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PAPER

Evaluation of Attendance at the Glossary Activity in a Technically Oriented E-Learning Course

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ABSTRACT

During the COVID-19 pandemic, online education became increasingly attractive once again. This was mainly due to the fact that, during the peak of the current epidemic, schools at various levels were closed. To enable pupils and students to continue their studies, teaching was transferred to a safer online space. In this paper, we focus on the use of the Dictionary of Foreign Technical Terms (ENG-SLO) activity to determine the extent to which participants need this dictionary to explain unfamiliar technical terms. To obtain relevant results using this activity, we decided to test the frequency of its use (visits) and rank each participant according to the resulting evaluation. As the experiment was conducted in vocational high schools, we kept the familiar rating scale of these schools, ranging from one to five, where 1 is the best rating and 5 the worst, indicating a failure. The results indicate that above-average use was recorded among participants who failed and those who scored 4, while the other scoring groups used the glossary activity rather below average.

KEYWORDS

didactic effectiveness, evaluation, grade, lift, study materials

1 INTRODUCTION

Online education, derived from distance learning, has a long tradition worldwide. It originated from times when students (whether due to long distances, illness, or other obstacles) could not be in daily direct contact with their instructors [1]. Online education has its advantages and disadvantages, which have been frequently discussed by researchers and the professional community [2], [3].

From the perspective of higher education, universities are institutions that play a key role in supporting their students' academic success [4]. In pandemic situations, where contact needed to be significantly limited, online education played a crucial role [5]. During the recent COVID-19 pandemic, when schools were intermittently closed (not uniformly across all countries) from 2019 to 2021, online education represented the only form of student-teacher social interaction [6]. However, the

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main problem with online education turned out to be its challenging application across all levels and various fields of education. Teachers had to improvise; for example, in physical education, instructors would demonstrate exercises in front of a camera, which students watched on their monitors. Similar approaches were taken in music and art education. Where personal teacher contact was necessary, ingenuity and simple solutions helped ensure that students felt a sense of personal connection with their instructors [7].

In vocational schools with a technical focus, the situation was even more complicated. For instance, schools with a chemistry focus had difficulties conducting professional chemical experiments or had to limit them to ensure students' safety [8], [9]. In such cases, teachers often performed the experiments themselves, without the possibility for students to repeat them. Similarly, schools focused on computer science and electrical engineering, specifically microprocessor programming (e.g., programming the Arduino microcontroller), faced challenges [10]. Typically, students would regularly attend these schools and participate in practical laboratory exercises. They would use electronic components, properly connecting them to the Arduino microcontroller based on instructions, and then program them as directed by the teacher. However, during the pandemic, all these opportunities were eliminated. Teachers had to provide an adequate substitute (e.g., TinkerCad) to ensure that students did not miss out on acquiring knowledge and skills [11].

As mentioned in the paper [12], this method of education had its limitations. It was particularly interesting, from the perspective of time efficiency, to observe how students managed not only with the hardware but also with creating specific software.

Currently, as schools have long returned to their original regime, it is very important and interesting to analyze the data [13] on how teachers and students utilized the online environment to acquire and develop their knowledge and skills. This can help us not only understand individual behaviors [14] but also eliminate problematic parts of the educational process [15], [16].

The paper describes the way the glossary activity is used by students at four secondary schools focused on technical education. The glossary activity is of great importance to students, as it helps them more easily understand the meaning of foreign, technically oriented terms. During the COVID-19 pandemic, when direct face-to-face interaction between teachers and students was lacking, this activity proved to be extremely valuable. In Section 2, we present studies that had the most significant impact on research related to data collection and processing in the field of educational data mining (EDM). The results of these studies allow other researchers to better understand student behavior in e-learning environments, uncover potential issues related to the didactic effectiveness and efficiency of study materials, and propose appropriate learning strategies. In Section 3, we outline the approach we used in the experiment to obtain the necessary results. In Sections 4 and 5, we present the complete results along with their evaluation.

2 RELATED WORK

The role of the teacher has evolved into that of a mentor or coach. E-learning, with its advantageous features, is attracting increasing attention. Particularly during the pandemic crisis, there was a sudden shift from traditional face-to-face learning to e-learning systems in many parts of the world [17]. Engineering education is one of the applied disciplines that requires practical laboratories and design experience [18]. Despite this, e-learning at that time provided virtual laboratories, simulations, and opportunities for various experiments [19]. Technical subjects have a specific characteristic: practical experience. Therefore, they are very difficult to replace with traditional teaching methods. The current innovative methods in engineering pedagogy include the use of non-standard methods that combine traditional teaching methods with new trends, for example, the use of virtual reality [20], [21], and artificial intelligence [22], [23], such as ChatGPT [24], [25], [26]. According to a study [27], standard teaching methods can be applied to technical subjects, but a sufficiently diverse range of activities must be used to support students' critical thinking, along with the development of their knowledge and skills. The study examined and analyzed the effects of these methods, with educational activities divided into theoretical and practical sessions, self-tests, assignments, and solutions. According to the results of the student satisfaction survey, blended learning demonstrated higher satisfaction than simply providing study materials without feedback. There is no single teaching method that can fully achieve educational goals, which is why a combination of methods is necessary. Teaching technical subjects in technically oriented schools is even more challenging due to fundamental issues such as a lack of specific laboratories, a shortage of teachers with broad knowledge, and poor funding for these institutions [28]. Currently, researchers are focusing on studying the implementation of strategies for developing critical thinking skills in technical subjects across various types of schools (from elementary to universities), with an emphasis on cognitive, interpersonal, technical, and communication skills [29]. It is important that the provided study materials are not merely static but actively stimulate the student's imagination through various prompts (electronic interactive teaching materials – EITMs). A study conducted in 2022 showed that students who used EITMs demonstrated a higher success rate in mastering the material compared to those who used static study materials (e.g., PDFs) [30].

In the case of technically oriented subjects, it is crucial to ensure that students understand the correct meaning of technical terms and can apply them correctly [31], [32]. Misunderstanding the meaning of a technical term can result in students failing to grasp the content of the study material (or misunderstanding it), leading to a decrease in academic success [33].

The application of data mining methods in the field of education (EDM) is not a novel topic. For more than 15 years, it has been actively used to discover new and potentially useful information or meaningful results from large volumes of data [34], [35], [36], [37] generated by various systems using different classification algorithms [38], [39]. EDM can be used not only to obtain and process data on educational outcomes (e.g., exam results) but also to analyze student participation in online classes and the way they interact with online courses. It is an effective tool for uncovering hidden patterns of student behavior in a course, predicting their academic results, and setting appropriate teaching styles [40] to enhance the didactic effectiveness and time efficiency of online course use [41].

In terms of defining academic success, it involves achieving educational goals, acquiring the required skills, and developing competencies concerning satisfaction, persistence, and postgraduate performance [42]. One possible measure is to use an appropriate predictive model within the LMS to forecast student behavior [43]. Many researchers therefore address this issue by designing and testing suitable predictive models [44]. For example, [45] reduced academic failure by 14% with their predictive model compared to the previous academic year's results. The percentage by which didactic effectiveness can be increased or academic failure can be reduced is highly individual and depends on several factors (student age, social policy, current emotional state of the students, etc.). For example, Pecuchova [46] using the CRISP-DM analysis methodology points out which factors characterize student performance and interactions in a course. These can be considered the most significant for identifying students at risk of dropping out. The results showed that overall accuracy and F1 score improved by 2–4%.

Previous research in predictive models also indicates that predicting academic performance [47] is not only dependent on the time required for study [48] but also on identifying the level of professional knowledge among all students, unifying baseline knowledge, and setting appropriate strategies to increase interest in learning and understanding technical (terminological) terms [49], [50], [51].

3 MATERIALS AND METHODS

During the COVID-19 pandemic, schools in Slovakia were intermittently closed from 2020 to 2022. Some primary, secondary, and higher education institutions transitioned to various online education platforms. They primarily used Google's Meet system, but most schools also used the LMS Moodle for communication, assignment submission, and assessment. Through LMS Moodle, teachers (tutors), in cooperation with the Meet system, could provide students not only with professional explanations in real-time but also guide them during testing and the use of various activities in LMS Moodle. Data on the use of the e-learning course focused on programming the Arduino microcontroller was obtained from the following four vocational secondary schools:

- Secondary Vocational School of Technology and Services, Pod amfiteátrom 7, Levice,
- Secondary Industrial School of Mechanical Engineering and Electrical Engineering, Ul. Františka Hečku 25, Levice,
- Secondary Vocational Technical School, Vráble
- Secondary Vocational Technical School, Kozmálovská cesta 9, Tlmače.

The course was conducted as part of the experiment from September 2022 to January 2023. A total of 213 participants attended the course. To evaluate the method of work, we used log files based on the number of participants, activities, and behaviors within the course.

We conducted the statistical evaluation of participant activity within our course by analyzing log files. With the output from a sophisticated logging system integrated into the LMS Moodle and the Treport plugin [52], we can obtain a detailed overview of behavioral data categorized by individual participants. The records typically include the following attributes:

- participant id,
- name and surname of the participant (anonymized to comply with GDPR),
- name of sessions,
- number of clicks (*count_of_clicks*) within the course,
- number of running sessions (*count_of_session*),
- total time spent in the course (*total_time*), and
- residual information (*residuals*), unimportant data for us.

Overall, the following supportive study materials were created for students on the various topics:

- Course definition: This topic is purely informational for course participants and includes an introductory test.

– Basics, introduction, minimum
– Requirements: As the name suggests, this topic covers the theoretical basics of microcontrollers and the additional tools required to work with them.
– First programs, basic components of working programs, serial communication: This topic focuses on practical work with the microcontroller, either standalone or in collaboration with a PC.
– Using external components: This topic expands the capabilities of the microcontroller to interact with the external world (sensors, control, etc.).
– What components can we control with simple logic or analog signal? A general topic aimed at introducing various available external components controllable by logic and analog signals and how to work with them.
– Finalization of knowledge: The concluding topic, which includes a summary and an exit test.

Since each topic contained numerous technical terms, we created a glossary of foreign technical terms as an activity within the course. The terms were translated from technical jargon in English into the natural Slovak language of the participants. Our goal in the experiment (during data analysis) was to determine the extent to which participants needed explanations for potentially unfamiliar technical terms. To obtain relevant results on the use of this activity, we decided to test the frequency of visits and classify each participant according to their final evaluation.

As the experiment was conducted in vocational secondary schools, we maintained the familiar grading scale used in these schools, ranging from 1 to 5, where 1 is the best grade and 5 is the worst – failure. After participants completed the course, we manually and automatically assessed their knowledge through testing. Subsequently, we organized the results into a table for each participant and provided a final evaluation for each. We used the percentages summarized in Table 1 for grading purposes.

Table 1. Percentage grading based on points earned

Score (%)	Grade
0–59	5
60–69	4
70–79	3
80–89	2
90+	1

4 MAIN RESULTS

These segments were identified based on the usage patterns observed among the students during the course:

– First segment: Consisting of components such as book, forum, and glossary
– Second segment: Comprising components such as assignment, file submissions, and page
– Third segment: Including components such as quiz, URL, and User tours
– Fourth segment: Consisting of the system component

From the results of Table 2, it is evident that the glossary most frequently appeared alongside the components book and forum.

Table 2. Frequency of sessions in each component

Frequent Itemsets	Number of Items	Frequency	Support (%)
Book, Forum, Glossary	3	66	33
Assignment, File submissions, Page	3	79	39.5
Quiz, URL, User tours	3	90	45
System	1	200	100

This table can also be represented by the graph (see Figure 1).

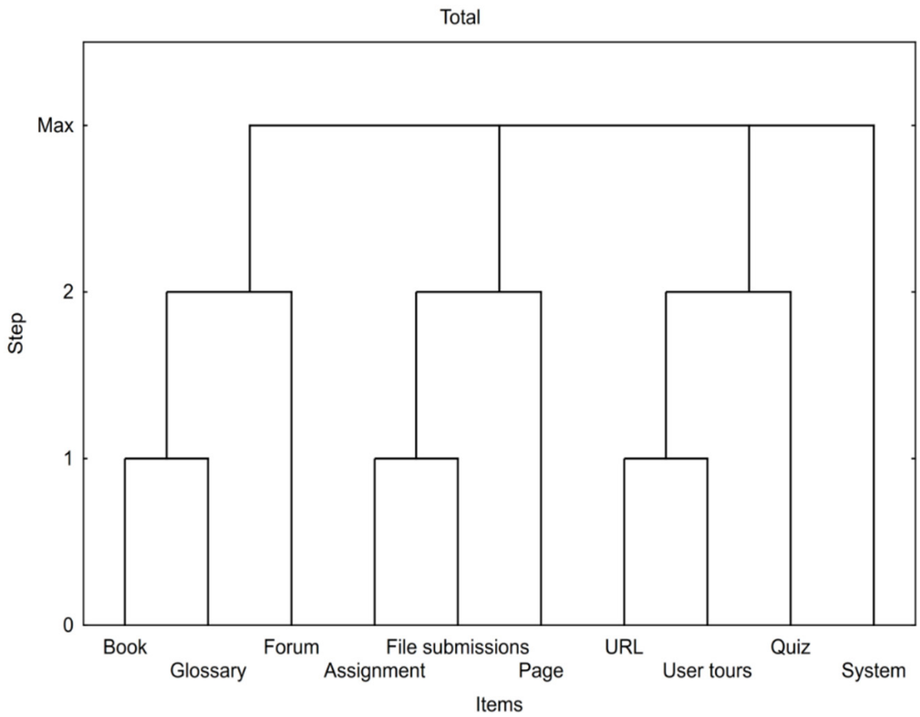

Fig. 1. Cluster of frequent itemsets, total

The following association rules were extracted under the conditions min: support = 20.0%, confidence = 10.0%, max. size of an itemset = 3, conclusion (head) rulers = glossary.

We have extracted a total of 43 rules (*Valid N* = 43) with an average characteristic lift of 1.632 (*Lift Mean* = 1.632), as shown in Table 3.

Table 3. Summary of association rules with selected items, total

Body	==>	Head	Support (%)	Confidence (%)	Lift
Book, URL	==>	Glossary	31.000	89.855	2.275
Book, User tours	==>	Glossary	30.000	89.552	2.267
Assignment, URL	==>	Glossary	29.000	84.058	2.128
Book, Forum	==>	Glossary	33.000	77.647	1.966

(Continued)

Table 3. Summary of association rules with selected items, total *(Continued)*

Body	==>	Head	Support (%)	Confidence (%)	Lift
Book, Quiz	==>	Glossary	35.000	76.087	1.926
Forum, URL	==>	Glossary	34.000	75.556	1.913
Assignment, User tours	==>	Glossary	28.000	73.684	1.865
Book	==>	Glossary	35.000	73.684	1.865
Book, System	==>	Glossary	35.000	73.684	1.865
Book, Page	==>	Glossary	35.000	73.684	1.865
Assignment, Book	==>	Glossary	32.000	73.563	1.862
Assignment, Forum	==>	Glossary	31.000	72.941	1.847
Forum, User tours	==>	Glossary	32.000	72.727	1.841
Quiz, URL	==>	Glossary	35.000	71.429	1.808
File submissions, Forum	==>	Glossary	21.000	71.186	1.802
Book, File submissions	==>	Glossary	22.000	68.750	1.741
Forum, Page	==>	Glossary	36.500	66.972	1.696
Page, URL	==>	Glossary	35.000	66.667	1.688
Forum, Quiz	==>	Glossary	36.500	66.364	1.680
Forum	==>	Glossary	36.500	65.766	1.665
Forum, System	==>	Glossary	36.500	65.766	1.665
URL, User tours	==>	Glossary	32.000	65.306	1.653
URL	==>	Glossary	35.000	64.815	1.641
System, URL	==>	Glossary	35.000	64.815	1.641
Assignment, Page	==>	Glossary	33.000	61.682	1.562
Page, User tours	==>	Glossary	34.500	61.607	1.560
Assignment, Quiz	==>	Glossary	33.000	61.111	1.547
File submissions, Quiz	==>	Glossary	22.500	58.442	1.480
Assignment	==>	Glossary	33.000	57.391	1.453
Assignment, System	==>	Glossary	33.000	57.391	1.453
File submissions, Page	==>	Glossary	22.500	56.962	1.442
Page, Quiz	==>	Glossary	39.500	56.429	1.429
Assignment, File submissions	==>	Glossary	22.500	55.556	1.406
File submissions	==>	Glossary	22.500	55.556	1.406
File submissions, System	==>	Glossary	22.500	55.556	1.406
Quiz, User tours	==>	Glossary	34.500	54.762	1.386
Page	==>	Glossary	39.500	50.968	1.290
Page, System	==>	Glossary	39.500	50.968	1.290
User tours	==>	Glossary	34.500	48.592	1.230
System, User tours	==>	Glossary	34.500	48.592	1.230
Quiz	==>	Glossary	39.500	48.171	1.220
Quiz, System	==>	Glossary	39.500	48.171	1.220
System	==>	Glossary	39.500	39.500	1.000

Explanation of Table 3: Body is the premise of the rule, Head is the conclusion of the rule, and support is the probability with which the set of components (in this case: book, URL, glossary) appears in the identified sessions. Confidence is the conditional probability, meaning in this case, if components Book and URL appear in sessions, then Glossary appears with a probability of 90%.

Lift is the correlation between the premise and the conclusion of the rule. If it is greater than one, there is a positive correlation (the components in the premise occur more frequently together with Glossary in sessions than separately). If it equals one, there is independence, and if it is less than one, there is a negative correlation (the components in the premise occur more frequently separately from Glossary in sessions).

In this case, the components Book and URL occur together with the component Glossary 2.275 times more frequently than separately. From these results, it is evident with which components and their combinations Glossary appeared most frequently in sessions. By evaluating each participant, we were able to add another value called *GRADE* to the log files to evaluate the frequency of use of the glossary activity for each category of students. During evaluation, we filtered out from the log files and final score matrix those participants who did not meet all the course completion criteria (did not complete the entire course). We took this step to avoid biased data with a higher number of final grade five results (refer to Table 4). In total, there were 35 participants affected.

Table 4. Cluster of frequent itemsets, including condition: *Grade* = "unclassified"

Frequent Itemsets	Number of Items	Frequency	Support (%)
Book, Forum, Glossary	3	31	24.2188
Assignment, File submissions, Page	3	37	28.9063
Quiz, URL, User tours	3	57	44.5313
System	1	128	100.0000

Summary of association rules with selected items, *Valid N* = 35, *Lift Mean* = 1.856. We include the condition: *Grade* = "unclassified" (refer to Table 5).

Table 5. Summary of association rules

Body	==>	Head	Support (%)	Confidence (%)	Lift
Book, URL	==>	Glossary	23.4375	88.23529	2.895928
Book, User tours	==>	Glossary	24.21875	86.11111	2.826211
Book, Forum	==>	Glossary	24.21875	70.45455	2.312354
Book, Quiz	==>	Glossary	25	69.56522	2.283166
Forum, URL	==>	Glossary	27.34375	68.62745	2.252388
Assignment, User tours	==>	Glossary	21.09375	65.85366	2.161351
Forum, User tours	==>	Glossary	28.125	65.45455	2.148252
Book	==>	Glossary	25	65.30612	2.14338
Book, System	==>	Glossary	25	65.30612	2.14338
Book, Page	==>	Glossary	25	65.30612	2.14338
Assignment, Forum	==>	Glossary	20.3125	63.41463	2.081301

(Continued)

Table 5. Summary of association rules *(Continued)*

Body	==>	Head	Support (%)	Confidence (%)	Lift
Quiz, URL	==>	Glossary	28.125	63.15789	2.072874
Assignment, Book	==>	Glossary	21.09375	62.7907	2.060823
URL, User tours	==>	Glossary	28.125	59.01639	1.936948
Page, URL	==>	Glossary	28.125	58.06452	1.905707
Forum, Quiz	==>	Glossary	28.90625	57.8125	1.897436
Forum, Page	==>	Glossary	28.90625	57.8125	1.897436
URL	==>	Glossary	28.125	57.14286	1.875458
System, URL	==>	Glossary	28.125	57.14286	1.875458
Forum	==>	Glossary	28.90625	56.92308	1.868245
Forum, System	==>	Glossary	28.90625	56.92308	1.868245
Page, User tours	==>	Glossary	29.6875	54.28571	1.781685
Assignment, Quiz	==>	Glossary	21.875	50.90909	1.670862
Assignment, Page	==>	Glossary	21.875	50	1.641026
Page, Quiz	==>	Glossary	30.46875	47.56098	1.560976
Assignment	==>	Glossary	21.875	46.66667	1.531624
Assignment, System	==>	Glossary	21.875	46.66667	1.531624
Quiz, User tours	==>	Glossary	29.6875	46.34146	1.520951
Page	==>	Glossary	30.46875	42.3913	1.391304
Page, System	==>	Glossary	30.46875	42.3913	1.391304
User tours	==>	Glossary	29.6875	41.30435	1.35563
System, User tours	==>	Glossary	29.6875	41.30435	1.35563
Quiz	==>	Glossary	30.46875	39	1.28
Quiz, System	==>	Glossary	30.46875	39	1.28
System	==>	Glossary	30.46875	30.46875	1

Similarly, we created association rules for participants who achieved a grade of one to four. In the following tables (refer to Table 6a, b, c, d), we provide summaries for individual conditions, including the *Grade* = 1–4 value.

Table 6a. Cluster of frequent item sets, including condition: *Grade* = 1

Frequent Item Sets	Number of Items	Frequency	Support (%)
Book, Forum, Glossary	3	13	52
Assignment, File submissions, Quiz	3	17	68
Page, URL, User tours	3	9	36
System	1	25	100

Table 6b. Cluster of frequent item sets, Include condition: *Grade* = 2

Frequent Item Sets	Number of Items	Frequency	Support (%)
Glossary, URL, User tours	3	4	36.3636
Book, Forum	2	9	81.8182
Assignment, File submissions	2	8	72.7273
Page, Quiz	2	11	100
System	1	11	100

Table 6c. Cluster of frequent item sets, Include condition: *Grade* = 3

Frequent Item Sets	Number of Items	Frequency	Support (%)
Book, File submissions, Glossary	3	8	36.36364
Assignment, Forum, URL	3	10	45.45455
Page, Quiz	2	17	77.27273
System, User tours	2	17	77.27273

Table 6d. Cluster of frequent item sets, Include condition: *Grade* = 4

Frequent Item Sets	Number of Items	Frequency	Support (%)
Book, Glossary, URL	3	9	60
Assignment, File submissions, Forum	3	7	46.6667
Page, Quiz, User tours	3	10	66.6667
System	1	15	100

5 DISCUSSION

Various studies have analyzed user behavior in e-learning courses [14], [46]. However, if we focus on the COVID-19 pandemic period, it becomes interesting to analyze which tools in the Moodle LMS were most frequently used during the pandemic [53], [54], [55]. Such analyses are important not only for understanding user behavior but also for determining the significance of specific activities (plugins) in a course and developing them further. For instance, a study by Lapevska et al. [56] shows that the total number of activities used in their university's Moodle LMS in 2020 increased threefold compared to the same period in 2019. In the case of the Glossary activity, which recorded 4,932 accesses in 2019, this number rose to 6,503 in 2020. The study does not specify the number of students who actively used Moodle during the pandemic in 2019 and 2020.

According to a study focused on teaching and learning styles in Moodle, published in 2021, participants who achieved a higher success rate in mastering the material utilized 66.55% of all available activities in Moodle LMS, while average and below-average students used only 33.33% of them. However, there are activities that both groups consistently used ("Assignment," "Feedback," "Forum," "Glossary," "Quiz") at an average rate of 30%. Participants with better grades, according to the study, used more resources and activities in Moodle LMS, which may be related to enhancing all metacognitive skills. On the other hand, participants with poorer academic results primarily used activities related to orientation and planning skills, likely compensating by using other skills. This is also confirmed by our findings, although we observe a key difference in how they approached the activities from the perspective of their overall success rate.

As we can see from the individual tables (refer to Table 6a–d), participants approached the glossary activity differently based on their achieved grades. For instance, participants with a *Grade* = 1 first read the book activity, then contributed to or extracted information from the forum, and only afterwards engaged with the glossary activity. Interestingly, participants with *Grade* = 2 accessed the glossary activity first, followed by navigating through URLs, and then accessed the book activity to study the necessary study materials. Participants with *Grade* = 3 first studied the materials using the book activity, submitted their assignments (file submissions activity), and then accessed the glossary activity to better understand technical terms. Participants who achieved the lowest acceptable grade, *Grade* = 4, transitioned from the book activity to the glossary activity and subsequently used URLs to check grades, submit assignments, or visit the forum activity.

Finally, we summarized the correlations and calculated the median (refer to Table 7) to determine if the glossary activity was used above or below average in each grade category.

Table 7. Overall summary of correlations.

Grade	Valid N	Lift Mean
Grade = 1	45	1.379
Grade = 2	44	1.251
Grade = 3	44	1.467
Grade = 4	45	1.480
Grade = "unclassified"	35	1.856

The median lift value was 1.470. As we can see from Table 7, above-average usage was observed among the unclassified participants and those with a grade of four. The other grading groups used the glossary activity less than average.

It follows that students do not always approach the completion of activities containing study materials (such as the book module) in the same way. This essentially depends on the fundamental technological resources they have at their disposal. Analysis of the available data also shows that the glossary activity was used by all students, regardless of their performance, though its use was also a matter of priority (students with lower grades used it more frequently). The glossary activity plays a significant role in acquiring and reinforcing knowledge; however, its importance should be enhanced through additional activities (e.g., feedback).

6 CONCLUSIONS

In this paper, we analyzed the behavior of participants in an e-learning course in terms of their achieved grades and their usage of the glossary activity, which helped them understand technical terms. The e-learning course focused on supporting high school students in the subject of computer science, specifically in programming the Arduino microcontroller. The results indicate that students who achieved excellent (or even average) grades did not need to access the glossary activity as frequently as students with low grades (*grade* = 4 and "unclassified"). This suggests that while students with low grades did not demonstrate increased didactic efficiency, they were interested in the content and actively sought out the necessary information themselves. This factor is particularly important because these students need support in their further studies, which could better develop their skills and abilities. Neglecting supervision of these students could risk their disinterest in studying and possibly lead to inadequate grades in other subjects as well. According to our findings, the glossary activity can positively influence the educational process. Study materials in electronic form often contain complex technical terms that not every student may immediately understand. In this regard, the glossary activity can, to some extent, substitute for a teacher who would otherwise explain the technical term. However, our data analysis revealed that not all students used this activity in the same way. In future research, it would be beneficial to focus on whether the way the term was explained helped students understand the subject matter correctly. Therefore, we believe that the glossary activity should also include a feedback option.

7 STATEMENTS AND DECLARATIONS

The authors declare no conflicts of interest. This study was approved by the Ethics Committee, number UKF/556/2024/191013:002. The authors confirm that all subjects provided appropriate informed consent and that details of how this consent was obtained are specified in the manuscript.

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