EFFECTS OF DASHBOARD USAGE ON ELEARNING INTERACTIONS AND ACADEMIC ACHIEVEMENT OF DISTANCE EDUCATION STUDENTS

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ABSTRACT

Learning processes can now be transferred to digital environments, allowing for the tracking of learners' digital footprints. The field of learning analytics focuses on the efficient use of these digital records to improve both learning experiences and processes. Dashboards are the tangible outputs of learning analytics. The use of dashboards in elearning has gained attention due to their potential impact on student interactions and academic success. In this study, we used a posttest control group design to examine the effects of dashboard use on 15,321 distance education students' elearning involvement and academic achievement. Results showed that dashboard use was associated with higher elearning interactions, but we observed no significant difference in end-of-term grades. This suggests that while dashboards may enhance student engagement in online learning, their effect on academic performance may be limited. The academic effects of dashboard use may only be observed in the long term.

Keywords: *learning analytics, dashboards, elearning interactions, open and distance learning*

INTRODUCTION

The shift from traditional learning environments to digital environments has made it possible to track a learner's digital activities and use that information to improve the learning process. Learning analytics is a discipline of science uses big data, data visualization, data mining, instructional design, and decision support systems to improve learning. Learning analytics was characterized as educational data mining during the Second International Conference on Educational Data Mining (Barnes et al., 2009). Data mining techniques were applied to educational data to evaluate and address academic research challenges. At the 1st International Learning Analytics and Information Conference in 2011, learning analytics was defined as the measurement, collection, analysis, and reporting of data about learners within the framework of the learner to understand and optimize learning and the environments in which learning occurs (Conole et al., 2011). According to Pelletier et al. (2021), learning analytics has become necessary as more data on teaching and learning processes becomes available in higher education institutions. Learning analytics has been used for various purposes as open and remote learning has grown in popularity in recent years. As a result, it may be classified as determining the needs of learners in general, increasing their learning processes, and better understanding and interpreting their behavior in the system (Jayaprakash et al., 2014; Kokoç & Altun, 2021; Santoso et al., 2018). According to Elias (2011), learning analytics is a field in which advanced data analysis technologies are utilized to improve learning and education.

Learning analytics plays an important role in storing and evaluating the activities of the learning process and monitoring and improving the instruction process (Klašnja Milićević et al., 2017). In addition, learning analytics focuses on storing, analyzing, and discovering learners' digital data in order to determine the cognitive characteristics of learners and to understand their perspectives on decision-making methods (Kazanidis et al., 2021).

A rapid rise in data sets has been seen today due to the growth of technology and the internet, as well as people's increasing use of vast amounts of data in internet environments. It is critical to use this data in a meaningful way to produce relevant products and outputs. In elearning environments, learners' activities in the course are saved as data, which are also referred to as digital footprints. These data include learners' interactions with the learning environment and resources, time spent on learning activities, and homework and exam scores. In addition, apart from the learning environments, the demographic information of the learners, the questions, and the opinions written to the support centers are also recorded. With the recording of the digital footprints of the learners, the learning processes can easily be followed (Ulfa et al., 2019). Learning analytics can be used to deliver these data to learners in a meaningful way. It includes a variety of learning analytics application domains, and to apply learning analytics successfully, one must be an expert in these fields (Fırat, 2015). One of those areas is data visualization.

Data visualization is used to interpret and make sense of the data obtained by learners and teachers as a result of learning analytics (Conde et al., 2015; Duval, 2011). The data stored in web environments can be presented with various images, mind maps, diagrams, and visualizations, rather than in a plain table, so that learners, trainers, participants, and administrators can readily see and analyze the data. In contrast to standard reporting approaches, data visualization is characterized as research on reflecting data using a visual or artistic approach (Yuk & Diamond, 2014, p. 7). There are millions of bytes of data stored in the background of the Anadolu University Open Plan Education System. One of the essential aims of data visualization, according to Gürsoy (2012, p. 99), is to present complex data in an easily understandable manner utilizing visual elements and graphical interfaces.

In online learning environments, dashboards, which are a component of learning analytics, are used so that learners can follow and make sense of their own learning processes (Jivet et al., 2017; Kemsley, 2021; Knight et al., 2015). As a result, dashboards, which are tangible components of learning analytics, are crucial for all participants in open and distance learning systems. The dashboard is a learning analytics tool that provides learners with real-time and scalable information on learning processes, allows them to compare previous periods, and assists in identifying at-risk learners or predicting high performers, as well as providing appropriate feedback and directions for learners (Yoo et al., 2015). Research shows that the dashboards have been shown to impact the learners' interactions and academic performance in the elearning environment.

Related Literature

Because the student is accountable for their learning, interaction is crucial in the open and distance learning process. Learner-content, learner-teacher, and learner-learner are three different dimensions of interaction, according to Moore (1989). Learner-learner interaction is the peer-to-peer or group interaction between learners in learning environments with or without the teacher. In addition to the content, it is important for learners to exchange ideas, participate in discussions with each other, and evaluate each other in terms of learning processes. Moore and Kearsley (2012) emphasized that social networking technologies continue to gain importance today with the use of blogs, wikis, and social media as technologies that enable the sharing of ideas and experiences. Collaborative learning, research and design, project-based learning, discussion forums, study groups, and virtual communities can be used to support learner-learner interaction (Madland, 2014). Learner-learner interaction can be provided asynchronously with tools such as peer assessment, discussion forums, and email, as well as synchronously with audio, video, screen sharing, and instant correspondence through virtual classroom technologies (Anderson, 2003; Einfeld, 2014; Yu, 2013).

Even if learners have the ability to motivate themselves and interact well with course content, they may need guidance on implementation. For this reason, the feedback and guidance provided by the teacher is of great importance when the learner applies newly learned knowledge (Moore, 1989). In distance education, teachers have duties such as motivating learners, increasing their interest in the subject, and providing support and mentoring. Learner-teacher interaction can be provided asynchronously with tools such as discussion forums, assessment environments, and email, and it can also be provided synchronously with audio, video, screen sharing, and instant correspondence through virtual classroom technologies (Anderson, 2003; Einfeld, 2014; Yu, 2013). In online learning environments, it is very difficult to provide learner-teacher interaction when considering a course attended by hundreds of learners. For this reason, course design can be structured based on learner-content interaction (Madland, 2014).

Learner-interface interaction and learner-environment interaction are examples of learner-content interactions (Hilman et al., 1994). Learner-content interaction is defined as a mental interaction process with content that causes changes in learners' comprehension, perspective, or cognitive structures (Moore, 1989). Learner-content interaction in online learning environments refers to the time spent in textbooks, course presentations, web pages, and discussion forums (Su et al., 2005). In addition, Madland (2014) interpreted learner-content interaction as watching educational videos, reading comments on the subject in a learning management system or in printed learning resources, taking notes, doing research and analysis, keeping a diary, and solving problems.

In online learning environments, learner-content interaction is usually determined by the number of clicks on the content and the time it takes to navigate the content. Interactions in an elearning environment can be clicks within the system. In their study, Kumtepe et al. (2017) measured interactions in the elearning environment by counting how many times students clicked on different learning resources. Also, Jiang et al. (2022) used learner click data to explore retrospective tracking patterns of digital textbook use and to reveal the relationship between academic performance and learning styles. The ability for learners to observe and understand their circumstances during the course makes it easier for them to follow the course process and remain engaged. At the same time, dashboards are critical for comparing oneself to other students enrolled in the course.

Dashboards in the elearning environment have an impact on students' academic success. Kokoç and Altun (2021) wanted to see how learners interacted with the dashboards and if these data could be utilized to predict academic success and guide learners. For this purpose, they created a learning analytics platform that integrates a predictive dashboard into an elearning environment. Learners who interact with the dashboard have more active participation in the elearning environment, more access to discussion forums, and higher final grades than learners who do not interact with it (Aljohani et al., 2019). Jayashanka et al. (2022) developed an instrument panel at the University of Colombo to increase the motivation, participation, and academic success of the learners, and as a result of this research, they observed that the motivation and participation of the learners increased and their success scores improved. Foung and Kwan (2022) observed that learners who use dashboards in an online learning environment have a high willingness to take action. According to Kia et al. (2020), there are differential patterns in the usage of dashboards between different levels of academic achievement and self-regulated learning for students with poor achievement and strong self-regulation.

Importance and Purpose of the Research

Studies on learning analytics and data visualization at universities and institutions that provide open and distance learning education are becoming increasingly important. Student behaviors can be observed, and a lot of data can be created with learning analytics in elearning environments with many students. Data visualization is required so that others can comprehend the information. Within the scope of this study, students had the ability to obtain information about their individual use of course materials and compare themselves to other students in an elearning environment using the dashboard we developed due to the learning analytics and data visualization it provided. At the same time, students can view the progress of the other students in the course. Furthermore, determining the interplay of the dashboards in the elearning environment and effects on students' academic progress is critical in personalizing the elearning environment and allowing students to follow their learning processes. There are few large-scale studies on the effect of dashboards on supporting learner achievement; however, there is a need for research in the context of large-scale learners with different characteristics (Ifenthaler & Yau, 2020; Jivet et al., 2020). In this context, the study's purpose is to show that using the dashboard in Anadolum e-Campus improved the effects of learners' interface interactions and academic achievement. In this respect, the study's hypothesis was formulated as follows:

H1: Using dashboards will increase learners' elearning interactions.

H2: Using the dashboard will increase learners' academic success.

METHODOLOGY

Research Model

The quasi-experimental paradigm is used when groups cannot be established randomly, or the experimental setting is not controlled (Shadishet al., 2002, p. 12). We used a model with a Posttest Control Group as summarized in Table 1 below.

Table 1.
The Model with the Posttest Control Group

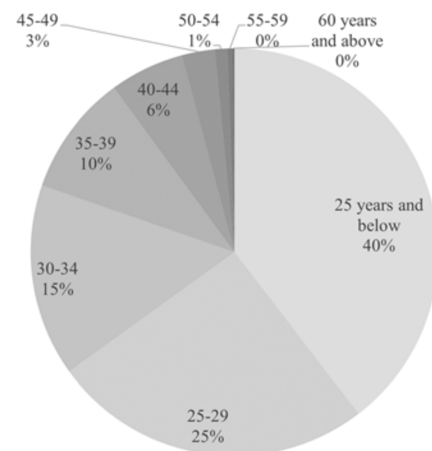
	Groups	Process	Posttest
R	D (Experimental group) (Number)	x (Dashboard)	01 (Total Grade Point Average, Term e-Campus Interactions)
R	K (Control group)		01 (Total Grade Point Average, Term e-Campus Interactions)

The experimental and control groups were determined using the last digits of the students' T.R. Identity numbers. ID numbers consist of 11 digits and they all end with an even number. Since these IDs are private, the IDs were not shared with us. At our request, masked data were obtained from the University IT team. The experimental group had the last digit of 0, 2, and 4, and the control group had the last digit of 6 and 8. The students in the experimental group who used the dashboard were compared to the students in the control group who did not use the dashboard.

Participants

This research consists of a sample of 15,386 students who took the 2020-2021 Fall term Introduction to Social Service course. Of the participants, 21% were male and 79% were female. Furthermore, 40% of the participants were under the age of 25 and 40% were between 25 and 39., The lowest age distribution was 60 years and older with 0.15% of the population. Figure 1 shows the age distribution of students who took part in the e-Campus.

Figure 1.
Recovery Cycle 3: Age Distribution



Participants are divided into age groups according to age ranges. The first group was 25 years and below. Age groups over 25 were divided equally spaced (5 years).

Data Collection Tools

Before data collection, we received the IRB and Ethics Committee approvals from Anadolu University Open Education Faculty and Anadolu University Ethics Committee. Anadolum e-Campus interaction analytics and FINAL GRADE data relating to the student's academic accomplishment were used in this study. Anadolum e-Campus is an elearning environment created by the Anadolu University Open Plan Education System, where students can view course materials, participate in live lessons, read notifications about the courses and the system, and participate in student groups and discussions.

Data Analysis

We used SPSS to analyze quantitative data in this research. The quantitative data was edited and cleaned using Microsoft Excel. To see if the quantitative data fit the normal distribution, we used the Kolmogorov Smirnov test. Then we used Mann-Whitney U test to analyze quantitative data because it did not show a normal distribution. The Independent Two-Sample T-Test was used to look at the averages of normally distributed data to see if there was a statistically significant difference between the experimental and control groups. Since the experimental and control groups were determined by random assignment and a high number of students was reached in each group, we assumed that the FINAL GRADEs of the students in the groups at the beginning of the semester were not different. Therefore, a model with a posttest control group was used.

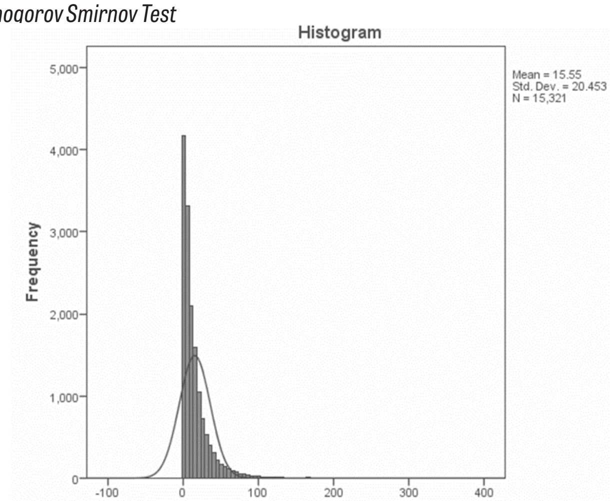
RESULTS

The results of the statistical analyses for the study's hypotheses are shown in the tables below.

H1: Using dashboards will increase learners' elearning interactions.

During a semester, the e-Campus clicks of students who took the 2020-2021 Fall Term Introduction to Social Service course for the experimental group (those who saw the dashboard) and the control group (those who did not use the dashboard) were compared. Click counts and quiz interactions are used as dashboard data. In the e-Campus system, which provides mass education and serves millions of students, click-based data were also used in this study, since learning resources interactions are based on clicks. To begin, we used the Kolmogorov Smirnov test to determine whether the data fit into a normal distribution. The interaction statistics did not appear to have a normal distribution due to the test ($Z = 4.410$, $p < .001$). In addition, Figure 2 shows normal distribution graph of the data.

Figure 2.
Kolmogorov Smirnov Test



Next, we used the Mann-Whitney U test, the nonparametric counterpart of the independent two-sample *t*-test, because the data did not have a normal distribution. Table 2 shows the results of the Mann-Whitney U test.

Table 2.
Findings from the Mann-Whitney U test for Material Clicks

Group	N	Rank Average (R.A)	Rank TOTAL (R.T)	U	z	p
Dashboard viewers	9075	7989.17	72501713.00	25363087.00	–11.089	<.001
Those who did not use the dashboard	6246	7184.19	44872468.00			

As shown in Table 2, the experimental group's number of clicks throughout the period was significantly higher than the control group's number of clicks during the period ($U = 25363087.00$, $p < .001$). This finding indicates that students who saw the dashboard during the semester (R.A. = 7989.17) had statistically more elearning interactions than students who did not use the dashboard (R.A. = 7184.19).

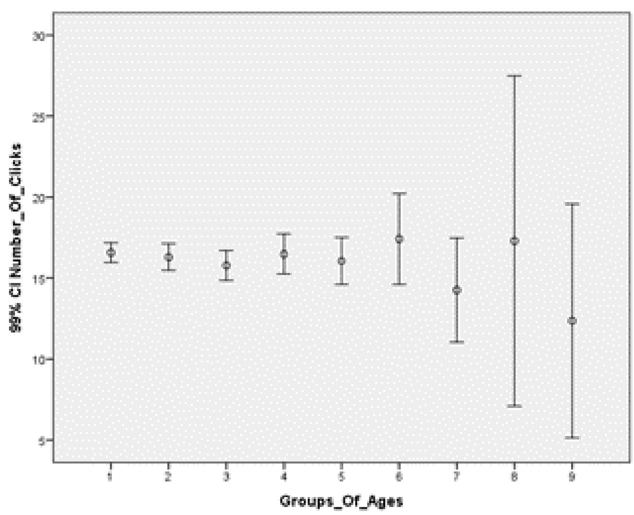
We examined the differentiation status of the interactions of the learners according to their age groups. There were nine age groups in the study. Since the sample was larger than 300, the histograms were examined without considering the z-values. Reference values were used as –2 or +2 to determine normality. When $n > 300$ (Mishra et al., 2019), normality was achieved when the absolute skewness value did not exceed 2.00 and the absolute kurtosis value did not exceed 7.00 (Kim, 2013). When the skewness/kurtosis values of the data were examined, we saw that the normal distribution was not achieved. Since the age groups did not show normal distribution, we used the nonparametric equivalent Kruskal Wallis analysis.

Table 3.
Findings from the Kruskal Wallis Test Statistic Number of Clicks, Group of Ages.

	Number of Clicks
Chi-Square	4,510
df	8
Asymp. Sig.	.808

The "Asymp. Shallow. (2-sided)" value was found to be higher than .01 ($p > .01$). Therefore, we concluded that there was no significant difference between age groups. In addition, the Error Bars graphic supports this result (Figure 3).

Figure 3.
Error Bars Graphic



We analyzed the interaction status of learners with and without dashboards according to age groups and genders (Figure 4 and Figure 5).

Figure 4.
Interaction Averages of Students Who Used Dashboard According to Ages and Genders

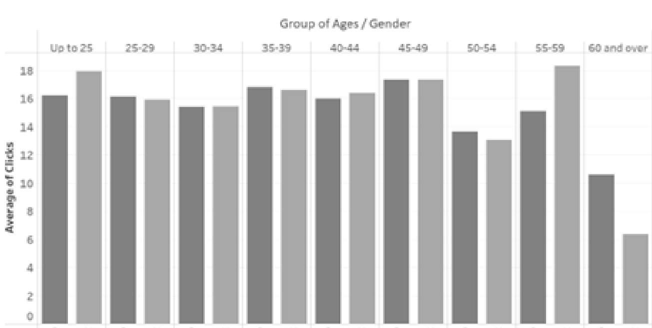
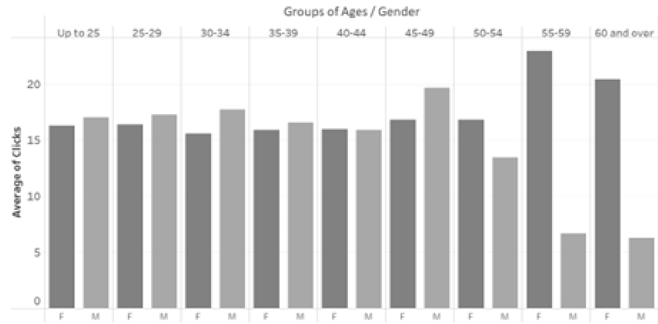


Figure 5.
Interactions Averages of Students Who Did Not Use Dashboard According to Ages and Genders



As seen in Figure 4 and Figure 5, students who used dashboard have more interactions. This difference supports the Mann-Whitney U test finding.

H2: Using the dashboard will increase learners' academic success.

We compared the students' final grades to understand better the impact of using the dashboard on academic progress. First and foremost, the data were reviewed to see if they were regularly distributed. The data statistics were found to have a normal distribution as a result of the test ($Z = 571$, $p = .9 > .05$). Table 4 shows the results of two independent samples *t*-tests.

Table 4.
Independent Two-Sample t-test Results

	Group	N	Mean	SD	df	p
Final Grades	Experimental Group	9120	66.01	24.2	15390	.663
	Control Group	6272	65.9	23.9		

In terms of the experimental and control groups, the course final grades of the students were compared. There was no significant difference between the final grades of the groups, according to the independent two-sample *t*-test ($t_{(15390)} = .280$, $p = .663 > .05$).

DISCUSSION

We statistically examined the impacts of using the dashboard on the students' interaction status and academic success. The number of clicks on the learning resources in the e-Campus elearning environment revealed the interaction status. According to the analysis results, the number of clicks of the experimental group throughout the period was significantly higher than the control group during the period. In other words, students who used the dashboard during the semester had more access to the e-Campus learning tools than students who did not. This research indicates that using the dashboard during the term boosts students' elearning interactions. Students who interact more with dashboards in Massive Open Online Course environments, on the other hand, are more likely to graduate, according to Jivet (2021). According to other studies, those who use dashboards perform better than students who do not (Manganello et al., 2021). Foung and Kwan (2022), on the other hand, observed learners by integrating the instrument panel into the elearning environment, and, as a result, they concluded that the learners using the dashboard had a high motivation to take action. In this context, it is possible to say that learners are more motivated in elearning environments and their self-regulated learning skills are improved, since the dashboard offers advantages such as the ability to follow their own learning processes and compare their learning process with other learners (Bodily et al., 2018; Kebede & Bhattacharya, 2022). In addition, the dashboard's instantaneous presentation of learning experiences opens the way for learners to manage their own learning processes. Thus, it can be said that with the dashboards, learners have the opportunity to evaluate their learning processes holistically on a single screen (Sclater et al., 2016).

We compared the semester's final grades of the experimental and control groups to determine the effect of the instrument panel on the students' academic success. Our study revealed no statistically significant difference between the experimental and control groups' final grades. This may be because the learners' dashboard use did not reach a high level during this time frame. When students spend more time with the dashboard and better understand it, the dashboard will be used per its intended purpose. Thus, students can remain focused on the dashboard for their purposes (Manganello et al., 2021). In future research, students' encounters with the instrument panel in other courses and other semesters may result in different academic success. Given the increased adoption of distance education during the COVID-19 pandemic, elearning processes should continue to grow, necessitating additional research on this topic.

The finding of the effects of the use of the dashboard on elearning interactions is consistent with the finding of the research conducted by Kia et al. (2020), which showed that using the instrument panel affected the performance of the students' interaction and their academic success. In terms of academic success, however, it is different. In the research conducted by Ulfa et al. (2019), learning interactions affecting online learning success were examined using the dashboard. The research shows that the students' dashboard interactions were advantageous since they allowed them to undertake self-assessment. Again, this research demonstrates how dashboards add to elearning interactions by allowing learners to track their learning processes. Aljohani et al. (2019) concluded that learners who interact with the dashboard are more interested in the elearning environment and participate more in discussion forums compared to learners who do not interact with the dashboard. Similarly, as a result of the use of a dashboard in which gamification components are integrated, learner interaction seems to increase significantly (Akçapınar & Uz Bilgin, 2020). This study's finding on academic performance differs from Kokoç and Altun (2021), who found that when students interacted with the dashboards it promoted their success. The statistical difference in academic achievement that was not attained in this study could be because long-term use has not reached a level that will alter the learners' academic success. The consequences of longer-term use on academic achievement can be investigated in future studies.

The contribution of the dashboards to learner interactions in the elearning environment demonstrates that these environments can be customized based on learner characteristics. Learners can track their learning processes using dashboards as part of learning analytics. According to the literature, learning analytics support both the individualization of the elearning environment and the learner's learning process. In addition, early intervention applications can be implemented for learners who are likely to leave the system by making predictions for the future. The findings of Ulfa et al. (2019), which emphasized the need to use student data to understand student behavior in order to create an individualized learning experience by processing and analyzing the data in the system, support the findings of this study.

CONCLUSION

The main goal of this study was to show how the dashboard in the elearning environment affects the learners' interface interactions and academic achievement. The hypotheses we developed in this context yielded the following outcomes.

H1: Using dashboards will increase learners' elearning interactions.

The experimental and control groups of students who took the Introduction to Social Service course in the 2020-2021 Fall Term were compared on the number of clicks on learning resources in the e-Campus, which is retained in the system for a semester. The Mann-Whitney U test, the nonparametric counterpart of the independent two-sample *t*-test, was used because the data did not have a normal distribution. The number of clicks in the experimental group was statistically higher than the number of clicks in the control group during the period. This finding is also supported by the studies examined in the literature such as Kia et al. (2020) and Ulfa et al. (2019).

H2: Using the dashboard will increase learners' academic success.

The final grades for the experimental and control groups for the Introduction to Social Service course were compared to understand better the effect of using the dashboard on academic achievement in this fully asynchronous course. No statistically significant difference was discovered between the experimental and control groups, which differs from the literature evaluation.

RECOMMENDATIONS

Dashboards were meant to be used in elearning settings for an extended period. Students need to get used to these tools to investigate in greater depth the effect of the instrument panel on student academic success and reach valid results. The comparisons conducted at the end of this process may yield valuable data. To better understand the effects of dashboards, researchers should incorporate outcome evaluation and process evaluation in their academic success measurements.

Dashboards have been found to affect learners' elearning interactions in this study and the literature. Future research can examine how this interaction differs depending on the topic area studied, the elearning environment, and the individual demographics of the students (e.g., age, gender, technology use proficiency, learning styles, study strategies, etc.).

Given the extensive usage of distance education applications, the importance of learner engagement in the elearning environment and the contribution of these interactions to academic performance have grown. Like the ones used in this study, rich dashboard designs can be applied to facilitate elearning interactions between students and teachers in distance education institutions.

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