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Extracting student patterns from log file Moodle course: A case study

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ABSTRACT

This paper introduces a set of extracted factors from Moodle log file of the selected course as a case study that aims to capture student Engagement (E), Behavior (B), Personality (Pers) and Performance (P). The factors are applied to identify students' EBPersP with different course activities. The data set used in this paper was selected from the "Introduction to Computer Science" online course that captures 273,906 records as a log file for 29 students, delivered in Spring 2020. The paper also tries to show whether there is a relationship between student engagement, behavior and personality and their performance. Results show different patterns of students' interactions with course contents, activities, and assessments. Specifically, our findings highlight that students' EBPersP could be extracted from Moodle log files. In addition, the extracted factors could assist instructors on how to focus more on students with low and average performance, giving them more attention to enhancing their performance.

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1. INTRODUCTION

Many colleges and universities have begun to adopt online learning environments to be able to deliver online courses to their students, especially during the COVID-19 pandemic. The entire learning environment must be efficient, with more effective learning management in order to improve smart education [1]. By monitoring students' engagement and performance in online courses, learning analytics make it simple to examine and refine course design for students [2]. Successful learning necessitates students' drive to achieve their desired learning outcomes [3]. However, not all students will be able to develop a practical route that would enable them to study independently [4]. Many institutions, on the other hand, use Learning Management Systems (such as Moodle) to aid in the learning process. Without needing to start from scratch, this application might be reused more effectively. Furthermore, one of the most common Moodle problems is a lack of student participation in various course activities [5]. Moodle is a free, open-source software program for creating online classes that is used by educators. It has a flexible architecture that makes it simple to incorporate engaging material and encourages students to use social constructionist pedagogy [6]. Moodle does not have the ability to track a student's Engagement, Behavior, Personality and Performance (EBPersP). It simply collects basic information about students and such as how many times they visit the course and when they submit their assignments.

"The degree to which a student engages in activities that have been proved to be associated to high-quality learning outcomes" is how the word "student engagement" has been defined [7]. Student behavior is defined as "a two-way interaction between students and the learning environment that aims to cause reasonably consistent changes in what students know and can do" [8]. "A consistent predictor of student satisfaction, academic motivation, and academic performance" is a student's personality [9].

"The outcomes of the teaching and learning process in terms of knowledge and skills in students acquired from schools and colleges as measured by exam scores" is how student performance is defined. [10]. The results obtained from this study could help instructors develop courses that suit their students based on their preferences for learning materials. This includes a better grasp of the EBPersP of students, which increases the opportunities for effective teaching and learning.

Current Moodle learning management system (LMS) does not help instructors in how they can track their students' engagement, behavior, personality and performance in courses. Therefore, the authors shed light on how instructors can keep monitoring their students through analyzing the log files of any selected course in Moodle. Hence, the authors study how they engage and behave in those courses by taking one case study to prove the concept which presents the importance of studying the log files of any courses in Moodle by following the proposed EBPres predictive model. This model gathers EBPers data from students via a log file saved in Moodle database. Then produces patterns of engagement, behavior, personality, and performance among students. The information is then passed on to the instructor, who can use it to create customized learning materials for low and average students [11]. As a result, important needs such as student engagement, behavior, personality, and performance must be studied in order to provide a smart learning behavior setting that meets the demands of students [12].

The authors examined how the other authors measure the four factors (student engagement, student behavior, student personality and student performance) before the authors sets the measurement factors that are supposed to follow. For example, despite the absence of studies tying LMS usage data to other measures of student engagement, LMS (i.e. Moodle) data is increasingly being used as a predictor of student engagement for institutional planning [13]. Academic involvement is usually classified into two categories: "Academic engagement" linked to the learning process, such as time spent on a task or participation in planned learning events, and "academic involvement," which is not directly linked to the learning process [14]; by combining student self-reports of involvement with data from an online course management system that tracks student actions [15].

The online student engagement scale was validated. On the online student engagement survey, it was expected that student involvement would be strongly linked to observational and application learning activities. In addition, when using the Moodle system, researchers looked at student preferences. [16] advocated using the Integrated Felder Silverman learning style model into the establishment of student qualities. Students' preferences matched the Felder Silverman model's descriptions of learning styles, they discovered. [17] developed a mechanism for classifying pupils dynamically based on their learning styles a Moodle online course with 35 students was used to test the strategy. Felder and Silverman's approach were used to determine each student's learning type based on their behavior and data from the Moodle log. Personality, on the other hand, influences students' behavior in a variety of ways, including peer and teacher interactions, learning outcomes, and academic assignments [18].

In the context of distance and online education, the relationship between personality and performance has lately been investigated. Despite the fact that the outcomes are diverse, they all point to a substantial link between personality and performance [19]. As an example of student performance previous studies, in 23 online courses at two colleges, [20] investigated the link between each quality area and student end-of-semester performance. The quality of interpersonal contact in a classroom, according to the statistics, has a favorable and significant relationship with student grades [21] in two online courses, researchers looked into the impact of student characteristics on their performance. Students' end-of-semester grades can be predicted based on their learning preferences at the start of the course, according to a self-assessment tool utilized on 272 students using a logistic regression framework.

2. RESEARCH METHOD

With so much data to sort through, which were collected from the a case study, the authors needs something more from these data. For example, what is the exact data that need to be extracted to respond to the research questions. In brief, the authors needs better data analysis. The accurate data analysis process and method lead to achieving the research target [22]. As a result, the authors adhere the data analysis process as shown in Figure 1, which consists of five main processes: i) Define research questions; ii) Set measurement priorities; iii) Collect data; iv) Analyze data; and v) Interpret results.

Figure 1. Data analysis processes

2.1. Define research questions

The main questions the authors want to get an answer for from the case study in this paper are: i) RQ 1: How can students' engagement, behavior, personality and performance be extracted from the log file of course in Moodle?; ii) RQ 2: What kinds of patterns can be extracted from the student EBPersP of the selected course?

2.2. Set measurement priorities

The authors treat with a vast amount of information gathered from a Moodle log file. From this log file, the authors focus on four factors: i) Student engagement: The term "student engagement" has been used to describe a variety of subjects. These could include things like interest, time on task studies that look at effort quality and willingness to participate in learning activities [23]; ii) Student behavior: Students and the learning environment interact in two ways through behaviors, with the goal of causing desired changes in what students know and can do [24]; iii) Student personality: Individual variances in cognition, emotion, and behavior patterns are referred to as personality [25]; iv) Student performance: Normally, student performance is based on students' grades in any course. The idea is to help instructors predict their students' performance and analyze data in a more intelligent way in the classroom [26].

2.3. Collect data (Moodle log file)

Moodle generated a large amount of data that can be used to research student interactions. It keeps track of each student's activities [27]. The data for this paper was taken from the Moodle log file of the course "Introduction to Computer Science," which was taught by the Department of Computer Science at the College of Science in Spring 2020. It has 29 undergraduate students enrolled. This course covers some essential computer science concepts. The authors extract 273,906 data from the course's log file. Figure 2 depicts a sample of the log file taken from the course.

Moodle's environment not only allows students to easily access educational resources. It also allows higher education organizations to collect massive volumes of data on student experiences. This data allows for in-depth analysis of student EBPersP, as well as determining whether there are any patterns that contribute to better learning outcomes [11].

Course: In	System	Course vi	The user v	web
File: Cour	File	Course m	The user v	web
Course: In	System	Course vi	The user v	web
Course: In	System	Course vi	The user v	web
Course: In	System	Course vi	The user v	web
Course: In	System	Role assig	The user v	web
Course: In	System	User enro	The user v	web
Course: In	System	User profi	The user v	web
File: Cour	File	Course m	The user v	ws
File: Cour	File	Course m	The user v	ws
File: EdPy	File	Course m	The user v	ws
File: EdPy	File	Course m	The user v	ws
File: EdPy	File	Course m	The user v	ws
Course: In	System	Course vi	The user v	ws
Course: In	User repo	Grade use	The user v	ws
Course: In	System	User list v	The user v	ws
File: L2: Cl	File	Course m	The user v	ws
File: L2: Cl	File	Course m	The user v	ws
Course: In	System	Course vi	The user v	ws
Course: In	System	User profi	The user v	ws
Course: In	System	Role assig	The user v	ws
Course: In	System	User enro	The user v	ws

Figure 2. A sample log file from SQU Moodle's "Introduction to computer science" course

2.4. Data analysis

The authors looked at four factors from the log file: student engagement, student behavior, student personality, and student performance. Based on the acquired data, the authors devised the following measurement to determine what to measure and how to measure it. Table 1 provides more information about the measurement factors of the study.

Table 1. Measurement factors of the study

Factor	Metrics	How to measure
Engagement (E)	Count all of the student's activities in the course.	The activities of student based on Event name column
Behavior (B)	(The number of elements that the student has interacted with ÷ total number of elements available in the course)	The elements that the student has interacted with, based on element column
Personality (Pers)	Count the student's elements that have been accessed.	The elements that the student has interacted with, based on element column
Performance (P)	Summation of the marks of assessments	The marks of students

2.4.1. Performance factor

The overall mark of all assessments (such as examinations, quizzes, assignments, and projects) in this course represents the performance factor. The total value (performance) is 100. The percentiles method was used to divide the numerical data into groups in this study. It works by separating the data into uneven intervals, each of which corresponds to a distinct category. Students' grades are divided into three groups (High, Average, and Low) by dividing the period into: Low (0.00-35), Average (35.1–75), High (75.1-100.0). The marks of students using categories are shown in Table 2.

Table 2. Student performance factor based on categories

Student ID	Performance value	Performance category
ST1	79.25	High
ST2	77.8	High
ST3	63.62	Average
ST4	88.08	High
ST5	97.4	High
ST6	86.08	High
ST7	82.05	High
ST8	86.07	High
ST9	93.7	High
ST10	83.8	High
ST11	88.5	High
ST12	79.41	High
ST13	88.26	High
ST14	82.03	High
ST15	85.07	High
ST16	87.02	High
ST17	89.27	High
ST18	92.35	High
ST19	85.33	High
ST20	90.13	High
ST21	61.78	Average
ST22	93.16	High
ST23	90.4	High
ST24	83.53	High
ST25	86.55	High
ST26	66.1	Average
ST27	91.7	High
ST28	93.8	High
ST29	91.74	High

2.4.2. Engagement factor

The number of activities that a student takes in response to the event name represents the student's engagement. Table 3 shows the results of counting the events for each student. In addition, these values are represented by three categories (High, Average, Low) by dividing the period as: Low (0.00-35); Average (35.1-75); and High (75.1-100.0)

Table 3. Student engagement factor based on categories

Student ID	Engagement value	Engagement category
ST1	68.9	Average
ST2	38.5	Average
ST3	52.8	Average
ST4	51.2	Average
ST5	84.5	High
ST6	55.7	Average
ST7	73.0	Average
ST8	47.9	Average
ST9	47.7	Average
ST10	48.9	Average
ST11	55.3	Average
ST12	60.3	Average
ST13	53.1	Average
ST14	59.4	Average
ST15	84.8	High
ST16	51.5	Average
ST17	58.0	Average
ST18	77.0	High
ST19	63.3	Average
ST20	51.1	Average
ST21	36.6	Average
ST22	100.0	High
ST23	68.6	Average
ST24	73.1	Average
ST25	76.4	High
ST26	19.2	Low
ST27	73.3	Average
ST28	73.3	Average
ST29	60.0	Average

2.4.3. Behavior factor

Each student's behavior is represented by the percentage of access elements. The log file's "Element" column is a required field. Table 4 shows the percentage of accessed components as well as the behavior type for each student. The (1) is used to calculate the value of behavior.

$$Behavior\ of\ Student\ i = \frac{(number\ of\ accessed\ elements\ without\ duplicates\ of\ Student\ i)}{(the\ maximum\ number\ of\ accessed\ elements)} \times 100 \quad (1)$$

Table 4. The categories of behavior for students

Student ID	Behavior value	Behavior category
ST1	76.5	High
ST2	52.9	Average
ST3	82.4	High
ST4	76.5	High
ST5	76.5	High
ST6	70.6	Average
ST7	64.7	Average
ST8	76.5	High
ST9	58.8	Average
ST10	76.5	High
ST11	58.8	Average
ST12	64.7	Average
ST13	70.6	Average
ST14	64.7	Average
ST15	82.4	High
ST16	76.5	High
ST17	76.5	High
ST18	76.5	High
ST19	88.2	High
ST20	70.6	Average
ST21	64.7	Average
ST22	82.4	High
ST23	82.4	High
ST24	82.4	High
ST25	70.6	Average
ST26	52.9	Average
ST27	70.6	Average
ST28	82.4	High
ST29	70.6	Average

2.4.4. Personality factor

The number of accessed elements is used to calculate the personality factor. We trace each student manually, for the student who has action in the element, we put 1; otherwise, we put 0. Finally, we count the number of ones to set the value of total and then we make the value common like other factors from 100. Table 5 depicts students' interactions with all aspects.

Table 5. The category of personality for each student

Student ID	Personality value	Personality category
ST1	86.58	High
ST2	59.94	Average
ST3	93.24	High
ST4	86.58	High
ST5	86.58	High
ST6	79.92	High
ST7	73.26	Average
ST8	86.58	High
ST9	66.6	Average
ST10	86.58	High
ST11	66.6	Average
ST12	73.26	Average
ST13	79.92	High
ST14	73.26	Average
ST15	93.24	High
ST16	86.58	High
ST17	86.58	High
ST18	86.58	High
ST19	99.9	High
ST20	79.92	High
ST21	73.26	Average
ST22	93.24	High
ST23	93.24	High
ST24	93.24	High
ST25	79.92	High
ST26	59.94	Average
ST27	79.92	High
ST28	93.24	High
ST29	79.92	High

3. RESULTS AND DISCUSSION

3.1. Results

3.1.1. The relationship between student EBP and performance factors

Tables 6 and 7 provide the details of the EBPres as well as the students' performance in this case study. Figure 3 reveals the clear relationships between EBPresP factors. The factors, for the most part, impact each other. When any factor's value is high, the performance factor is high, and when all of the factors are average, the performance is average. In rules, these findings are more obvious.

Table 8 shows that there is a relationship between Students' Engagement and Students' Behavior. There are 12 cases when the student's behavior Average their engagement also Average (this is a pure pattern), as well there are four cases when the student's behavior High their engagement also High (this is a pure pattern). Additionally, there is a relationship between student behavior and student personality. There are 15 students out of 29 have one pattern (which are high personality with high behavior, this is a pure pattern). There are eight students out of 29 have also pure pattern, when their Behavior Average their Personality is also Average. Besides, there is a relationship between Student Engagement and Student Personality.

There are two pure patterns as shown in Table 8. All the patterns give an indicator that Performance is influenced by Engagement, Behavior and Personality but with different degrees. The most influential factor with Performance is Personality with 22 cases as pure patterns following by Behavior with 16 cases as pure patterns and Engagement with seven cases as pure pattern.

Table 6. The details of EBPers factors and P with numbers

Student ID	E	B	Pers	P
ST1	68.9	76.5	86.58	79.25
ST2	38.5	52.9	59.94	77.8
ST3	52.8	82.4	93.24	63.62
ST4	51.2	76.5	86.58	88.08
ST5	84.5	76.5	86.58	97.4
ST6	55.7	70.6	79.92	86.08
ST7	73.0	64.7	73.26	82.05
ST8	47.9	76.5	86.58	86.07
ST9	47.7	58.8	66.6	93.7
ST10	48.9	76.5	86.58	83.8
ST11	55.3	58.8	66.6	88.5
ST12	60.3	64.7	73.26	79.41
ST13	53.1	70.6	79.92	88.26
ST14	59.4	64.7	73.26	82.03
ST15	84.8	82.4	93.24	85.07
ST16	51.5	76.5	86.58	87.02
ST17	58.0	76.5	86.58	89.27
ST18	77.0	76.5	86.58	92.35
ST19	63.3	88.2	99.9	85.33
ST20	51.1	70.6	79.92	90.13
ST21	36.6	64.7	73.26	61.78
ST22	100.0	82.4	93.24	93.16
ST23	68.6	82.4	93.24	90.4
ST24	73.1	82.4	93.24	83.53
ST25	76.4	70.6	79.92	86.55
ST26	19.2	52.9	59.94	66.1
ST27	73.3	70.6	79.92	91.7
ST28	73.3	82.4	93.24	93.8
ST29	60.0	70.6	79.92	91.74

Table 7. The details of EBPers factors and P with categories

Student ID	E	B	Pers	P
ST1	Average	High	High	High
ST2	Average	Average	Average	High
ST3	Average	High	High	Average
ST4	Average	High	High	High
ST5	High	High	High	High
ST6	Average	Average	High	High
ST7	Average	Average	Average	High
ST8	Average	High	High	High
ST9	Average	Average	Average	High
ST10	Average	High	High	High
ST11	Average	Average	Average	High
ST12	Average	Average	Average	High
ST13	Average	Average	High	High
ST14	Average	Average	Average	High
ST15	High	High	High	High
ST16	Average	High	High	High
ST17	Average	High	High	High
ST18	High	High	High	High
ST19	Average	High	High	High
ST20	Average	Average	High	High
ST21	Average	Average	Average	Average
ST22	High	High	High	High
ST23	Average	High	High	High
ST24	Average	High	High	High
ST25	High	Average	High	High
ST26	Low	Average	Average	Average
ST27	Average	Average	High	High
ST28	Average	High	High	High
ST29	Average	Average	High	High

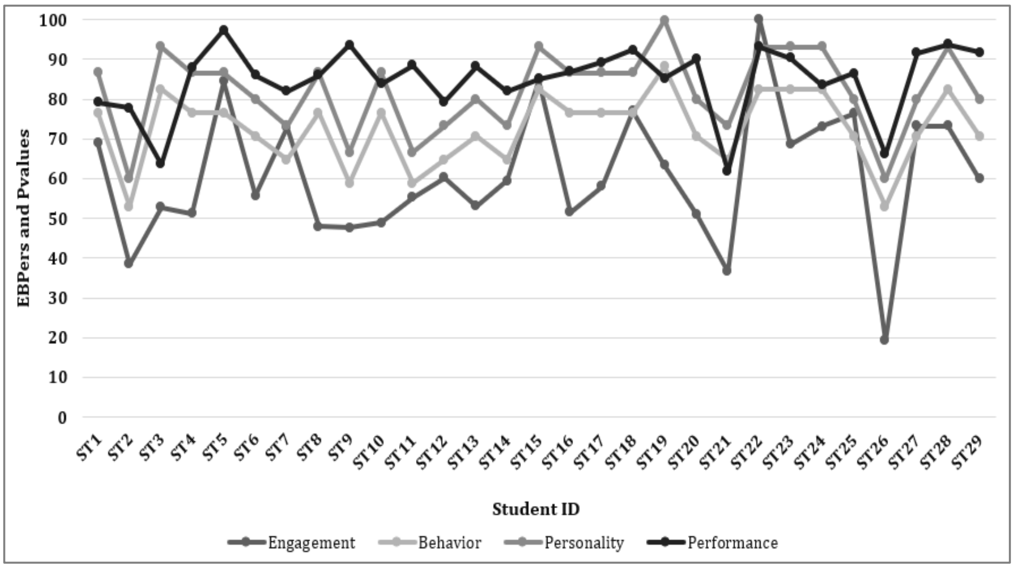

Figure 3. Relationship between performance and EBPers factors

3.1.2. Extracting patterns

A pattern is a collection of data that appears to repeat itself in a predictable pattern [28]. A pattern is a collection of rows with the same values. There are four patterns in the selected case study, according to Table 8, although there are four cases that cannot be called patterns because they only appeared once. Based on Table 8, the two most frequent patterns are (Pattern 4 and Pattern 2). This demonstrates that EBPres factors have an impact on student performance. However, we can see that in both patterns, the performance is High.

Table 8. Patterns of students in the case study with their frequencies

Pattern No.	E	B	Pers	P	Frequency
1	High	High	High	High	4
2	Average	Average	Average	High	6
3	Average	Average	High	High	5
4	Average	High	High	High	10

3.1.3. Rules

These pattern outcomes could also be described using AND/OR rules, as seen: i) If [(Behavior=High OR Average) AND (Personality=High) AND (Engagement=High)], then (Performance=High); ii) If [(Behavior=Average) AND (Personality=High OR Average) AND (Engagement=Average)], then (Performance=High OR Average); iii) If [(Behavior=Average) AND (Personality=Average) AND [(Engagement=Low)], then (Performance=Average).

3.2. Discussion

In this paper, the authors analyzed the log file of the course of 29 students. The analysis focuses on extracting the main factors of students, which are engagement, behavior, personality and performance. Followed by finding the relationship among these factors, deriving the rules, finding the patterns. The finding revealed that we can extract EBPers and P factors from Moodle log file. There is a relationship between these factors. Information on each student's engagement, behaviors, personality, and performance help teachers alter their teaching methods and take any required precautions to improve learning settings [26]. The availability of a tool that can clearly comprehend and regulate student's EBPersP. When they perform various learning activities, it would be a huge aid in enhancing the learning process and assist the instructor easily to track his/her students [29].

Researchers can use good analysis techniques to intelligently evaluate students' log files in educational systems [30]. Current e-learning platforms allow for the recording of student activity, which allows for the study of LMS events [31]. Furthermore, one of the key ways the increasing LMS is affecting e-learning design is the need for trackable data to understand how courses and students are performing. The instructor can have a deeper understanding of their students as well as information about how their classes are running [32].

4. CONCLUSION

The study provides evidence for instructors to make more effort to encourage students to engage in the course and, therefore how can the instructors evaluate the usage and effectiveness of course modules. Instructors are motivated to optimize student EBPersP in order to ensure that students' learning performance improves. Understanding students' personality is helpful to create a more conducive learning environment for better student engagement, behavior and improving their performance to be more successful. Instructors might choose to utilize the findings from such a study to identify students who require more attention to improve their performance. Such data could assist teachers and educational institutions in establishing or revising online course programs and promoting student success in those classes. A part of the future work, the authors, are looking at the possibility of developing a prototype that let the instructors to check their student EBPers and P automatically.

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