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The impact of LMS usage on cognitive load in a programming course: an evaluation using NASA-TLX

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Abstract

In the Learning Management System (LMS), the student's cognitive load affects learning. In this study, the cognitive load of students using LMS in object-oriented programming courses was examined. The research was carried out with 35 students who used LMS to learn a new topic related to the course. After completing the tasks given, the cognitive load levels of students were evaluated using the NASA-TLX scale. Findings were classified according to individual characteristics such as gender, LMS experience, and academic success. The results were interpreted as the presence of moderate cognitive load. It was also observed that cognitive load differed depending on gender, LMS experience, and academic success level. The study emphasises that individual differences should be considered in LMS design. In addition, the concept of cognitive load in digital education environments has become increasingly important for understanding the relationship between students and various influencing factors. It is suggested that cognitive load can be reduced in LMS with future improvements.

Keywords: Cognitive Load, LMS, NASA-TLX, Programming Course

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1. Introduction

The learning management system (LMS) is one of the most fundamental tools of digital transformation in the educational environment. LMS is defined as web software that manages learning processes in the Internet environment [1]. These systems have played a critical role in transferring education and training activities to a digital environment. In this context, the experiences students encounter during the LMS use process have been the subject of many studies. It has been concluded that what students perceive while using LMS is related to ease of use, technological self-sufficiency, and the interface design of the system [2]. In the comparison of students' face-to-face and online education experiences, students' prejudice against LMS and external factors negatively affected learning [3].

LMS used for online learning adds new perspectives to learning. User experience, interface design, and functionality have been the main factors affecting student performance in the LMS environment [4]. These systems have caused changes in students' cognitive load factors. It is very important to understand the level of cognitive load of students in the LMS environment and to optimize this load. Cognitive Load Theory (CLT) covers the effective use of mental capacity in learning [5]. It should be taken into consideration when learning takes place in a technological environment such as LMS. While a task is being performed in the learning process, there are three basic demands on the mind: intrinsic cognitive load, extrinsic cognitive load, and meaningful cognitive load [6]. The effective completion of the learning process in the LMS environment is closely related to the cognitive load level.

There are important studies in the literature on the cognitive load of students in LMS environments. In a special journal issue created on cognitive load theory, many cognitive load studies have been conducted [7]. There are also studies examining the effect of student control on cognitive load and performance. In asynchronous online learning environments, a relationship between cognitive load and self-regulated learning skills has been observed [8]. [9], examined students' perceptions of cognitive load and the effect of this load on learning while online learning was carried out. In the study, cognitive load was evaluated with the dimensions of learning quality, content quality, and LMS design. Log data, session time, and click count variables were used to estimate cognitive load in the LMS environment. Cognitive load models were created using LMS log data (e.g. session times, click counts), and these models were used to identify students experiencing high cognitive load [10]. In another study, it was concluded that visual and textual materials in the LMs environment reduced internal and external cognitive load, while additional materials increased [11].

The problem of this study is what is the cognitive load level of students while performing a task in the Moodle LMS environment. The aim is to analyze the cognitive load level in the LMS environment depending on the individual characteristics of the students, their academic success in the course, and their previous LMS experience. The cognitive load of university students taking the Programming course in the LMS environment is included in the scope of this study. The limitations of the study are that it was conducted with a small group of students and that it was not generalized for all courses. The study aims to improve the student experience and to give cognitive load theory a wide place in the design of LMS.

2. Experiments

The study was conducted with the voluntary participation of 35 students studying in the computer programming department. Students were given tasks to learn a topic on Moodle, solve questions about the topic, and complete a given assignment. The purpose of assigning these tasks was to assess the cognitive load experienced by students while completing them. After students completed these tasks, their cognitive load levels were measured. First, a reading text was presented to the students in Moodle. The purpose of this activity was explained to the students in the reading text. The aim of the activity was for the student to learn the topic of Polymorphism in Java and 4 tasks were given to complete this activity. The student was informed that these tasks had to be completed in a total of 40 minutes. The requirement to complete the tasks within specific time frames is crucial for assessing whether the student experiences cognitive load related to time. Also, students were informed that they would receive a homework grade if they completed all the tasks in the given time. This is important in order to see the effect of performance on cognitive load. The scope of the study was determined as learning the topic of Polymorphism in Java in the LMS, solving questions, and explaining what they learned. Student's homework answers were not checked, only that they completed the task was important. Future selection analyses were performed using the data obtained because of this measurement in the R Studio. The analyses investigated the features affecting cognitive load and the relationship between these features.

2.1. Tasks

The tasks given to the students are as follows.

- Try to learn the subject in the best way possible by reading the presentation named 'Polymorphism' on Moodle.
- Answer the exam named ‘Quiz’ on Moodle. There are 5 test questions in the exam. The

exam duration is 8 minutes.

- Download the added document from the homework area on Moodle. After writing what you have learned about the subject in a few sentences in the document, add a sample code related to the subject. Save your document and upload it to the homework area on Moodle.
- After the document upload is completed, answer the 'Cognitive Load Scale' on Moodle.

2.2. Cognitive Load Measurement

In order to measure the cognitive load (NASA workload index test named "NASA TLX: Task Load Index") was used. Designed by Hart and Staveland (1988), it is a subjective measurement method used to measure the cognitive resources required to perform a task and the perceived cognitive workload of the task according to the person performing that task [12]. NASA-TLX method subjectively measures and evaluates the workload of an action in six factors: mental demand, physical demand, temporal demand, performance, effort, and frustration. It is a method consisting of three stages: 1-proportioning. 2-weighting and 3-determining general workload. In the proportioning stage, the effect of the six sub-factors on the work performed; the scale created between "very low" and "very high" is determined. According to these markings, the values corresponding to scores between 0-100 are unweighted workload values. In the second stage, the weighting stage, each participant weighs six factors in proportion to their contribution to the workload. The Pairwise Technique (PWT), also known as the pairwise comparison technique, is used to determine the weights. In this technique, 15 comparisons are made to compare the level of importance between the six factors. Participants mark the criterion that they think contributes the most to the workload during pairwise comparisons. Thus, the number of times each criterion is selected, that is, the frequency value, is obtained. At the end of the counting, the value obtained for the six factors is divided by 15 to obtain the weight value for that factor. In the final stage, the general workload index is obtained by combining the results of the ratio and the weight value of each criterion [12].

3. Results and discussion

In this section, a correlation matrix and heat map were used to summarize the participants' demographic characteristics, cognitive load levels, and the relationships between the variables.

```
  Gender        Age         Experience Moodle.Difficulty Midterm.Score   Course.Difficulty
 Man  :20   Min.   :19.00   No :10     No :27            Min.   :48.00   Hard: 7
 Woman:15   1st Qu.:19.00   Yes:25     Yes: 8            1st Qu.:64.00   Mid :28
            Median :20.00                                Median :72.00
            Mean   :20.11                                Mean   :72.46
            3rd Qu.:20.00                                3rd Qu.:84.00
            Max.   :25.00                                Max.   :92.00
   Time        Result
 0-20 : 6   High  : 9
 20-30: 7   Low   : 4
 31-40:16   Middle:22
 41+  : 6
```

Figure 1. General report of dataset

Students' cognitive load levels were analyzed in terms of their characteristics such as gender, age, experience, Moodle-difficultly, midterm score, course-difficulty, and time. The findings obtained according to these variables are presented in detail in Figure 1.

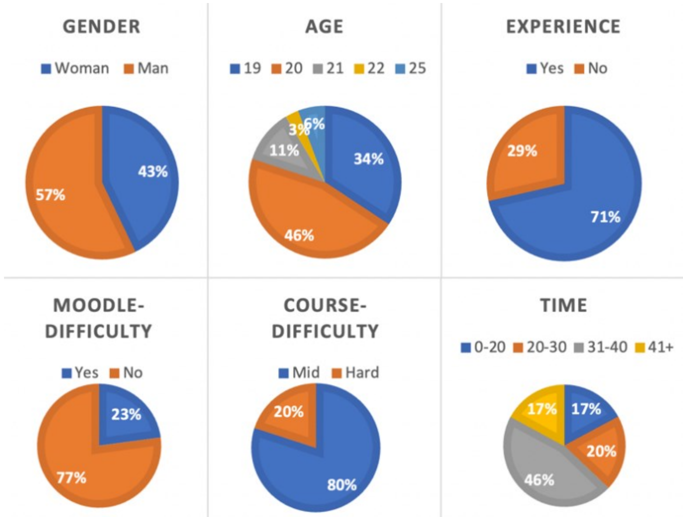

Figure 2. Percentage distribution of gender, age, experience, moodle-difficulty, course - difficulty, and time.

15 female and 20 male students have participated in the study. There are 25 students with previous LMS experience and 10 students who are experiencing LMS for the first time. The student's success in the course has been categorized according to his midterm exam grade. Participating students have exam grades between 48 and 92. They are between 19 and 25 years old. The percentage distribution of gender, age, experience, moodle-difficulty, course - difficulty, and time are shown in Figure 2.

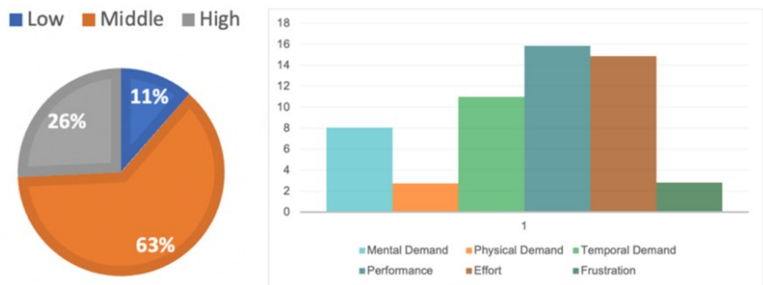

Figure 3. Cognitive load comparison by distribution of factors.

In the measurements made with NASA TLX, the average cognitive load score of the students was found to be 55. The cognitive load values of six factors, namely mental demand, physical demand, temporal demand, performance, effort, and frustration are shown in Figure 3. The cognitive loads of the students were divided into 3 categories as low, medium and high.

```
                       Gender          Age  Experience Moodle.Difficulty Midterm.Score
Gender             1.000000000 -0.009229615  0.29211870       -0.05892557   -0.37093652
Age               -0.009229615  1.000000000  0.19884055       -0.10514632    0.03397062
Experience         0.292118697  0.198840546  1.00000000       -0.10758287   -0.09764774
Moodle.Difficulty -0.058925565 -0.105146316 -0.10758287        1.00000000    0.10844103
Midterm.Score     -0.370936524  0.033970616 -0.09764774        0.10844103    1.00000000
Course.Difficulty -0.144337567 -0.186505217  0.15811388       -0.23814484   -0.01422992
Time              -0.473417127 -0.193424526 -0.43216873        0.14663477    0.06679346
Result            -0.076747111 -0.308416599 -0.12793603       -0.20842212    0.10041832
                  Course.Difficulty        Time       Result
Gender                 -0.144337567 -0.47341713 -0.076747111
Age                    -0.186505217 -0.19342453 -0.308416599
Experience              0.158113883 -0.43216873 -0.127936029
Moodle.Difficulty      -0.238144836  0.14663477 -0.208422125
Midterm.Score          -0.014229920  0.06679346  0.100418322
Course.Difficulty       1.000000000  0.12765296  0.004128258
Time                    0.127652956  1.00000000  0.179497048
Result                  0.004128258  0.17949705  1.000000000
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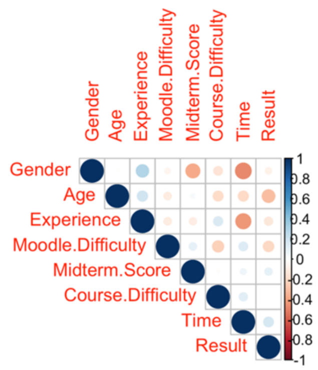

Figure 4. Correlation matrix and heat map.

Correlation matrix and heat maps were created with future selection methods. The effects of values and features affecting cognitive load on each other are seen in Figure 4. In addition, Recursive Feature Elimination analysis was performed to determine the 3 most significant variables for cognitive load. Age, Time, Moodle-Difficulty were seen as the 3 most important variables.

4. Conclusion

The study aimed to measure the cognitive load level of students learning Polymorphism in the Object-Oriented Programming course in an LMS environment. The study was conducted with 35 students and the NASA-TLX scale was used for cognitive load measurement. The findings were evaluated within the scope of age, experience, Moodle-difficultly, midterm score, course-difficulty, time, and cognitive load factors. When the correlation values are examined, it is seen that they are generally at a medium-weak level. Therefore, it was not possible to see direct strong relationships for this study. However, the existence of some relationships is clear.

The highest negative correlation is seen with age. As age increases, cognitive load decreases. It has been observed that cognitive load decreases as the feeling of difficulty in using Moodle increases. It has also been observed that the cognitive load of students who need more time management increases. In this context, the student's self-regulation skills should also be taken into account in such a study. When cognitive load was examined according to gender, it was determined that female students had higher cognitive load than male students. A strong negative relationship is seen between gender and time spent on the task. There may be changes in the level of cognitive load depending on the individual characteristics of the students. In this context, it is necessary to include many individual differences, not just gender-focused ones, in the evaluation [13]. When the cognitive load was examined according to LMS experience, it was seen that experienced students had a higher cognitive load. As the student's past experience increases, cognitive load decreases. When cognitive load was examined according to the student's success in the course, it was seen that students who received higher scores in the course had higher cognitive load. The fact that students with high academic performance have more cognitive load indicates that they need more mental effort while completing tasks in the LMS environment [14]. The general cognitive load average for all students was calculated as 55 and this value was classified as a moderate cognitive load according to the NASA-TLX scale. When the students' cognitive loads are examined according to the factors, they are seen as Performance, Effort, Temporal demand, mental demand, frustration, and physical demand, respectively, from high to low. Performance, with the highest score, shows that students showed high performance while performing the task. In addition, high effort is a problem compatible with performance. The possibility of students experiencing time anxiety can be explained by the high temporal demand factor. It has also been observed that the cognitive load of students who need more time for time management increases. In this context, the student's self-regulation skills should also be taken into account in such a study. It can be concluded that the physical demand is low because of the student's study in a technological department. On the other hand, the fact that the tasks are defined in detail in the first reading text given to the student and the time given is sufficient can be thought to be related to low frustration. Of these factors, mental demand, physical demand, and temporal demand represent the characteristics of the task; performance and effort represent the behavioral characteristic; disappointment constitutes the individual characteristic. In this context, it can be said that the most difficult part for students is the behavioral characteristics of the task.

This study shows that LMS usage creates a moderate cognitive load on students. It has been concluded that variables such as age, difficulty in using Moodle, and time affect cognitive load. The study is supported by descriptive statistics and graphs. This provides a general overview of the field. This study will make an innovative contribution to the studies in the literature by analyzing cognitive load in LMS using future learning techniques.

4.1 Future Works

This study has opened an area for future studies, as statistical analyses were not carried out in detail. In the study that developed a prototype to predict students' learning styles and cognitive characteristics through LMS, it was stated that the instructor load could be reduced with such studies [15]. Prototype development studies can be continued by considering such studies. In software developed for e-learning, a study aiming to improve distance education suggests incorporating technological infrastructures into the system that allow a virtual assistant to guide the student and to continuously update the education in distance education management systems [16]. The contribution of systems such as chatbots to the student's cognitive load can be measured by the design. In addition, according to this scale, the high cognitive workload required by the task has been associated with stress [17]. In this context, the relationship between the student's anxiety and stress should also be examined in cognitive workload studies. Data-based predictions can be made with machine learning methods. These methods allow for cognitive load estimation to improve user experience in the LMS environment. In this context, student individual characteristics, performance data, and behaviors in the system stand out as important inputs in cognitive load analysis. In the future, design improvements can be suggested to reduce cognitive load while students are learning with the LMS. In addition, the generalizability of these findings can be tested with similar studies conducted in different branches and larger sample groups.

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Authors' Declaration

There is no conflict of interest to declare.

Authors' Contribution Statement

Authors have equal contribution rates in all processes of the study.

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