($p<0.05$). However, there was no significant difference between Cluster #2 and Cluster #0 ($p<0.05$). Moreover, there was no significant difference between Cluster#1 and Cluster#2 ($p>0.05$). In short, the post-hoc test results indicate that the low-engaged cluster spends significantly more time on exercise compared to the after-school active learner cluster.

Evaluative variable 12: Number of subject areas tested

Based on Kruskal-Wallis analysis, there was a statistical significance among the clusters in terms of the number of subject areas tested $H(2)=83.00$, $p<0.05$ (Table 4.3). Dunn's test post hoc procedures revealed that Cluster #1 was significantly different from Cluster #0 ($p<0.05$). Similarly, Cluster #2 was significantly different from Cluster #0 ($p<0.05$), whereas there was no significant difference between Cluster#1 and Cluster#2 ($p>0.05$) (Table 4.3). In short, post-hoc analysis indicates that both after-school active learners and in-school active learners take tests about a significantly higher number of subjects than the low-engager cluster.

Evaluative variable 13: Average time on exams

Based on Kruskal-Wallis test result, there was no statistical significance among the clusters in terms of average time spent on exams $H(2)=1.32$, $p>0.05$ (Table 4.3).

Evaluative variable 14: Average exam score

A Kruskal-Wallis test was performed on the exam score of the three clusters (Cluster #0, Cluster #1, and Cluster #2). The differences between the rank totals of 75.55 (Cluster #0), 76.87 (Cluster #1) and 76.75 (Cluster #2) were not significant, $H(2) = 0.98$, $p>0.05$ (Table 4.3). As a result of this analysis, there is no statistical significance among the clusters regarding exam scores.

Evaluative variable 15: Number of exams taken

Based on the Kruskal-Wallis analyses, the number of exams taken differed significantly among the three clusters, $H(2)=72.52$, $p<0.05$. Dunn's test post hoc procedures revealed that Cluster #1 was significantly different from Cluster #0 (p

<0.05). Similarly, Cluster #2 was significantly different from Cluster #0 ($p<0.05$), whereas there was no significant difference between Cluster#1 and Cluster#2 ($p>0.05$) (Table 4.3). Hence, post-hoc analysis shows that both after-school active learners and in-school active learners take significantly more exams than the low-engager cluster.

Evaluative variable 16: Average time on games

A Kruskal-Wallis test was performed on the average time spent for games of the three clusters (Cluster #0, Cluster #1, and Cluster #2). The differences among clusters were not significant, $H(2) = 1.97$, $p>0.49$ (Table 4.3). As a result of this analysis, there is no statistical significance among the clusters in terms of average time spent for games.

Evaluative variable 17: Number of game interactions

After conducting the Kruskal-Wallis analysis, there was statistical significance among the clusters in terms of the number of game interactions $H(2)=14.04$, $p<0.05$ (Table 4.3). Pairwise comparisons using Dunn's test indicated that Cluster #1 was significantly different from Cluster #0 ($p<0.05$). However, there is no significant difference between Cluster #2 and Cluster #0 ($p>0.05$). Similarly, there was no significance Cluster#1 from Cluster#2 ($p>0.05$) (Table 4.3). Hence, post-hoc analysis shows that the low-engager cluster plays significantly fewer games compared to after-school active learners.

Evaluative variable 18: Number of game sessions

Based on Kruskal-Wallis analysis, there was statistical significance among the clusters in terms of the number of games session $H(2)=11.31$, $p<0.05$ (Table 4.3). Pairwise comparisons using Dunn's test indicated that Cluster #1 was significantly different from Cluster #0 ($p<0.05$). However, there is no significant difference between Cluster #2 and Cluster #0 ($p>0.05$). Similarly, there was no significance Cluster#1 from Cluster#2 ($p>0.05$) (Table 4.3). As a result of post-hoc analysis, the low-engager cluster plays games significantly in fewer sessions compared to after-school active learners.

CHAPTER 5

DISCUSSION AND CONCLUSION

This study investigated the interaction patterns of primary and secondary school students (grade 4-8) with an online learning platform integrated into traditional instruction as a supplementary tool. One-month log records of the students were analyzed, and the learners were clustered based on the hours in a day they interacted with the platform. In addition, the clusters were compared in terms of students' behavioral engagement.

The analysis of the students' lesson and exercise login hours indicates that the students are profiled in three distinct clusters (Table 4.2). **Cluster #0: Low engagers** refer to students who have equal but low engagement in and after school hours (81%), **Cluster #1: After-school active learners** refer to students who use the platform actively out of school while maintaining a minimal interaction in-school time (13%), and **Cluster #2 In-school active learners** refer to students who are active in the platform mostly during the school hours (6%). These results suggest the possibility that the teachers adopted the OLP differently, which may have resulted in the mentioned profiles. Integrating OLPs into traditional teaching with different approaches was noted in the literature depending on teachers' needs and pedagogical perspectives, as suggested by Rotelli et al. (2022). In this sense, teachers may have an impact on where, how, and for how long students use these platforms to effectively supplement in-class learning.

The most prominent profile was low-engaged learners (%81), which indicates that most students were not actively using the platform. This result might be due to various factors affecting the proper adoption of the learning platform by teachers. Classroom time is usually limited for conducting fundamental learning activities (Feng et al., 2009), which may leave very little time for teachers to take advantage of additional e-learning tools. Additionally, the literature notes that teachers in schools are mostly overloaded by the teaching workload and some other services (Monroy et al, 2014), which could affect their adoption of additional learning technologies. Thus, teachers may not find sufficient time and energy to refine their well-established teaching practices to suit better with new learning tools and platforms. Corroborating this point, teachers are often more willing to keep their traditional teaching practice (Cuban et al., 2001).

Another factor that leads to varying use of OLP is related to barriers to proper technology integration (Ertmer, 1999). The findings of this thesis research may suggest that such barriers might also exist in the context of this research. Similarly, it is also likely that instructors might use the learning platform to promote teacher-centered pedagogies, resulting in low level of engagement in this profile of learners. Playing an animation video to illustrate a concept might be an example of such use. Teachers may use the system mostly to engage the students in the lessons with animations or videos to attract attention and may elect to continue the rest of the lesson with traditional teaching methods.

In contrast, the other two profiles indicated high-level of student engagement but during different hours of the day. In particular, after-school active learners appeared to use the system during out-of-school hours to study the lessons and complete online exercises. This result suggests the potential use of OLPs to support and complement traditional instruction with online activities due to limited time at school, as noted in the literature previously (Thomsen et al., 2022). Two possible pedagogical approaches might explain after-school use. First, teachers may require students to study a unit beforehand and come to the class prepared. Alternatively, students might be assigned the lessons in the learning platform to review the concepts again and to complete some exercises as homework after class to facilitate learning with spaced learning practice that refer to learning practice is spread over time rather than being crammed into a single study session (Sobel et al., 2011).

Finally, in-school active learners use the system actively during their time in school. Although this profile was the least frequent (6%), its existence shows some teachers' efforts to integrate the platform into classroom teaching. The lessons in the platform usually contain video animations to explain the concepts in a unit, and these lessons might be powerful learning tools for illustrating abstract or difficult topics to young learners. Teachers' uses of the lessons may complement their teaching while providing students with richer learning opportunities. Similarly, this profile of students used exercises often during school time. Thus, probably, some teachers took advantage of the exercises in the online platform to offer more opportunities in class time to help students reinforce their learning. In this cluster, the way teachers teach and students learn may have mostly changed compared to traditional face-to-face teaching and learning.

The cluster analysis was effective in distinguishing three profiles of students based on their study-time behaviors. Comparing these profile clusters based on the determined evaluative variables was necessary to identify the relationship between study-time routines and their engagement levels. In this context, students' engagement with the OLP was measured using 18 evaluative variables. These variables were grouped under five subheadings. These are login events, lesson events, exercise events, exam events, and game events (Table 3.2).

When the students' login events were analyzed, it was determined that there was a significant difference among the three profiles, and based on the post-hoc test, both after-school active learners and in-school active learners clusters logged in the system more frequently and stayed in the platform longer for each login compared to low-engaged cluster. This result may be due to the fact that instruction in a low-engaged cluster is carried out with a teacher-centered approach in-class time, and no specific instructions were provided to plan students' use of the platform after school. On the other hand, there was no significant difference between in-school and after-school active learners in terms of login events. Thus, between the active learners, accessing the e-learning platform in or out of school did not affect the number of sessions and time spent in the platform.

The analysis of students' lesson events showed that both after-school active learners and in-school active learners clusters viewed more lessons and studied more unique content regarding the lesson compared to the low-engaged profile. On the other hand, there was no significant difference between in-school and after-school active learners in terms of viewing the number of lessons and unique subjects. This can be interpreted as students can benefit more from OLPs in a student-centered learning environment when the teacher plays only a guiding role in the student's learning process. However, although low engagers viewed fewer lessons and studied less unique content, they spent significantly more time viewing lessons than after-school active learners. It is worth noting that while low-engagers spent more time viewing lessons to complete the lessons as much as the other clusters did. This result may point out that teachers might present extra explanations, or ask or answer some questions related to lessons during class time working with OLPs.

According to the results of the analysis regarding students' exercise events, a significant difference was found among the three clusters. Based on the post-hoc test, both after-school active learners and in-school active learners do exercise more frequently for more unique lessons, in significantly less time, compared to the low-participation cluster. This result could hint that students can do a greater number of exercises in less time on their own or under the guidance of their teachers at their own individual pace. On the other hand, although there is a significant difference in completing the percentage of the exercises for all three clusters, the values are very close to each other. This result may indicate that the exercises were assigned as homework for each cluster, requiring students to complete exercises. Another reason why the compilation of exercises was high across the clusters might be due to spaced learning practice.

When the exam activities of the students were examined, there was no significant difference between the exam results and the time to complete the exams of the students among the three clusters. It has been observed that both after-school active learners and in-school active learners take more exams in more subjects compared to low-engaged learners. Despite the explicit effort of these two clusters in completing more exams, their test scores did not significantly differ from the low-engaged cluster. This result suggests that technology integration may not be considered as the sole factor in test score. Thus, it is consistent with the view that academic performance depends on various factors such as method, class size, class level (Ran, Kim & Secada, 2022) as well as the role of technology. Additionally, since the exams were probably taken in an uncontrolled setting, the scores may not reflect students' true knowledge and performance. The high frequency of scores between 80-100 range across three clusters support this argument about the representativeness of the exam scores. Nonetheless, the active learners engaged more with the exams as they took exams from a wide variety of subjects.

Analysis of students' gaming activities in the OLP shows that there is no significant difference in the amount of time students spend playing games among the three clusters. However, the number of sessions involving games and the number of games played by the after-school active learner's cluster are significantly higher than the low-engaged students. According to this result, students who use the platform in the home environment, which is less restrictive compared to the classroom setting, tend to interact with games more often. Although the games in the platform are educational and crafted carefully to support student learning, over-reliance on them may not lead to the optimal learning experience. However, given young learners' interest in playful learning, it is expected that students interact with the games after school.

In short, as a result of the interaction of primary and secondary school students with OLP, they can be profiled as limited users (low-engager), active users in school time (in-school active learners), and active users out of school time (after-school active learners). In addition, integrating OLP into traditional teacher-centered instruction prevents students and teachers from reaping the benefits of the platform. However, OLP could be more useful when the student-centered teaching approach is adopted, that is, the teacher guides the students during the teaching-learning process, or when the student interacts with OLP individually.

Implications

The findings of this study have several important implications, as listed below:

1. Given the high number of low-engaged students, online learning platforms should provide personalized support and guidance to promote young learners' engagement.
2. Teacher-facing dashboards can be an important component of online learning platforms to enable teachers to monitor students' activities. With powerful visualizations, teachers can quickly identify students who are in need of assistance and provide proper guidance to students.
3. To support the proper integration of these tools to the classroom instruction, teachers can be provided specific training about the effective student-centered use of online learning platforms. A portal where teachers share their best practices might be effective in this regard.
4. Online learning platforms should be used to set the spaced learning practices to promote and improve their learning.

Limitations and Future Research

The data of this study belonged to students from a wide range of grades, classes, and schools, where the specific pedagogical use of the online learning platform was not known. Although this variability increases the generalizability of the findings, a study focused on specific schools, where and how teachers integrated the system into their teaching was known, could allow for a deeper interpretation of the findings and offer stronger conclusions. A future study should explore the specific schools to understand how distinct pedagogical approaches impact students' engagement with the platform and their learning gains. In this regard, qualitative data collection and analysis could provide additional insight into teachers' perspectives and students' satisfaction and experiences.

Moreover, the analysis was performed on students from different grade levels combined. Although this approach shows the general trends regardless of the grade, it fails to demonstrate findings specific to each grade level and to make a comparison across grades. For example, students' use of the system at the fourth grade level might significantly differ from the eighth grade. Future research should be performed using such grade-specific analysis on a larger sample.

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