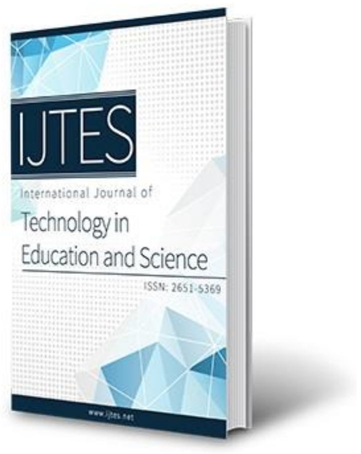

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Quality Assurance in Distance Education through Data Mining

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Quality Assurance in Distance Education through Data Mining

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Abstract

Learning Management Systems (LMS) are software applications that facilitate the management and monitoring of online teaching courses and/or training programs, workshops, webinars, forums, and other similar learning activities. The LMS provides learning and teaching benefits and possibilities for synchronous, asynchronous, and hybrid training. For instance, learning management systems (LMS) can store a wide variety of large-scale educational data. The stored data can be analyzed by employing educational data mining methods. Educational data mining (EDM) is a new discipline that deals with methods for exploring the unique and large-scale data generated by digital platforms to better understand students' learning progress and the learning environment itself. In this study, the data stored in the LMS used by Balıkesir University during the fall semester of the 2021–2022 academic year were analyzed by using educational data mining methods in order to reveal the current status of distance education activities and make suggestions to improve the quality.

Introduction

Developments in computer systems, particularly in terms of the increase in processing speed, power, and capacity, allow larger amounts of data to be produced, stored, and processed. Data mining is one of the methods for processing the data that has been created and stored. The process of extracting and discovering patterns or trends in large datasets using machine learning, statistics, and database systems is known as data mining (Chen et al., 1996; Hand, 2007). The information extracted from a large and complex data set can be used by using data mining methods to make it more understandable. Data mining methods are seen as almost the only solution for effectively analyzing, making sense of, and using the massive amounts of data accumulated in smart systems, social media, and web-based data warehouses. It is considered to be crucial to utilize such techniques that can process large amounts of data in the context of quality management and assurance.

Today, learning and training at a distance, in other words, distance education services are mostly offered through a Learning Management System (LMS). LMSs are a type of software that allows for the management and monitoring of educational programs as well as the delivery of courses (Bradley, 2021). LMSs are considered to be an effective educational tool and platform in that they support teaching, enable students to construct their knowledge, increase permanence of learning and the quality of education consequently (Bahçeci, 2015). Learners can interact with their peers and teachers while also receiving education in a LMS. Thanks to the cloud computing that educational institutions adapt it to improve their LMSs, providing solutions for multiple collaboration in real time, user-protected services, and productivity. Cloud Computing technology "is widely accepted to be suitable for online learning environment [or Learning Management Systems] with its capabilities in facilitating information managing, data sharing, and collaborating, and so on" (Sarıtaş, 2015, p. 167).

Educators or trainers, can create and organize learning resources, carry out assessment and evaluation activities, and apply different teaching methods and techniques according to the needs of their students within the LMS platform. As a result of all kinds of interactions and transactions between the users on the LMS platform, a large amount of digital data naturally accumulates in the system during this process. It is possible to collect, analyze, and report this data by various methods. The analysis conducted to reveal patterns related to big data, construct predictive models, and establish relationships among data is called *Educational Data Mining* (Romero & Ventura, 2013).

The fact that educational institutions have a LMS that enables them to continue their educational activities remotely, manage the process and store the data obtained as a result of the activities supports the quality of education and training offered (Karam et al., 2021). In order to increase the quality of learning processes and outputs in distance education at universities, Turkish Higher Education Quality Council (YÖKAK) determined quality and accreditation criteria by taking into account "The Standards and guidelines for quality assurance in the European Higher Education Area" (ESG, 2015). Turkish Higher Education Quality Council specified those criteria (see Table 1) under such three main headings as i) Quality Assurance System, ii) Learning and Teaching, and iii) Implementation and management system (YÖKAK, 2020).

Table 1. Distance Education Quality Assurance Criteria (YÖKAK, 2020)

A. Quality Assurance System	A.1 Mission and Strategic Objectives: A.1.1 Mission, vision, strategic objectives and targets A.1.2 Policies on quality assurance, learning and teaching, research and development, social contribution and governance system A.1.3 Institutional performance management
B. Learning and Teaching	B.1 Design and Approval of Programs: B.1.1 Design and approval of programs B.1.2 Assessment and evaluation B.2 Student Admission and Progression: B.2.1 Recognition and certification of degrees, diplomas and other qualifications B.3 Student-Centered Learning, Teaching and Evaluation B.3.1 Teaching methods and techniques B.3.2. Assessment and evaluation B.3.3. Student feedback B.4. Teaching Staff B.4.1 Teaching competence B.5. Learning Resources B.5.1 Learning resources B.5.2. Accessible university B.5.3. Guidance, psychological counseling and career services B.6. Monitoring and review of program outcomes (This also covers foreign language education programs in preparatory schools.)
C. Implementation and management system	C.1 Process management C.2 Information security and reliability

Table 2. Taxonomy for EDM Methods (Baker & Siemens, 2014) and Examples (Penteado et al., 2018)

Method	Aim	Approaches	Example
Prediction	To estimate the unknown value of a variable by means of a combination of other variables (predictors)	Classification Predicted variable can be binary or categorical.	Prediction of a student's likelihood to pass or fail, complete or drop out of a course, based on other variables (e.g. his/her interactions with instructors and peers).
		Regression Predicted variable is continuous.	Prediction of a student's score based on other variables collected in the learning environment.
		Latent knowledge estimation	Assessment of a student's proficiency on specific skills by his/her patterns of correct performance over time.
Structure discovery	To discover structures not known a priori, seeking to find out structures that emerge naturally from the data	Clustering Finding data points that naturally group together	Grouping students by their behavior profiles in the learning environment.
		Factor analysis Finding variables that naturally group together	Creating measurement scales based on items responded by the students.
		Social network analysis Developing models of the relationships and interactions between individual actors, as well as the patterns that emerge from those relationships and interactions	Understanding communication structure and flow among students and/or instructors.
		Domain structure Finding the structure of knowledge in an educational domain.	Discovering how skills being assessed in a topic could be modeled in a sequence that facilitates learning.
Relationship mining	To find significant relationships among different variables in data sets with a large number of variables.	Association Formulation of if/then rules - if variable y occurs, then variable z occurs.	Discovering conditions in the student's behavior in order to suggest better topics of study.
		Correlation Finding positive or negative linear correlations between variables	Discovering variables that are correlated when a student "games the system" (e.g. systematically guessing answers in order to obtain the correct response).
		Sequential patterns Finding temporal associations between events.	Define student's behavioral patterns that lead to a learning event (e.g. to achieve a given score, a student must watch videos 1 and 2, complete exercises 1-7 and solve his/her doubts through the standby support).
		Causal data Finding whether one event/construct was the cause of another event/construct	Understanding how different variables interact to cause poor learning on a given topic.
Distillation of data for human judgment	To visualize complex data to assist in decision making or in understanding phenomena	Data visualization (heat maps, learning curves, learnograms)	Using learning curves to represent how fast a user is learning a specific topic, avoiding over-practice and enabling the human understanding of patterns in student learning.
Discovery with models	To use an existing EDM/analytics model as a component in a new EDM/analytics	Modeling of constructs	Modeling affective states from the user's actions and use this model to predict learning behaviors in the course.

To ensure the quality in distance education, it is important to carry out studies such as educational data analytics. By using data analytics and reporting, the LMS, which has an important place in the distance education ecosystem, provides various opportunities to assess and evaluate the quality of learning and teaching processes, allowing to identify any educational deficiencies. Data mining methods make it possible to determine correlated variables in the system and identify the relations between them. Based on these variables, it would also be possible to explain future trends using estimation models, collect scattered data under similar clusters, and detect outliers in the data set (Romero & Ventura, 2013). From this standpoint, data mining methods provide potential solutions and suggestions for the quality assurance in distance education. The good news is that the educational institutions who do use educational data mining methods will have a plenty of benefits to tap into. Data mining helps to provide a comprehensive knowledge, for instance, the duration and frequency of student participation in a course, the number and type of course materials used in the system, student-content, student-teacher, teacher-content, student-student interactions, and students' current and retrospective course performances that could be analyzed in detail in almost all online activities.

Table 2 presents educational data mining methods, aims, and approaches compiled by Baker and Siemens (2014) and the examples given by Penteado et al. (2018). With the data obtained from the LMS, regression, classification, and latent knowledge estimation approaches are generally preferred in EVM studies to estimate the academic achievement of students (Costa et al., 2017; Dabhade et al., 2021). In addition, school dropouts (Iam-On & Boongoen, 2017; Jin, 2021; Palacios et al., 2021) and factors affecting student success (Hone & El-Said; 2016; Shingari et al., 2017; Yıldız & Börekci, 2020) can be examined with EVM. In studies to explore unknown structures in the data, students can be grouped according to their behaviours (Zhang et al., 2021) and their domain-specific skills can be revealed, various scales can be developed, and social networks can be developed using clustering analysis, factor analysis, social network analysis, and determining the structure of domain-specific knowledge. (Kaur & Singh, 2016). The relationships between various variables can be examined with the relationship mining method (Lwande et al., 2021). Similarly, passing the data through various filters, visualizing and revealing new models to make a judgment (Lemay et al., 2021) are among the methods of EVM.

This study aims to analyze the data generated within the Learning Management System of Balıkesir University - Türkiye's medium-sized university - in the fall semester of the 2021–2022 academic year by using data mining methods. Based on data mining from the system reports, the study examined the behaviors and habits of users in distance education and provided visual and tabulate representations, which is believed to be meaningful information especially for the quality assurance.

Method

The methodology used in this study is based on a very common methodology in the field of data mining, namely the CRoss Industry Standard Process for Data Mining (CRISP-DM). The process consists of six stages as a systematic step-by-step procedure to ensure a reliable and standardized methodology proposed by Wirth & Hipp, (2000). This methodology (see Figure 1) follows a cyclical process that includes such stages as understanding the business, understanding the data, data preparation, modelling, evaluation, and reporting.

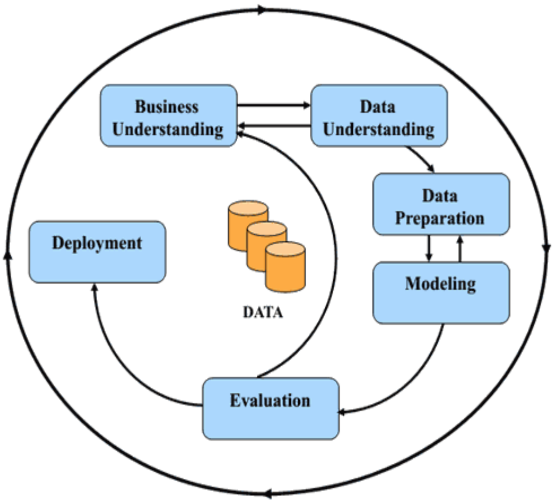


Figure 1. CRISP-DM (Wirth & Hipp, 2000, p.5)

A total of 33176 users were registered to the Microsoft Teams platform of the university. 24902 of these users were active users in the fall semester of the 2021–2022 academic year when the data for this study was collected. 23.250 of the active users were students and 1.237 of those were academic and administrative staff. 415 users were registered trainees to the programs of the center for continuing education.

The university teachers and students took advantage of Microsoft Office 365 and its components, particularly the Microsoft (MS) Teams platform as the Learning Management System. This study, henceforth, analyzed the data compiled from the reports obtained from the management panel. Data were collected in three different categories: i) *general reports* including the data on the number of users, the total number of events, the size of the data stored in the system, and the number of files in the system, ii) *user reports* including data on each user's activities (i.e. system logins, duration of use, number of messages, number of files viewed, absenteeism), user habits (i.e. preferred platform, device), and number and size of files uploaded and shared, and iii) *course reports*, where a course is defined as a “team”, include the data regarding the duration of the online meetings in each team, characteristics of the meetings, and the methods used for teamwork.

At the end of the data collection process, a wide variety of large amounts of data were analyzed. The information obtained was used to develop suggestions for the quality of distance education offered in terms of student-centered education and student participation, diversity of learning resources, measurement and evaluation, and guidance and counselling.

Findings

The reports obtained from the LMS have been analyzed and presented in this section. To obtain information about student-centered education and student participation, the following data were collected: data on the number of users in the system, the programs they use in the LMS, the devices they prefer to connect to the LMS, teams activities, individual activities, and the number and types of files they create. There were 24825 teachers and students using LMS for educational activities (see Figure 2) including a variety of Office 365 applications. 22551 users actively used the SharePoint environment where documents related to training activities were shared. In other words, approximately 90% of LMS users shared files, viewed and acted on the shared files. More than 50% of the users benefitted from the cloud storage service. The total number of courses offered at the university in the fall semester is 4925, and 1065 of these courses were offered via distance education through Teams LMS platform. In addition, the courses offered as face-to-face with the decision of the university senate were also created in the LMS. This decision was made as a precaution in case of an emergent situation where face-to-face education could not be done. Thanks to these courses created in the LMS, the instructors had the opportunity to share the course materials, collect assignments and use different communication tools.

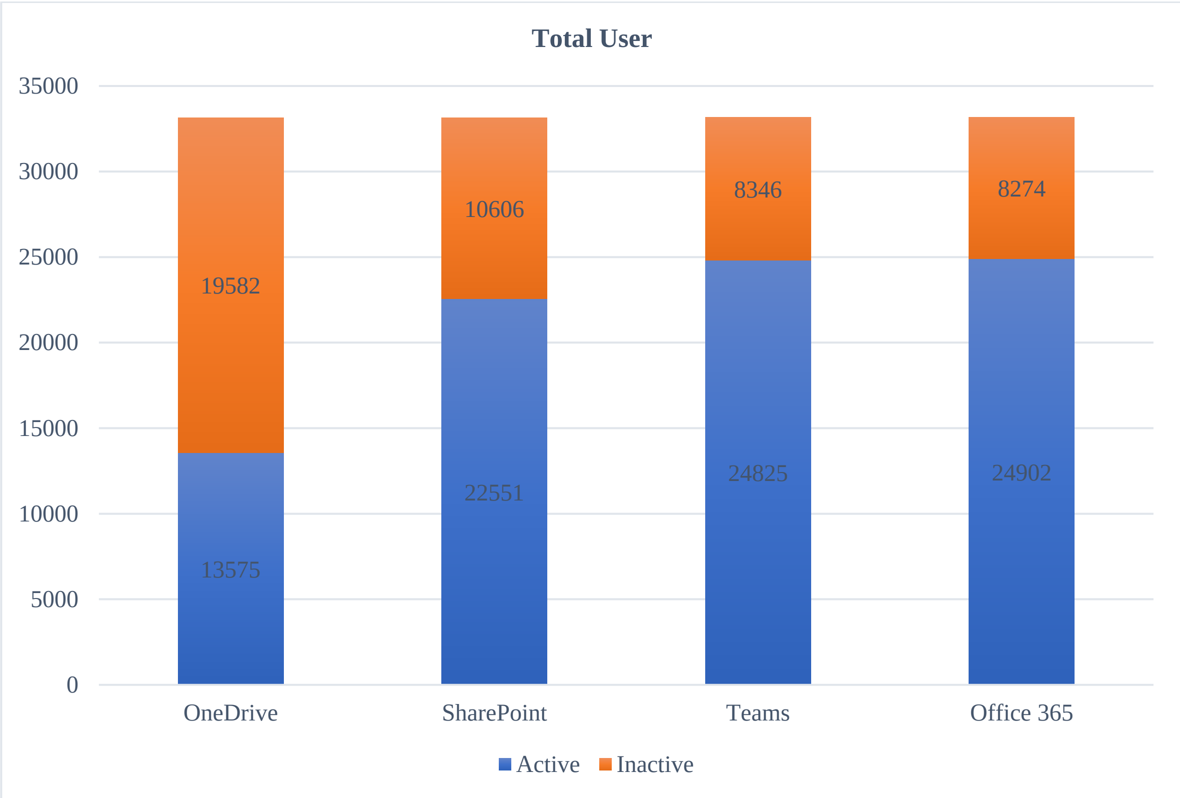


Figure 2. LMS User Statistics

According to Figure 3, the total number of teams formed by the instructors for the course activities in the LMS is 18266. The total number of active teams in the fall semester is 5955. It was found that the activities in Teams reached at their highest level during the midterm and final exam weeks of the semester (see Figure 3). Considering the number of most active Teams on a daily basis, that is to say, the most action detected within Teams, for instance, the number of Teams in which activities such as meetings, assignment submissions, and other learning tasks and events taking place the most on a daily basis is 2898. The number of active Teams was sometimes greater than the number of courses due to the fact that instructors teaching face-to-face classes also created teams in the system that provided additional data for user activity.

The average number of users in a Teams class was 38. In the beginning of the fall semester, the number of files in various types such as pictures, videos, word processors, spreadsheets, presentations, etc. registered in the system was 1362000, then it reached the number of 1578000 at the end of the semester, and 215700 new files were added to the LMS within that period. It can be seen from the figure 3 that access to the files increased during exam periods. The total storage space used during the period varied between 84.6 TB and 92.4 TB. Stored files consisted of learning materials and video recordings of lectures.

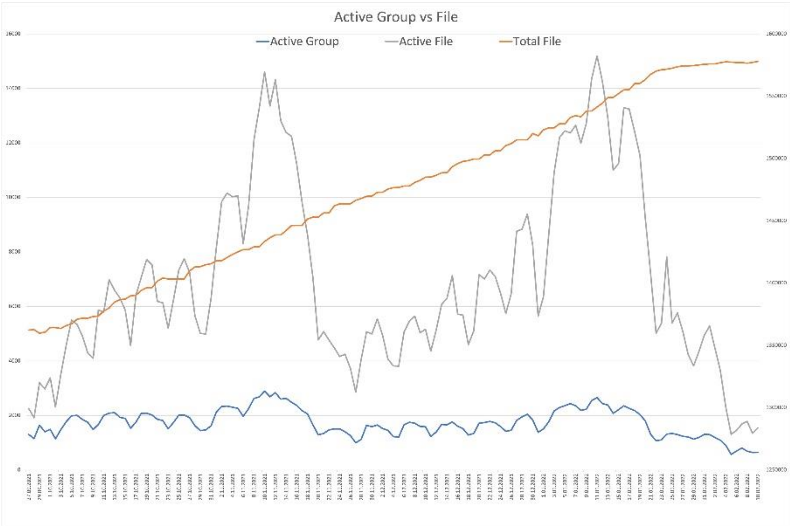
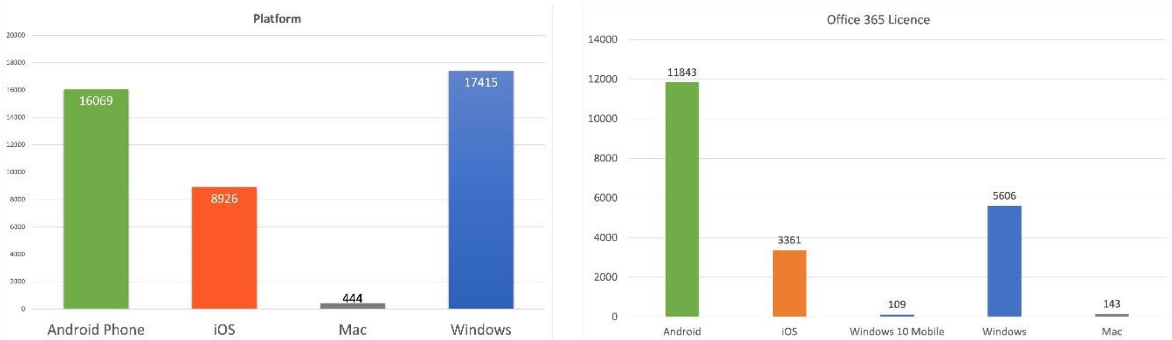


Figure 3. Active Groups & Files Used Actively

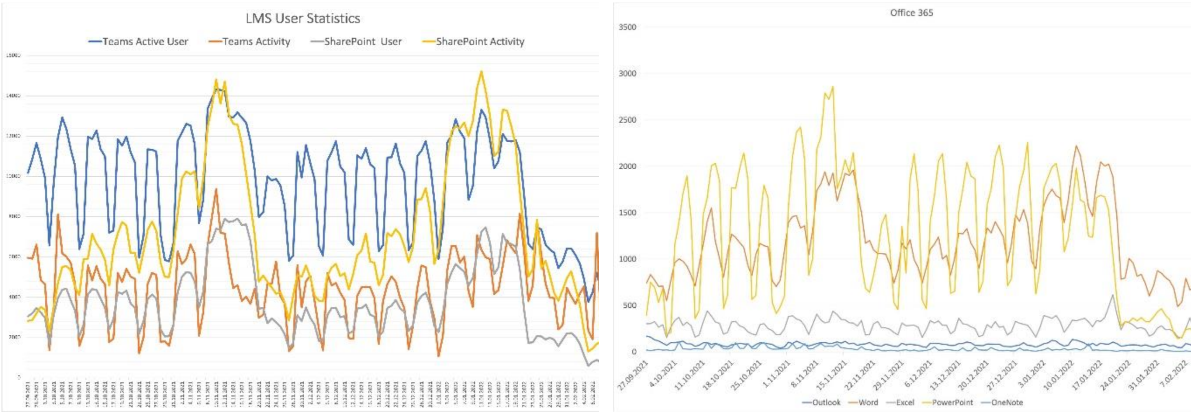
In terms of an operating system preferred by the users, it was seen that 17415 of those used Windows, 16069 used Android, 8926 used IOS, and 444 used MacOS (see Figure 4a). To keep in mind that a user could use the LMS on more than one device (e.g., desktop, mobile). Whilst 31254 users (i.e., instructors and students) had Office 365 (Word, Excel, PowerPoint, Outlook, OneNote) licenses, only 14769 of those activated their licenses on at least one device. According to the data, licenses were used with different operating systems (n=11843 for Android, n=5606 for Windows, n=3361 for IOS and n=109 for Windows 10 Mobile) (see Figure 4b). More specifically, the number of students using LMS only on their mobile devices (with Android operating system) was 3,092; and the number of students using LMS only on their mobile devices with the IOS operating system was 1189. Therefore, a total number of 4281 students used the LMS only on their mobile devices. In other words, 18.4% of students accessed to the LMS only from their mobile devices.



a. Operating Systems (OS) b. Office 365 Licenses Used with an OS

Figure 4. Preferred Operating Systems to access to LMS & Office 365 Licenses Used with an OS

Data were collected on file types used in the system, group and individual activities, meeting times, camera use in meetings, and screen sharing. The graph regarding the file-sharing of students and instructors within the LMS is given in Figure 5. It was seen that shares and activities of users intensified throughout the week, whereas they decreased partially on the weekends and at the end of the academic period. During the make-up exams held at the end of the semester, it was observed that an average of 4000 users were active and 1000 users visited the system to share or view files. It was determined that there were more than 10000 users in the system during the periods when the user density increased. In terms of the Microsoft Office applications, it was observed that MS Word and MS PowerPoint were the most preferred ones by users (see Figure 5a, b).



a. LMS User Statistics b. Office 365 User Statistics

Figure 5. LMS & Office 365 User Statistics

The study also analyzed the data regarding the meetings (courses). Table 3 below shows only a part of the findings in the Annex (please see Annex for the whole findings): the average number of meetings based on faculty (school) and department, the average duration of the classes with screen sharing, the average duration of the meetings with cameras, and the average duration of the meetings with audio.

Tablo 3. Information on the Online Course Meetings (A sample data found in Annex)

Faculty / VET	Number of Students	Average Number of Meetings	Average Meetings with Camera-On (Minutes)	Average Screen Sharing (Minutes)	Average Meeting Time (Minutes)
Faculty of Law	57	20.96	333.27	713.85	840.50
Vocational School of Health Services	335	33.30	22.10	1038.32	1367.83
Faculty of Architecture	430	61.78	372.20	1981.46	3959.81
Faculty of Engineering	3008	37.38	208.21	670.22	2222.49
Faculty of Education	2478	44.85	178.61	1710.89	2386.55
Faculty of Veterinary Medicine	344	45.43	7.57	477.24	1264.29
Total	6655	41.80	189.03	1151.53	2291.06

The findings showed that the number, duration and methods of the meetings differed according to the departments. It is seen that the duration of video meetings (lessons) was only half duration of the online meeting time, and screen sharing did not reach 10% of the meetings (see Annex).

a. Tests b. Assignments

Figure 6. Tests and Assignments Assigned to Students

To determine the assessment and evaluation activities carried out in the LMS, data on both exams and assignments created in the system were collected. It is observed that the exams created with Microsoft Form application are concentrated in the midterm and final exam periods, and are used less frequently at other times (see Figure 6a). It is determined that a total of 1874 exams were created within the LMS and 49623 answers were given to these exams. The peak on the left of the graph belongs to the exams held at the beginning of the semester, and these exams were the ones for determining the level of students (Figure 6a). By examining the data on exams, it is discovered that multiple-choice and short- and long-answer question types were mainly preferred by teachers. Considering the data on assignments, it is found that a continuous assessment and evaluation was made with research-based assignments throughout the semester. 9011 assignments were assigned to students in 4184 teams in the system (Figure 6b). It is also found that online evaluation activities in the LMS were not only limited to the online courses, but also conducted in face-to-face lessons.

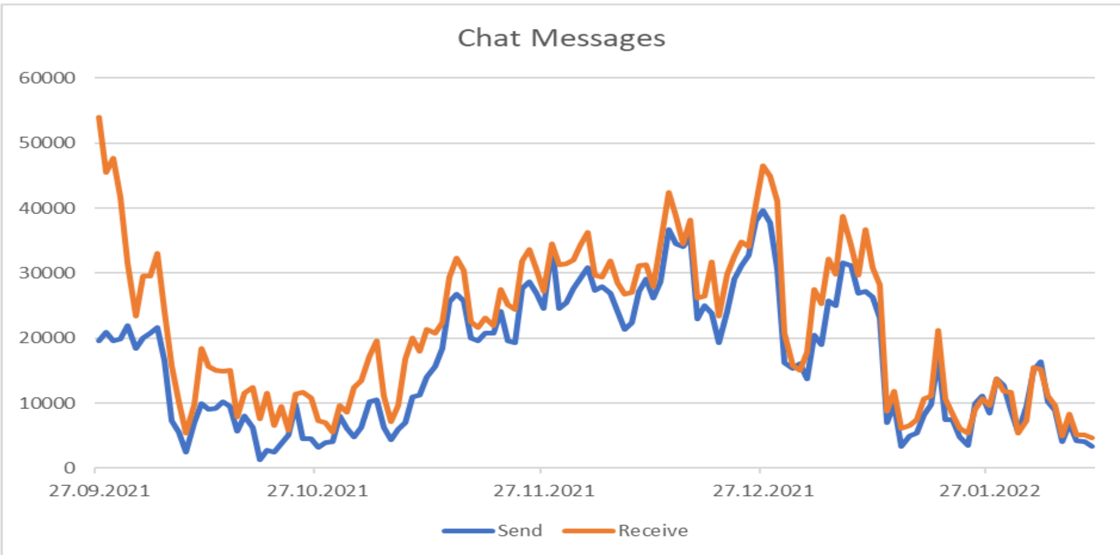


Figure 7. Chat Messages

Data on the number of text messages via the chat application as one of the direct communication channels were collected to obtain information about students' guidance and counselling activities. The majority of messaging appeared to be taken place between teachers and students. While an average of 16741 messages were found to be sent per day, 21141 messages were responded to those (see Figure 7). Given that there were 24825 active users in the system, there was at least one message per person per day. It is understood that the messaging application facilitates user communication.

Discussion and Conclusion

In this study, data mining methods were used to develop quality in distance education based on the findings of such learning and/or teaching tasks and processes at a distance as learner-centered education and learner participation, measurement and evaluation, diversity of learning resources, and guidance and counselling. Learner participation and learner-centered teaching approach in online learning environments are the two essential aspects of quality assurance studies.

- The results of the study showed that some students did or could not use the LMS which might negatively affect the academic achievement (Essel et al., 2018). Thus, it is suggested that the data specifically on the use of LMS should be examined to identify learners who could not access distance education and the reasons for it.
- It is found that technological tools and operating systems for using LMS preferred by users varied. These differences should be taken into account while designing and developing the course content. Standards for digital learning materials could be determined especially for the multimedia files (e.g., video, image, sound files, files prepared with word processors, spreadsheets, or presentation programs) compatible with many platforms.
- The findings revealed that 18.4% of students only use mobile devices to access online content through LMS environment. Therefore, the suitability and compatibility of course materials and activities, for instance, assessment activities (i.e., exams) with the mobile device platform should be considered and tested before offering the course. Arthur-Nyarko et al. (2020) advocate that incompatible content for mobile devices negatively affect mobile device users' learning and their access to the system.

Diversity of educational resources:

- The number of files created in the system grows over time and stored for the use of students at any time anywhere. Students could take advantage of studying various types of resources or files (image, audio, video, etc.) according to their needs and learning styles. Providing course materials in different versions and video recordings in the system could have a positive effect on academic success (Daş et al., 2021; Flottemesch, 2000; Sari & Nayir, 2020).
- It is observed that the duration of video lessons (with camera-on) was only half of those with camera-off lessons, and screen sharing did not reach 10% of live meetings with camera-off. Remote meetings with cameras-off and a lack of screen sharing were factors that may negatively affect learning (Day & Verbiest, 2021). Rehn et al. (2018) state that instructors should consider the way lectures offered at a distance, whether students seem to be making eye contact, whether the lecture tone is warm and interesting, and whether the lecturer is close enough to the camera so that students can see the facial expression and emotion of the lecturer. Aydın (2012) found a positive relationship between the learners'

perceptions of the "social attractiveness" of the lecturer and their perceptions of the content of the course, suggesting that social presence of the lecturer on the screen is important. Castelli & Sarvary (2021) suggest that educators should increase the effectiveness of video lessons. On the other hand, instead of forcing students to turn on their cameras during lectures, instructors could find alternative ways that explicitly encourage the use of camera and make clear explanations why it is good for them.

Measurement and evaluation activities:

- LMSs provide educators with many opportunities for assessment and evaluation. Based on findings, the instructors utilized various assessment methods throughout the semester, including multiple-choice, short- and long-answer questions, and research-based assignments. It is suggested that educators should prefer alternative assessment methods which focus on process evaluation rather than outcome evaluation in distance education (Clark, 2000; Liu, 2020). Moreover, evaluation activities through LMS platform are not only restricted to distance education courses but also used within face-to-face courses. It is lately seen that face-to-face trainings have evolved into hybrid training formats which are the training method offering the combination of traditional in-class education and education at a distance (Graham, 2018) allowing a transition from teacher-centered education to a student-centered understanding (Saichaie, 2020). In hybrid education, it is important to choose techniques which help assess and evaluate active participation and collaborative activities of students that promote higher cognitive processes (Mayhew et al., 2016).

Guidance and counseling activities:

- It is observed that users can communicate with one another directly and easily through LMS platform. This communication channel can be used effectively for student guidance and counselling. The quality of guidance and counselling services in distance education has a significant relationship with students' academic achievement (Farajollahi & Moenikia, 2010). It is suggested that educators should be trained in using appropriate digital tools within the LMS in order to provide guidance and counselling services (Aini & Mudjran, 2020).

It is critical for educational institutions to carry out continuous monitoring and analytics studies for distance education processes and activities. Educational institutions should regularly evaluate the education they offer in terms of curriculum, technology, process of learning and teaching, course structure, learning outcomes, needs of teaching staff, student support services, digital learning objects, administrative issues, and measurement-evaluation. Based especially on data mining and educational analytics studies, remedial measures and quality improvement actions could be applied. This study is meaningful in terms of showing that the information obtained by data mining can be used for evaluating the current situation and quality improvement studies. Using educational data mining methods, further studies can be conducted to predict students’ academic achievement (by machine learning algorithms) and retention and dropout rates, to assess students’ proficiency in specific skills, to group students into learning contexts based on their behavior profiles, and to understand the communication structure and flow at a distance.

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Annex

Faculty / Vocational School	Number of Students	Average Number of Meetings	Average Meetings with Camera-On (Minutes)	Average Screen Sharing (Minutes)	Average Meeting Time (Minutes)
Altınoluk Vocational School	192	20.05	3309.63	16974.53	48398.25
Ayvalık Vocational School	415	20.32	790.20	29031.93	62397.81
Balıkesir Vocational School	1853	26.98	2915.20	25031.48	70322.24
Bigadiç Vocational School	584	21.59	14183.41	50774.93	78249.22
Burhaniye Vocational School	241	18.02	246.14	14631.54	44324.32
Burhaniye Vocational School of Applied Sciences	628	16.53	4154.40	31688.99	46249.95
Dursunbey Vocational School	240	40.87	2568.44	29001.62	90885.63
Edremit Vocational School	333	17.77	2855.93	29141.61	43367.53
Edremit School of Civil Aviation	231	34.74	984.86	35482.77	80562.76
Faculty of Arts and Sciences	2316	22.71	1350.05	39872.46	69992.04
Faculty of Fine Arts	226	32.82	21835.82	57156.88	116554.07
Havran Vocational School	85	19.18	10093.11	23142.06	44710.93
Faculty of Law	57	20.96	19995.98	42831.12	50429.81
Faculty of Economics and Administrative Sciences	1486	19.48	881.87	23426.16	57405.60
Faculty of Theology	523	51.28	7456.45	98930.11	178401.08
İvrindi Vocational School of Health Services	335	33.30	22.10	1038.32	1367.83
Kepsut Vocational School	186	52.59	10542.46	71700.43	124329.76
Faculty of Architecture	430	61.78	22332.14	118887.51	237588.36
Faculty of Engineering	3008	37.38	12492.34	40213.32	133349.22
Necatibey Faculty of Education	2478	44.85	10716.80	102653.55	143193.27
Faculty of Health Sciences	956	48.84	1819.19	81680.22	137231.53
Sındırgı Vocational School	217	32.14	756.02	36949.46	75189.49
Sports Science Faculty	827	23.71	7195.92	13763.00	45394.24
Medical Faculty	560	19.49	1363.02	19940.96	54976.74
Tourism Faculty	744	16.59	2485.13	30782.23	42589.29
Faculty of Veterinary Medicine	344	45.43	453.90	28634.13	75857.40
Total	19498	31.56	6213.39	48113.19	95502.29