JOURNAL OF LEARNING ANALYTICS
Volume 11(1), 101–115. https://doi.org/10.18608/jla.2024.8133

Uncovering Engagement Profiles of Young Learners in K–8 Education through Learning Analytics

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Abstract
E-learning platforms have become increasingly popular in K–8 education to promote student learning and enhance classroom teaching. Student interactions with these platforms produce trace data, which are digital records of learning processes. Although trace data have been effective in identifying learners' engagement profiles in higher education and lifelong learning (e.g., MOOCs), similar research on young learners has been very scarce. This study makes a timely and novel contribution to the field by identifying emerging profiles of young students from Grades 1 to 8 based on their engagement in an e-learning platform. The k-means cluster analysis yielded seven distinct profiles in total. While the dominance of profiles differed across grade levels, some profiles were not even present at specific grades, indicating the changing engagement behaviours of young learners in different years. In addition, all emerging profiles suggest students tended to focus on specific components of the platform, thus lacking balanced engagement with all resources. In particular, while primary school students showed relatively higher interest in game-based learning, middle school students focused more on exams than their counterparts. The findings yielded seven specific considerations for the design of effective e-learning platforms.

Notes for Practice

- Trace data hold potential for understanding the online engagement of young learners, but research on the online behaviour of K–8 students is scarce.
- This study identified grade-specific profiles of primary and middle school students based on online engagement behaviour, with varying prevalence and absence of specific profiles across grades.
- Young learners displayed imbalanced engagement with platform components, with primary school students showing higher interest in game-based learning and middle school students focusing more on exams.
- E-learning platforms should adapt to distinct student profiles, depending on the grade level, and promote comprehensive engagement.
- An orientation period for Grade 1 students and learning analytics solutions can enhance learning experiences and timely intervention.

Keywords
Engagement profiles, clustering, K–8 education, e-learning

Submitted: 07/07/2023 — **Accepted:** 11/02/2024 — **Published:** 07/03/2024

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1. Introduction

Engagement is an essential component of learning. Student learning gains increase because of persistent and productive engagement with coursework (Wefald & Downey, 2009). Student engagement might cover various activities, including participation in class discussions, completing assignments on time, and attending lectures regularly. As online learning gains popularity worldwide, engagement in educational settings has expanded to include online environments (Hu et al., 2016). Nowadays, online learning is not limited to remote education. In fact, many traditional face-to-face courses require students to complete online activities or tasks both inside and outside the classroom (Kiili et al., 2020). In this sense, online learning has become an increasingly important aspect of traditional education, and student engagement expanded beyond the classrooms

(Smith & Suzuki, 2015). This shift has increased the opportunities for students to engage in various ways, including posting in online discussions (Chiu et al., 2010), accessing resources on the internet (Kiili et al., 2020), or watching interactive videos (Su & Chiu, 2021).

A distinct characteristic of online learning is that student engagement records can be tracked and stored in a database. Such data capture student learning processes and are called digital traces or footprints in the field of learning analytics (Gašević et al., 2015). The emergence of Massive Open Online Courses (MOOCs) and the shift toward online learning in large university classrooms has led to a huge increase in the amount of trace data. This unprecedented amount of data has attracted much attention in learning analytics studies to improve our understanding of the engagement construct. The literature so far has yielded many novel insights into this construct (Fincham et al., 2019; Khosravi & Cooper, 2017; Toro-Troconis et al., 2019), which would not be possible through traditional self-report methods such as questionnaires.

A prevalent approach in recent literature for analyzing student online engagement is to profile learners based on their online activity levels and types (Alario-Hoyos et al., 2014; Corrin et al., 2017; Mirriahi et al., 2016). When profiling learners, engagement indicators are typically derived from trace data deemed significant by researchers and practitioners. These indicators are used to cluster students and identify different learner profiles (Khalil & Ebner, 2017). By identifying learner profiles, researchers and educators can understand the factors that promote engagement or cause disengagement and develop effective strategies to support student learning (Kizilcec et al., 2013). For example, a particular profile of students who actively participate in discussion forums but seldom access learning materials might be detected, and interventions might be designed to guide these students to benefit from learning resources in a more balanced fashion.

Although the literature has been very informative in revealing distinct profiles of learners based on their engagement in online environments, most of the studies were conducted in higher education or MOOC contexts (Ferguson & Clow, 2015; Kizilcec et al., 2013; Sher et al., 2022). The findings from these contexts might provide some relevant perspective but are unlikely to offer accurate explanations regarding young learners' engagement behaviour. Though, in the last few years, learning analytics research has been on the rise in pre-tertiary education (Kovanovic et al., 2021), efforts are primarily concentrated in high school settings (Aguerrebere et al., 2022; de Sousa et al., 2021). Few research studies have explored the application of learning analytics in primary and middle schools (Krumm et al., 2021; Väisänen et al., 2022), while, to the best of our knowledge, no study leveraged big educational data to derive insights into young learners' online engagement behaviour. Therefore, it remains a crucial gap to exploit learning analytics to gain a comprehensive understanding of how primary and middle school students engage with online learning platforms. Insights about learner engagement profiles could inform the development of effective e-learning solutions that cater to students' varying needs while complementing in-class learning. Nonetheless, revealing younger learners' online engagement behaviour through learning analytics research is still in its early stages, and further research is needed to advance our understanding in this area.

This study aims to make a timely contribution to the literature by profiling learners from Grades 1 to 8 based on their engagement in an e-learning platform. This platform is widely used in Turkish schools at various grade levels to provide supplementary learning activities both inside and outside the classroom. Student interactions with the diverse range of content types available on this platform represent a significant opportunity to produce valuable data that can help identify different types of engagement behaviour in primary and middle school education. This study exploits such data about young learners and reports the results of the clustering analysis aimed at profiling engagement behaviour. It is important to note that the cognitive abilities and learning characteristics of the young age group can vary significantly across different grade levels (Abdelkarim et al., 2017), which can lead to significant differences in their engagement behaviour. Accordingly, this study profiles students at each grade level separately. The findings reveal distinct student profiles at different grade levels. In addition, a comparison of the distribution of the profiles across grades was provided to capture how student engagement profiles may change as they progress through their education. This study addresses the following research questions:

- RQ1: What profiles of students emerge from online activity logs at different grade levels?
- RQ2: How does the distribution of the emerging profiles differ across Grades 1 to 8?

2. Background

Engagement refers to student efforts toward achieving learning goals in a learning environment (Junco, 2012). Students with higher levels of engagement tend to exhibit more versatile study behaviours and are more likely to perform better than their peers (Lee, 2014). Student engagement is typically categorized into behavioural, affective, and cognitive components (Fredricks et al., 2004). Among those, behavioural engagement in online environments has been a focus in the field of learning analytics. Behavioural engagement in online engagement can include such activities as visiting course pages, accessing online learning materials, watching course videos, making posts in online discussions, and so on (Dixson, 2015). All these student actions generate trace data that provide insights into how students (behaviorally) engage in online learning environments. These trace data of engagement have been vastly exploited using various learning analytics approaches to advance our understanding of engagement (Bote-Lorenzo & Gómez-Sánchez, 2017; Liu et al., 2015; Milligan et al., 2013; Ramesh et al., 2013, 2014).

Trace data have been dominantly utilized in two strands to study student engagement within the learning analytics literature. The first strand involves the development of student engagement models based on trace data, aiming to predict student success or failure statuses (Whitehill et al., 2017; Xing et al., 2016; Xing & Du, 2019; Ye & Biswas, 2014). In the prediction research, behavioural engagement has been accurately modelled based on different metrics derived from activity logs, including the time spent on learning resources, the number of active days, and the duration of videos watched (Er et al., 2019; Fincham et al., 2019). The prediction models have been very powerful in detecting students at risk of failure (Gardner & Brooks, 2018; Kennedy et al., 2015), suggesting a correlation between low engagement levels and failure (Caspari-Sadeghi, 2022). Thus, the studies so far provide sufficient evidence about the validity of online metrics in modelling student engagement.

Another strand of research has focused on profiling learners according to their engagement in online activities (Cobo et al., 2011; Khalil & Ebner, 2017). This approach aims to categorize students into distinct profiles based on their similar behavioural patterns by employing various clustering techniques. Unlike prediction research, which focuses solely on forecasting success or failure outcomes, the profiling approach strives to identify and comprehend the diverse engagement profiles that can emerge in various online learning contexts (Bouchet et al., 2013; Kovanović et al., 2016). Thus, the profiling approach enables researchers to obtain a deeper understanding of engagement profiles beyond merely assessing their failure or success.

Different engagement patterns may arise based on the variables included in the cluster analysis, allowing for flexibility in the emphasized aspect of the engagement. For example, in a study conducted by Jovanović et al. (2017), five distinct student profiles were identified, each characterized by employing different learning strategies when working on the preparatory learning activities in a flipped classroom. The clusters in this study were assigned specific names based on the exhibited engagement behaviours. For instance, the cluster characterized by high levels and diversity of engagement was labelled as intensive, while the cluster with a lower level of effort was labelled as highly selective. Furthermore, the practice of profiling students based on various aspects of engagement behaviours has been widely documented in the literature, including profiling based on engagement with help-seeking in MOOCs (Corrin et al., 2017), with intelligent tutoring systems (Bouchet et al., 2013), with educational videos (Mirriahi et al., 2016), and so on. The exploration of different dimensions of engagement allows researchers to gain a comprehensive understanding of how students interact and participate in various educational settings.

The online engagement of young learners with e-learning platforms has been a topic of growing interest since the early 2010s. Earlier research mostly focused on identifying the factors affecting student use of online learning platforms and presented ways to improve their engagement through more effective technology integration. For instance, Journell (2010) highlighted the importance of understanding student perceptions of e-learning, while Abbad et al. (2009) emphasized the significance of factors affecting student adoption of e-learning systems and, thus, their engagement with them. Young learners' online engagement behaviour gained greater attention, particularly during and after the COVID-19 pandemic (Fauzi & Sastra Khusuma, 2020). In recent years, many research studies have been conducted to understand how students engage and learn online. For example, Aguilar et al. (2022) found a strong correlation between live instruction and student engagement in online learning among elementary school students. Moreover, Liao et al. (2021) identified the critical role of teacher–student interaction and student–student interaction in increasing online learning motivation, cognitive development, and engagement.

Although previous research has produced significant findings regarding young learners' online engagement and learning, they are limited to measuring student perceptions of engagement through surveys. As a result, they cannot afford to provide new insights based on actual engagement behaviour. Thus, while significant progress has been made in learning analytics research, it is crucial for the field to expand research efforts to K–8 contexts, including primary and elementary schools, where e-learning has been gaining popularity, in particular, since the COVID-19 pandemic. By exploring the engagement patterns and behaviours of younger learners, researchers can gain insights into how engagement develops and evolves throughout different stages of education. Such insights can inform the development of tailored interventions and instructional strategies that effectively foster engagement and enhance learning outcomes in early education settings.

This timely study aims to contribute to the literature by profiling learners in Grades 1 to 8 based on their engagement with an e-learning platform widely used in Turkish schools. By leveraging the rich data generated from student interactions with various content types, this research provides valuable insights into different types of engagement behaviour in primary and middle school education. The study profiles students at each grade level separately, revealing distinct profiles and offering a comparison of how engagement profiles may evolve as students advance through their educational journey.

3. Methods

3.1. E-Learning Platform

The e-learning platform is a comprehensive online system that contains a wide range of structured learning resources and activities to support the education of students from Grades 1 to 8 in the following subjects: Preparation for Reading and

Writing, Turkish, Life Sciences, Mathematics, English, Science (covering physics, chemistry, and biology), and Social Studies. All content in these subject areas follows the national curriculum of Turkey's Ministry of Education. This platform can be accessed anytime and anywhere using a web browser or mobile application.

The context in which this platform is used might vary. First, the platform is not offered without charge, and it is typically procured by private schools for deployment as an educational service to their students. In cases where it is not made available within school settings, students can purchase the platform for their individual use. In the private schools where this platform is used, instructors are usually free to decide how to integrate it into their teaching. However, no related data have been collected or made available for research purposes. Nonetheless, the extensive sampling in this study, which incorporates anonymized student data from more than 10,000 schools, facilitates a thorough exploration of student interaction with the platform in diverse educational settings, enhancing the generalizability of the findings.

In the platform, a module comprises four main components: lessons, exercises (or practices), exams, and games. Concepts are taught through the lessons, which are designed as animated videos according to student grade level. Figure 1 illustrates a science lesson for Grade 5 students. Typically, in the platform, lessons are followed by interactive exercises or practices to help students apply the newly acquired topics and reinforce their learning. A sample exercise is provided in Figure 2. In the remainder of the paper, exercises and practices will be used interchangeably to refer to the same component in the platform. At the end of each module, there is an exam (see Figure 3) to help students assess their learning. These module exams contain mostly multiple-choice or true/false questions. In each module, student learning is accompanied by game-based learning. That is, at the end of a module, students can practise their learning further by playing an educational game (see Figure 4). The content and main components of the modules are not customizable or adaptive to the diverse needs of learners. The identical content is uniformly presented to all learners of the same grade level, irrespective of their individual needs, proficiency levels, backgrounds, or prior experiences.

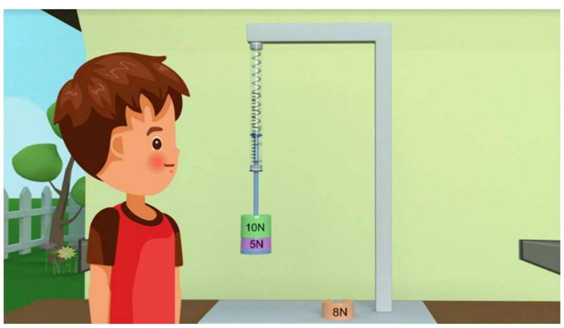

Figure 1. Animated science lesson for Grade 5.

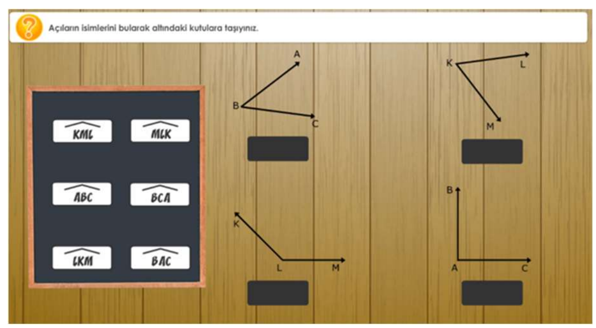

Figure 2. Matching geometry exercise for Grade 6.

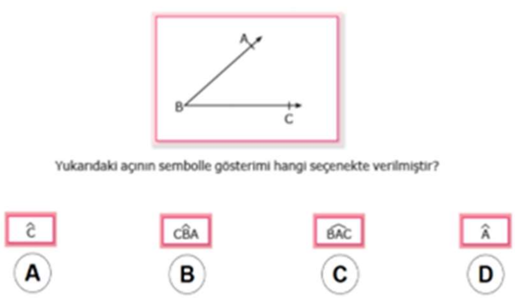

Figure 3. Geometry test question for Grade 6.

Figure 4. Educational game for primary school students.

3.2. The Data and Preprocessing

The data set used in this study contains online learning activity logs of primary and middle school students in Grades 1 through 8. The logs contained activity data for one month and were grouped into several data tables based on the components of the online learning system interacted with, including lessons (around 777,000 logs), practices (around 454,000 logs), exams (around 353,000 logs), and games (around 271,000 logs). Each data table contains the anonymized student IDs, start and end times of the activity, and IDs of the components interacted with. All data was anonymized to prevent students from being identified or identifiable.

The data cleaning process involved several steps to ensure quality and integrity. First, any sessions that lasted less than 30 seconds and logs about the practice and exam activities lasting less than 20 seconds were excluded from the analysis. These cut-off thresholds were determined by the instructional designers of the e-learning platform since they considered any sessions lasting less than 30 seconds may represent brief and potentially accidental access, while any practice and exam activities lasting less than 20 seconds would not provide enough time for users to engage meaningfully with the content. Moreover, students who had a 0% participation rate in lessons and practices, as well as those who scored zero in practices and exams, were removed due to their extremely low level of engagement. After applying these filters, the data set was reduced from 82,189 student log records to 67,686, representing a loss of 17.8% of the initial data. This reduction was necessary to eliminate noise and ensure that only meaningful interactions were included in the analysis. The students included in the final dataset came from 26,742 different classes across 10,872 schools located in 81 different cities throughout Turkey. Due to privacy restrictions, demographic information about the students, including gender and age, was unavailable for analysis.

3.3. Data Analysis

The methods used consist of clustering analysis and the chi-square test for each research question. These methods are described in the following subsections.

3.3.1. Clustering analysis (RQ1)

Clustering algorithms can be a powerful approach to uncovering hidden patterns in complex educational datasets (Antonenko et al., 2012; Dutt et al., 2015). K-means is one of the most popular clustering algorithms applied in learning analytics (Khalil & Ebner, 2017; Kovanović et al., 2016; Tseng et al., 2016) and is also used in this study to identify student engagement profiles. K-means involves a repeating process of determining the centroids of a certain set of clusters and adding each instance to a cluster with the closest centroid (Antonenko et al., 2012). Prior to clustering, the optimal number of clusters was determined for each grade level separately using both Elbow (Khalil & Ebner, 2017) and Silhouette methods (Rousseeuw, 1987), which allowed for cross-checking the results. The number of clusters that yielded the highest performance with the k-means clustering algorithm was chosen as the optimal number.

We identified four features to capture students' preferred way of engagement with the learning system, each corresponding to lessons, practices, exams, and games. These features were utilized to cluster students based on their engagement level with different components and, therefore, identify their engagement profiles. All features were based on counts of student interactions with these components; however, to better capture and emphasize student preferences for specific components, these counts were subsequently transformed into percentages. To derive these features, daily percentages of activities corresponding to lessons, practices, exams, and games were calculated for each student. For example, on a specific day, if a student had a total of 10 activities, with two activities involving lessons, four activities involving practices, and four activities involving exams, then the feature values for this student on that day would be 20%, 40%, 40% and 0% for lesson, practice, exam, and game engagement, respectively.

The representation of the engagement in terms of percentages rather than counts allowed for a more comparable representation of engagement levels in different components of the learning system. These values were computed for each day and then averaged per student separately for the whole month. This method ensures that the percentages computed are not influenced by the number of active days, allowing us to obtain students' preferred engagement in the system consistently regardless of whether they were active for a few days or several weeks. Thus, the resulting feature values represent the percentages (or relative frequencies) of how often students preferred to engage with each distinct type of component in the system.

3.3.2. Chi-square test analysis (RQ2)

To address the second research question, which concerns the differences in the distribution of learner profiles across grade levels, the chi-square test for goodness of fit was performed. One common use of the chi-square test is to identify significant changes in the proportions between different groups (Agresti, 2019). Accordingly, in our study, this test was employed to compare the frequency distribution of student profiles between consecutive grade levels and to identify any significant changes. Prior to the analysis, the percentages (or proportions) of students falling into each profile was calculated per grade level.

4. Results

4.1. Emerging Student Profiles

The analysis yielded seven clusters for Grades 2 to 5 and six for the other grade levels. To label distinct profiles of students, we followed a person-oriented approach (Wormington & Linnenbrink-Garcia, 2017), increasingly used in recent literature for distinguishing students by their behaviour (Fong et al., 2021; Schmidt et al., 2018).

Based on the guidelines suggested by the person-oriented approach, we focused on the most prominent features of each profile. As a result, we identified seven unique profiles of learners:

1. Content-focused
2. Assessment-driven
3. Game-oriented

4. Practice-driven
5. Traditional comprehensive
6. Theory-into-practice
7. Theory-into-game

These profiles across grade levels are provided in Table 1. The average percentages of exam, practice, lesson, and game engagement are also presented for each intersection of the cluster and the grade level. The averages for each component type across all grade levels are included in parentheses. The salient values are highlighted in bold text. Please note that empty cells signify the absence of a profile for the corresponding grade level but do not imply the exclusion of their data.

Table 1. Student Profiles Across Grade Levels and Salient Values

Learner Profile/Grade	1	2	3	4	5	6	7	8	Component
Lesson-focused	2.36	3.60	4.65	4.21	4.66	4.44	3.78	4.23	Exam (3.99%)
Passive learners with the desire	4.99	3.50	6.18	5.84	6.28	7.50	7.08	5.66	Practice (5.88%)
to acquire the lessons presented	**90.40**	**91.02**	**85.83**	**86.91**	**86.84**	**86.20**	**87.41**	**89.13**	Lesson (87.97%)
	2.25	1.87	3.34	3.04	2.23	1.86	1.74	0.97	Game (2.16%)
Assessment-driven	**41.48**	**79.34**	**78.62**	**79.41**	**82.83**	**82.30**	**84.86**	**89.10**	Exam (77.24%)
Learners prioritizing	21.00	6.43	6.79	6.23	5.79	7.65	6.61	5.34	Practice (8.23%)
exams over other activities	28.82	8.37	9.49	10.07	8.76	8.55	7.57	4.44	Lesson (10.76%)
	8.70	5.87	5.09	4.29	2.62	1.50	0.95	1.12	Game (3.77%)
Game-oriented	3.04	2.69	2.66	2.60	1.28	6.29	5.19	6.95	Exam (3.83%)
Learners who prefer learning	4.41	2.02	2.79	3.05	1.57	12.04	12.43	9.17	Practice (5.94%)
via educational games	9.18	3.09	3.57	3.77	2.03	15.20	13.36	10.12	Lesson (7.54%)
	83.37	**92.20**	**90.98**	**90.59**	**95.12**	**66.48**	**69.02**	**73.76**	Game (82.69%)
Practice-driven	4.91	7.08	8.63	6.59	7.05	7.51	7.14	8.90	Exam (7.23%)
Learners who prioritize	**71.82**	**75.98**	**73.84**	**76.12**	**77.41**	**76.65**	**79.43**	**79.29**	Practice (76.32%)
exercises to improve	14.28	13.09	12.31	12.09	11.06	11.91	10.65	9.64	Lesson (11.88%)
their learning	8.99	3.86	5.23	5.20	4.49	3.93	2.79	2.17	Game (4.58%)
Traditional, comprehensive		**35.44**	**34.65**	**35.18**	**35.10**	**35.28**	**36.78**	**46.45**	Exam (36.98%)
Learners who utilize multiple		**27.76**	**27.25**	**25.34**	**26.52**	**27.64**	**27.68**	**26.23**	Practice (26.92%)
yet typical resources		**31.46**	**33.22**	**34.95**	**35.16**	**32.98**	**31.53**	**24.56**	Lesson (37.98%)
		5.35	4.88	4.53	3.22	4.10	4.01	2.76	Game (4.12%)
Theory-into-practice	10.35	9.83	10.81	9.95	7.98	7.90	6.57	11.18	Exam (9.32%)
Learners who study the	**25.54**	**31.26**	**32.81**	**31.95**	**36.01**	**37.32**	**40.43**	**36.40**	Practice (33.97%)
lessons and then apply their	**59.09**	**54.07**	**51.81**	**53.59**	**52.14**	**49.88**	**49.27**	**49.04**	Lesson (53.36%)
knowledge in practice exercises	5.02	4.84	4.57	4.51	3.87	4.90	3.73	3.38	Game (4.35%)
Theory-into-game	7.35	14.19	13.71	11.11	11.38				Exam (11.55%)
Learners who study the lessons	13.08	16.75	17.93	16.87	18.70				Practice (16.67%)
and then apply their knowledge	**38.98**	**24.16**	**26.69**	**30.92**	**27.92**				Lesson (29.73%)
in educational games	**40.59**	**44.89**	**41.67**	**41.10**	**42.00**				Game (42.05%)

Lesson-focused learners are characterized by their preference for mastering the concepts by mainly studying the lessons (which include animated videos) in the online learning system. These learners tend to demonstrate minimal interest in hands-on activities, including practice exercises, exams, and games, which are designed to reinforce and test their learning. As a result, they may be considered passive learners, as they prioritize knowledge transfer to active engagement with the interactive components of the learning system. In contrast, assessment-driven learners are defined by their high engagement in the end-of-lesson exams. This group of students could also be referred to as performance-oriented learners since they prioritize performing well on exams over mastery of the content. Interestingly, among learners in this profile, Grade 1 students exhibited a distinct pattern of engagement. While still demonstrating high levels of engagement in practice exercises and lessons, their engagement in exams was comparatively lower than that of other grade levels.

As its name may suggest, game-oriented learners are identified by their preference for learning through gaming rather than the traditional method of studying lessons and completing practice activities. Students in this profile approach learning in a playful and exploratory way, seeing it as an enjoyable activity rather than a task to be completed. In Grades 1 to 5, students showed a stronger inclination toward game-oriented behaviour, with percentages ranging from 83% to 95%. While students in Grades 6 to 8 still predominantly played games (ranging from 66% to 73%), their engagement in lessons and exercises was relatively higher compared to students in other grade levels (ranging between 10% to 15%).

The students profiled as practice-driven learners demonstrated a strong preference for hands-on learning and focused on practices to improve their understanding of the materials. They were more interested in activities where they could try things and learn through trial and error rather than referring to the instructional materials in the lessons. The engagement with practices ranged between 71% to 78% consistently across grades. Next, traditional, comprehensive learners were characterized by their preference for conventional ways of learning by utilizing multiple resources in a balanced way, including lessons, practices, and exams. These students placed importance on mastering the content through focused studying, practice, and assessment while showing relatively little interest in game-based learning. Interestingly, this profile did not emerge among the Grade 1 students, suggesting that this very young group of learners did not exhibit a balanced engagement with multiple components.

The remaining two profiles identified in this study are those of “theory-into-practice” and “theory-into-game” learners. The theory-into-practice profile represents the students who prefer to gain an understanding of concepts through studying lessons and then enhance their understanding through practical application. These learners are likely to enjoy applying what they learn in practice and see it as an essential part of the learning process. Remarkably, as the students advance to higher grade levels, their preference shifts from a focus on lessons to a greater emphasis on practice. The theory-into-game profile shares similarities with the theory-into-practice profile in terms of desiring to understand concepts through lessons. However, these students differ in that they prefer to apply their knowledge through games rather than practical activities. They enjoy activities that turn concepts into interactive learning experiences through educational games. Notably, the theory-into-game profile only emerged from Grades 1 to 5, while the theory-into-practice profile was observed across all grade levels.

4.2. Student Profile Distribution Across Grade Levels

To answer the second research question, the percentage of students belonging to each profile was computed for each grade level separately. The results are shown in Table 2, where the column-wise sums add up to 100%. According to the table, theory-into-practice, traditional comprehensive, and lesson-focused profiles were the most prevalent, while the practice-driven, assessment-driven, and game-oriented profiles were the least prevalent.

The percentages of students across grade levels for each profile were compared to obtain further insights into how popular a profile was at a particular grade level. To begin with, lesson-focused learners were prevalent across all grade levels, with the highest percentage in Grade 1 (26.47%) and the lowest percentage in Grade 2 (11.34%). Compared to the lesson-focused profile, the percentage of students in the assessment-driven profile remained relatively low across all grades, with the highest percentage found in Grade 8 (12.81%). The high percentage in the cluster of assessment-driven learners suggests that as students advance to higher grades, there might be more pressure to achieve high grades and perform well on tests.

Moreover, the game-oriented profile was more popular from Grades 1 to 2, with a decreasing prevalence as the grade level increased. The percentage of students with the practice-driven profile dropped sharply after Grade 1 but then gradually increased toward the end of middle school (i.e., Grade 8). The theory-into-game profile seemed to be adopted after Grade 1, decreased until Grade 5, and then disappeared. Overall, the theory-into-practice and the traditional comprehensive learners prevailed across all grades where they were present.

The chi-square test for goodness of fit was performed to compare the frequency distribution of student profiles between consecutive grade levels and to identify any significant changes. The results of the chi-square test are provided in Table 3. The profile distributions across the consecutive grades differed significantly, which is a typical outcome of chi-square tests with large sample sizes. The practical significance of these results was tested using Cohen’s w statistic (also reported in Table 3). A w value of around 0.1 indicates a small effect, 0.3 a medium effect, and 0.5 or greater a large effect (Cohen, 1992).

Table 2. Number and Percentage of Students Across Student Profiles and Grade Levels

Profiles/Grades	1	2	3	4	5	6	7	8
Lesson-focused learners	1278 26.47%	539 11.34%	542 13.31%	808 17.29%	902 18.93%	1228 18.70%	1033 19.53%	890 15.81%
Assessment-driven learners	410 8.49%	251 5.28%	215 5.29%	255 5.46%	290 6.09%	341 5.19%	357 6.75%	721 12.81%
Game-oriented learners	521 10.79%	608 12.79%	355 8.71%	309 6.61%	311 6.52%	547 8.33%	349 6.60%	300 5.33%
Practice-driven learners	882 18.27%	233 4.89%	206 5.07%	222 4.76%	321 6.74%	656 9.99%	743 14.05%	657 11.67%
Theory-into-game learners	206 4.27%	855 18.0	692 16.99%	660 14.12%	542 11.37%	-	-	-
Theory-into-practice learners	1531 31.71%	1076 22.64%	926 22.74%	1174 25.11%	1178 24.71%	2026 30.85%	1460 27.61%	1508 26.79%
Traditional comprehensive learners	-	2381 25.06%	1136 27.90%	1245 26.65%	1222 25.63%	1769 26.94%	1346 25.45%	1553 27.59%
TOTALS	4828 100%	4751 100%	4072 100%	4674 100%	4767 100%	6567 100%	5288 100%	5629 100%

According to Table 3, a significant change in the proportion of profiles was noted between Grades 1 and 2, indicating a very large effect size. This suggests that the way students engaged within the learning platform changed significantly between Grades 1 and 2. Additionally, a close to medium effect was noted between Grades 7 to 8. For the rest of the transitions between the grades, small effect sizes were noted.

Table 3. Chi-Square Test Results

Statistics/Grades	1–2	2–3	3–4	4–5	5–6	6–7	7–8
χ^2	6336.94	247.90	351.61	155.75	248.84	155.78	393.80
w	0.82	0.14	0.16	0.13	0.19	0.17	0.26

5. Discussion

The main findings are discussed in relation to the research questions as follows. The implications of the findings are also provided.

5.1. Student Profiles of Engagement

After analyzing students' preferred ways of engaging with different components of the learning system, several profiles emerged. It was observed that these profiles exist across different grade levels, but slight variations were noted in the levels of engagement within the same profiles, depending on the grade level. Despite the e-learning platform being designed with four principal components to provide a comprehensive educational experience for maximizing student learning, this study identified many engagement profiles that show how distinct groups of students interacted with the system in their preferred ways.

Four student profiles, namely the lesson-focused learners, assessment-driven learners, game-oriented learners, and practice-driven learners, were distinguished by their high level of engagement with a specific component and very low level of engagement with the other three components in the platform. These learner groups can be considered similar to the highly selective student profile identified by Jovanović et al. (2017), which contained students who applied only one learning strategy. However, by limiting their engagement to one component, the students in these four profiles might have missed valuable learning opportunities offered by the other components. This oversight could result in diminished academic performance, exemplified by the highly selective group that recorded the lowest exam scores in the study conducted by Jovanović et al. (2017). For example, a game-oriented student may have missed an animated video that explains a complex science concept, or a lesson-focused student may have missed an educational game illustrating the use of an abstract concept. The study's emphasis on the potential missed learning opportunities aligns with the work of Mulqueeny et al. (2015), who emphasized the importance of incorporating effective e-learning principles to improve students' limited engagement in educational settings.

In the other three profiles (traditional comprehensive learners, theory-into-practice learners, and theory-into-game learners), students demonstrated high levels of engagement with two or three different components. Traditional comprehensive learners engaged with three components (lessons, practices, and exams) in a more balanced way. Similar student profiles have been noted in previous research studies with different names, such as active learners (Yang, 2021) or perfect students (Khalil & Ebner, 2017) in other contexts. This profile was present in all grade levels except Grade 1. That is, a certain group of students from Grades 2 to 8 demonstrated a more well-rounded approach to learning on the e-learning platform. The absence of this profile among the Grade 1 students may be attributed to their lack of previous experience using this platform, as it is only introduced to them for the first time in Grade 1. Accordingly, previous research highlights the importance of prior experience and readiness level in effectively utilizing online learning platforms (Lau & Shaikh, 2012). As the new young users of the system, these students might have tended to engage with specific components. This finding indicates that previous exposure to the platform can increase student tendency to adopt a traditional comprehensive learning approach. This observation aligns with previous studies that have noted more effective engagement with learning platforms among students with greater prior experience (Abuhassna et al., 2020). Additionally, it is possible that the Grade 1 students who are getting accustomed to the school and study culture might need more explicit guidance to fully utilize the system for a more comprehensive learning experience that complements their classroom learning. Thus, the orientation period of the Grade 1 students should be different to maximize their initial engagement with online learning systems.

Moreover, the theory-into-game profile was observed only between Grades 1 to 5, suggesting that in the earlier grades, some students tended to use educational games to apply their newly acquired knowledge from lessons while paying less attention to practices and exams. This profile was not present among older students, indicating a potential shift in their preferences. Therefore, younger learners may find practising the learned concepts or topics through educational games more enjoyable and sufficient than their older counterparts. Given the positive influence of educational games on student learning at these early ages (Chuang & Chen, 2007), high-quality games in e-learning platforms may create a big impact on children's learning. The theory-into-practice profile, on the other hand, was present across all grades. However, within this profile, the degree of engagement with practices and lessons varied depending on the grade level. Specifically, as the grade level increased, students tended to balance the engagement between lessons and practices, while in the lower grades, lesson engagement seemed to weigh more. However, regardless of age, practising is essential for solidifying newly acquired knowledge in the memory (Iftikhar et al., 2022). Thus, younger learners might need more explicit guidance to complete the practices after the lessons, which will help them reinforce their learning.

Based on the percentage changes in engagement with the learning components from Grades 1 to 8, students' preferred way of engaging with the components evolves. Specifically, the results from different profiles show that in the earlier grades, students tended to favour educational games, whereas in the later grades, this preference shifted away from the games toward practices and exams. This finding aligns with the previous research, which has shown that in earlier grades, students tended to prefer learning with educational games (Abdul Rabu & Talib, 2017). Additionally, the educational games on the platform are animation-based, and the main game characteristics (such as game mechanics, graphics, and rules) do not differ significantly across the grades, with the only variation being the learning objectives. Given that student game orientations can change over the years (Greenberg et al., 2010), it is possible that the games on the platform were not as attractive to older students. Also, the shift toward exams could be due to the high-stakes exam that students are required to take at the end of Grade 8 since a competitive score from this exam is needed for admission to a good-quality high school.

None of the student profiles demonstrated a balanced engagement across all four components. Although the traditional comprehensive learners exhibited an integrated engagement involving lectures, practice, and exams, they did not use the educational games, which were designed purposefully to complement the learning experience in conjunction with the other components. These results may indicate that K–8 students prefer to engage with only one or two components. The lack of balanced engagement among all four components could be attributed to several factors. For instance, the learning platform by design may lack explicit embedded support to guide K–8 student use of the system in an integrated way. Additionally, the instructional approach that instructors or schools follow when integrating the platform into the curriculum could play a role. Pedagogical guidance and recommendations from instructors may be necessary to achieve complete student engagement with the system.

While our study has illuminated distinct learning profiles based on student preferences within the online learning platform, it is pertinent to consider the potential influence of class or subject type on these profiles. Some subject areas may leverage practical, application-oriented strategies, while others may rely more on traditional lessons (Prince & Felder, 2006). Therefore, the inherent characteristics of the subjects presented on the platform might have played an important role in the emergence of some profiles. Exploring the interplay between these learning profiles and specific subjects could offer valuable insights into the nuanced dynamics of student engagement.

5.2. Distribution of Profiles Across Grades

Percentage distributions of the profiles within and across grades provided insights into the popularity of the profiles and the changes between the grade levels. Overall, three profiles were consistently predominant across most grade levels: traditional comprehensive learners, theory-into-practice learners, and lesson-focused learners. This finding indicates that regardless of age, most students (57–74% depending on the grade level) engaged with the lessons to study and learn the concepts, and they mostly practised what they learned and/or tested their knowledge.

Consistent with the findings presented in the previous section, the assessment-driven profile was the most popular among Grade 8 students. At the same time, the game orientation was more prevalent among the lower graders. Although these findings note the prevalence of specific profiles depending on grade, neither of these two profiles was among the most predominant. Notably, however, the theory-into-game behaviour was considerably favoured by primary school students in Grades 2 to 5. This finding further accentuates the inclination of younger students to integrate educational games into their study routines.

Interestingly, Grade 1 students shared the second-highest proportion within the assessment-driven profile, very close to percentages observed for the game-oriented profile in the same grade level. While this discovery warrants further substantiation, it suggests a noteworthy possibility — the increasing emphasis on enhancing student competencies in solving tests starting from very early years. Previous research has already noted the influence of familial expectations and societal pressures in fostering this trend (Pinquart & Ebeling, 2020).

Moreover, this study compared the profile distributions between successive grade levels and found that, while most changes were statistically minor, substantial differences were found between Grades 1 and 2, as well as between Grades 7 and 8. In other words, student profiles were very different in Grade 1 in comparison to the following grades and in Grade 8 in comparison to the previous grades. That is, Grade 1 and 8 students showed engagement that diverged from their peers in closer grade levels. In parallel with the earlier discussion, these differences could be attributed to the fact that Grade 1 students were probably using the platform for the first time and that Grade 8 students were probably preparing for high-stakes exams. These findings further highlight the need for a different treatment in the platform for these grade levels.

6. Implications for the Design of Online Learning Platforms

The findings of this study have several important implications for the design of online learning platforms for young learners, as well as their integrations into K–12 education:

- **Adaptive learning catering to different student profiles**: An important implication of this study is that online learning platforms can be more effective tools if they can meaningfully adapt to the preferred ways of engagement of different student profiles. Adaptive learning is proven to be an effective strategy in promoting student experiences with such e-learning platforms (Chou et al., 2015). For example, if students tend to engage more with exercises or practices and less with lessons, the platform can adaptively suggest lesson materials based on the errors made during the exercises. Similarly, game-oriented learners can be pointed to relevant lesson content or exercises according to their success or struggles in the games. Thus, adaptive recommendations from the system based on student engagement can guide them to components they prefer while also benefiting from other components as necessary.
- **Guidance for more comprehensive engagement:** This study showed that most young learners tend to interact with specific components, which may result in them missing learning opportunities. As with the first implication, e-learning platforms may need to incorporate guidance for students according to their engagement behaviour and encourage them to benefit from the correct component at the right moment. For example, if a student takes a test after a lesson and performs poorly, the platform could recommend that the student check the exercises of the same module before retaking the same test. Such explicit guidance could be important in promoting self-regulated learning among young students (Zimmerman, 1990).
- **Orientation for Grade 1 students:** The previous implication may have more direct effects for Grade 1 students, who mostly interacted with one or two specific components. Students using the platform for the first time while adjusting to a new school environment could benefit from extra support for more effective use of online systems. An orientation period with proper training could help to familiarize these very young learners with using comprehensive learning systems effectively and correctly.
- **Test preparation support for older students:** High-stakes exams have become more widespread globally in K–12 education (Giersch, 2018; Musoleno & White, 2010), which amplifies the need for support to help students perform well in such competitive exams. Accordingly, the findings of this study showed that students approaching the end of middle school tended to show more interest in exams. An important implication is that online learning systems might be more relevant and effective for these students if proper support mechanisms for exam preparation are integrated. Such systems have proven to be effective in promoting achievement in high-stakes exams (Chakraborty et al., 2021).
- **More opportunities for game-based learning at lower grades:** Young students' preference for learning through games is noted in the literature (Abdul Rabu & Talib, 2017). Our study shows that this behaviour tends to persist in e-learning platforms with additional learning opportunities beyond games. This finding indicates that the educational games on these platforms might have a strong impact on primary school learning. Games should be carefully crafted to offer a more powerful learning experience for these students.
- **Monitoring tools for instructors:** Findings regarding student profiles could be translated into pedagogical solutions that empower teachers to intervene as necessary. For example, a teacher-facing dashboard (Chavan & Mitra, 2022) could be implemented to allow teachers to monitor students' emerging profiles and offer class-wide interventions to guide student transitions toward more effective profiles. Research has provided sufficient evidence about the effectiveness of teacher-facing dashboards in higher education contexts (Molenaar & Knoop-van Campen, 2019), and these learning analytics tools could be impactful in online learning among primary and middle school students.
- **Embracing a context-aware data collection approach:** The data used in this study allowed us to understand student engagement behaviour with an e-learning platform. This platform is used in schools, and teachers may adopt it differently in their pedagogies, which may have significant effects on student engagement (Rashid & Asghar, 2016). However, the data traced by the platform mostly considers student activities and does not provide a sufficient account of how teachers integrate this platform into their teaching practices. This limitation calls for a context-aware data collection approach to be adopted in online learning platforms (Eradze & Laanpere, 2017).

7. Conclusion

One principal goal of the learning analytics field is to offer in-depth, comprehensive insights into learning based on data traced as students interact and learn in online environments. Although the field has greatly matured, research efforts aimed at explaining the learning processes of primary and middle school students and profiling them using trace data remain limited. Previous research has utilized self-reported data to cluster young learners based on their engagement and motivation profiles (Bae & DeBusk-Lane, 2019; Yang et al., 2023), which is known to be prone to bias. Given this critical gap, this research makes a timely contribution to the field by offering valuable, novel insights into how primary and middle school students engage and learn through e-learning platforms. The study revealed varying engagement profiles of students from Grades 1 to 8 and the distributions of these profiles across grade levels. These findings resulted in seven critical implications for the design of online learning platforms for young learners.

One critical limitation of this study is the inability to explain the potential influence of teachers' adoption of the e-learning platform on the findings. How teachers adopted the platform could have played a significant role in forming student profiles. For example, the comprehensive mastery profile might have emerged due to the teachers requiring students to complete the modules in the platform regularly every week. Although the platform records some teacher activities, the primary data collected was centred on homework assignments, which may not fully reflect the level of platform integration into teaching. Therefore, it is necessary for e-learning platforms to collect more comprehensive data about teacher activities in the system as well as their approaches to integration for achieving a more complete interpretation of student engagement behaviour.

Another limitation is the lack of demographic information about the participants, which prevents us from exploring the role of other factors, such as gender, in the formation of learner profiles. Future research is needed to incorporate demographic data, allowing for a more nuanced exploration of factors like gender. Moreover, this study focused on the preferences of learners in terms of the percentage of their activities corresponding to different elements of the e-learning platform (such as lessons or games). The analysis could result in different clusters of learners if other engagement indicators were used, such as the days students were active or the total number of interactions. In follow-up studies, we plan to explore alternative engagement indicators to discover various learner profiles.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors declared no financial support for the research, authorship, and/or publication of this article.

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