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Interaction and Achievement in Online Synchronous Distance Education: Is More Always Better?

Çevrimiçi Senkron Uzaktan Eğitimde Etkileşim ve Başarı: Daha Fazlası Her Zaman Daha İyi Mi?

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Abstract: The COVID-19 pandemic accelerated the adoption of distance learning in higher education, making students' social presence and interaction in online synchronous classes an important research focus. This study analyses learning analytics on participation, camera use, and microphone use during online classes via Microsoft Teams at a public university in the 2020–2021 academic year. Data from 16,304 students in the autumn term and 14,042 in the spring term were examined. Using the K-Means algorithm, students were clustered into high, medium, and low interaction groups. The results show that students in the low interaction group had significantly lower academic performance. In the autumn term, medium interaction students outperformed those with high interaction, while in the spring term, no significant difference emerged between the medium and high groups. Among undergraduates, medium interaction students were more successful, whereas among associate degree students, those in the high interaction group achieved the best results. This may be linked to undergraduates' stronger independent study habits, while associate degree students tend to rely more on instructor guidance. The findings suggest that high interaction and social presence do not always enhance academic success, and interaction strategies should be tailored to the specific needs of student groups.

Keywords: Distance Education, interaction, learning analytics, academic achievement, clustering analysis

Öz: COVID-19 pandemisi, yükseköğretimde uzaktan eğitimin yaygınlaşmasına neden olmuş ve çevrimiçi senkron derslerde öğrencilerin sosyal bulunuşluğu ile etkileşim durumları önemli bir araştırma alanı hâline gelmiştir. Bu çalışma, 2020-2021 akademik yılında bir devlet üniversitesinde Microsoft Teams platformunda yürütülen çevrimiçi senkron derslere katılım sayısı, kamera ve mikrofon kullanım sürelerine ait öğrenme analitiklerini incelemektedir. 2020-2021 güz döneminde 16.304, bahar döneminde ise 14.042 öğrencinin verileri analiz edilmiştir. Öğrenciler, K-Ortalamalar algoritması ile yüksek, orta ve düşük etkileşim düzeylerine göre kümelendirilmiştir. Sonuçlar, düşük etkileşim grubundaki öğrencilerin akademik başarılarının anlamlı ölçüde daha düşük olduğunu göstermektedir. Güz döneminde orta düzeyde etkileşim gösteren öğrenciler, yüksek etkileşim grubundakilerden daha başarılı bulunurken, bahar döneminde orta ve yüksek etkileşim grupları arasında anlamlı bir fark görülmemiştir. Lisans öğrencileri arasında orta düzey etkileşim gösterenler daha başarılı olurken, ön lisans öğrencileri arasında en yüksek başarıya sahip grup, yüksek etkileşim gösterenler olmuştur. Bu farklılık, lisans öğrencilerinin bağımsız çalışma alışkanlıklarına, ön lisans öğrencilerinin ise öğretmen yönlendirmesine daha fazla ihtiyaç duymasına bağlanabilir. Sonuçlar, yüksek etkileşim ve sosyal bulunuşluğun her zaman akademik başarıyı artırmadığını, belirli öğrenci gruplarında orta düzey etkileşimin daha verimli öğrenme çıktıları sağlayabileceğini göstermektedir. Bu nedenle, etkileşim stratejilerinin öğrenci gruplarının ihtiyaçlarına göre uyarlanması gerekmektedir.

Anahtar Kelimeler: Uzaktan eğitim, etkileşim, öğrenme analitikleri, akademik başarı, kümeleme analizi

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Introduction

With the onset of the COVID-19 pandemic, higher education institutions rapidly adapted to remote teaching, and educators widely utilised video conferencing tools to facilitate online interaction. This transition heightened dependence on digital forms of engagement while making students' online interaction behaviours a subject of debate (Bonk, 2020). Research indicates that students largely do not support the assumption that interaction and social presence in synchronous classes enhance group belongingness and academic success (Lowenthal & Snelson, 2017). According to Wut and Xu (2021), student-teacher and student-student interactions have been found to be insufficient for the full development of cognitive and emotional social presence. This issue has been explicitly highlighted by studies examining students' reluctance to use webcams and participate verbally in online class sessions (Händel et al., 2022; Mirza & Samen, 2022), emphasizing the need for further in-depth investigations into the underlying causes.

Within the context of online distance education, the Community of Inquiry Model (Garrison, 2007; Garrison et al., 1999), the Theory of Transactional Distance (Moore, 1991, 2013), and SIPS (Sociability, Interaction, Social Presence, and Social Space) Model (Kreijns et al., 2013; Weidlich & Bastiaens, 2017) provide essential theoretical frameworks for understanding interactions and social dynamics in these learning environments. In online learning environments, there is a lack of direct interaction between instructors and students, which complicates the instructor's ability to manage the teaching and learning process and assess its quality (Pahl & Donnellan, 2002). The frequency of students' behaviours in online settings varies significantly. Categorising these behavioural differences provides a crucial basis for institutions and educators in managing and evaluating educational activities. Therefore, the segmentation of educational data plays a key role in grouping students who exhibit similar behaviours (DeFreitas & Bernard, 2015).

To make educational data comprehensible and interpretable, researchers generally require intelligent mechanisms that process, analyse, and support data interpretation (Luis Cavalcanti Ramos et al., 2016). Establishing an intelligent pattern recognition and clustering mechanism necessitates the appropriate segmentation of educational data and the evaluation of its performance

(Bharara et al., 2018; DeFreitas & Bernard, 2015; Fang et al., 2018; Oviedo et al., 2016; Yudhanegara & Lestari, 2019). Students' interactions within learning management systems (LMSs) are closely related to the three types of interaction outlined by Moore (1991). According to Moore (1991), students engage in three forms of interaction in distance education environments: student-student, student-content, and student-instructor interactions. In contemporary online learning environments, particularly during synchronous class sessions, the majority of interactions are student-instructor interactions. Although the extent of student interactions has expanded in recent years, fundamental interaction data continue to be recorded within LMSs (Romero & Ventura, 2010). With advancements in internet infrastructure, data on student interactions in synchronous online live lessons can now also be documented (Moore & Kearsley, 2012). Students not only interact with their peers, instructors, and course content but can now also engage in audio-visual communication and share their educational outputs in real time. These interaction behaviours in synchronous teaching and learning activities may vary in magnitude among different students. Interaction between students and instructors in distance education is of critical importance in instructional planning and the development of effective teaching methodologies (Burnham & Walden, 1997). To ensure effective instructional planning and improve teaching methods, it is essential to cluster student behaviours and apply appropriate analytical techniques.

The behavioural initiatives undertaken by students during educational activities reveal their learning profiles. When student interactions recorded within LMSs are examined from a theoretical perspective, they unveil behavioural and cognitive structures. This study approaches the subject from the perspective of learning analytics in synchronous online lessons, analysing the core dynamics of participation, webcam and microphone usage in synchronous courses in higher education through a clustering methodology, particularly in the context of the increasing prevalence of online learning.

Problem Statement and Aim

As in the rest of the world, all higher education institutions in Türkiye transitioned to remote learning due to COVID-19. In an announcement issued by the Turkish Council of Higher Education (YÖK) on 13 March 2020, it was declared that education would be suspended for three weeks starting from 16 March 2020 (YÖK, 2020). Subsequently, the remainder of the 2020 spring semester was conducted entirely through distance education in all institutions. Following the classification of the outbreak as a pandemic, during the 2020–2021 academic year, higher education institutions continued their activities through synchronous and asynchronous distance learning methods.

For the first time, such an extended period of remote education led to the generation of extensive learning analytics data within Learning Management Systems (LMSs). These large-scale datasets exhibited variations depending on students' interaction patterns. During the pandemic, it was observed that some students engaged more actively in synchronous classes, while others displayed lower levels of interaction. Based on these interaction patterns, this study aims to analyse the learning analytics generated during synchronous learning sessions throughout the pandemic. Specifically, it seeks to segment students according to their levels of interaction using a clustering algorithm and to compare these interaction levels with their academic performance.

Research Questions

Since online courses were conducted synchronously, the clustering of data from this process varies depending on students' level of activity, and these clustered interaction patterns may be associated with academic performance. Based on this assumption, this study analysed synchronous course data—such as participation rates, webcam usage durations, and microphone activation times—collected from undergraduate and associate degree programmes during the 2020–2021 autumn and spring semesters on Microsoft Teams. The data were classified into three clusters (high, moderate, and low interaction) using the K-Means algorithm. Within this context, the study seeks to address the following research questions (RQs):

- **RQ1:** How are the interaction cluster centres of learning analytics distributed?
- **RQ2:** Is there a significant difference in semester grade point averages among students in the high, moderate, and low interaction clusters?
- **RQ3:** Is there a significant difference in semester grade point averages among students in the high, moderate, and low interaction clusters across undergraduate and associate degree programmes?

Theoretical Framework

The Community of Inquiry Model incorporates not only cognitive and teaching presence but also the concept of social presence, which refers to individuals projecting their personal characteristics into the community, allowing them to be perceived as "real people" by other participants (Garrison et al., 1999). Social presence is considered a crucial element in online learning processes and is interpreted in various ways. Kreijns et al. (2022) view social presence as part of a broader concept of social interaction, arguing that it comprises the component that enables students to be perceived as "real" individuals. According to the SIPS Model the emergence of social presence in online learning environments is shaped by social interaction and the sociability of the learning setting, which collectively influence students' perception of social presence and foster a strong social space (Weidlich & Bastiaens, 2017). Developing a sense of belonging in online learning environments plays a critical role in students' academic success and interaction levels (Joksimović et al., 2015). However, fostering and maintaining this sense of belonging in online settings presents a challenge, as it complicates both the creation and perception of social presence (Lowenthal & Snelson, 2017). The perception of social presence in online learning environments has a significant impact on learning success and satisfaction; however, a misalignment between expectations and perceptions of social presence can lead to negative outcomes, particularly in courses where interaction is central (Orhan Göksün, 2020; Weidlich et al., 2023). The Theory of Transactional Distance (Moore, 2013) explains the complexity of communication processes in distance education by addressing the geographical separation between students and instructors. This theory posits that distance education inherently creates a "psychological and communicative gap" within which misunderstandings can arise between instructors and students (Moore, 1991). According to Moore (2013), this gap is shaped by key factors such as course structure, instructor-student dialogue, and student autonomy.

In online education, video conferencing tools, particularly the use of microphones and webcams, play a vital role in fostering direct interaction and dialogue (Al-Samarraie, 2019; Giesbers et al., 2013; Gillies, 2008). Students' learning activities in online environments generate extensive datasets, which contain valuable insights regarding student profiles, instructional practices, and institutional infrastructure. Learning analytics refer to the metrics that facilitate the understanding of student behaviour patterns and guide educators and institutions in the efficient utilisation of limited resources (Clow, 2013). Within networked educational environments, individuals engaged in learning activities leave digital traces, which serve as sources for learning analytics and provide clues about how students construct and share knowledge (Retalis et al., 2006). Asynchronous and synchronous educational activities in online environments are conducted through Learning Management Systems (LMSs) such as Moodle, Blackboard, Sakai, BigBlueButton, Google Classroom, Google Meet, and Microsoft Teams. Contemporary LMSs can store and process student activity data on their servers. These data form the basis of learning analytics, which, in turn, provide the necessary resources for Educational Data Mining (EDM). EDM is an interdisciplinary research field concerned with developing methods to explore educational data, employing statistical, machine learning, and data mining algorithms across various educational data types (Romero & Ventura, 2010). EDM is defined as "the application of data mining techniques to specific datasets from educational environments to address significant educational questions" (Romero & Ventura, 2020).

The availability of real-time student performance data can significantly aid the planning of instructional activities. For students, receiving insights about their peers' performance or progress toward personal goals can be motivating and encouraging. Meanwhile, administrators and policymakers face considerable uncertainty due to budget constraints and global competition in higher education. Learning analytics offer solutions to these uncertainties by informing decisions on resource allocation, competitive advantages, and, most importantly, enhancing the quality and value of the learning experience (Siemens, 2011). By analysing large datasets in online learning environments, it becomes possible to gain insights into learning processes and student behaviours, as well as to identify groups of students exhibiting similar behaviours (Eryilmaz, 2019).

Romero and Ventura (2007) highlight that the key research areas of EDM include statistics, prediction, association rule mining, classification, outlier detection, and clustering. The learning analytics derived from students' activity traces on LMSs reflect their real learning experiences and provide valuable indicators of their academic progress. EDM, when integrated with machine learning techniques, enables the processing of learning analytics, thereby revealing students' behavioural and cognitive characteristics. In the identification and extraction of patterns related to students' online learning activities, unsupervised learning methods such as clustering techniques are widely applied (Zaiane & Luo, 2001). Clustering analysis is a form of unsupervised learning used to categorise data when definitive conclusions about the data are unavailable. It is one of the primary methods used in EDM and involves segmenting datasets into subgroups. These subgroups are structured so that objects within the same cluster are more similar to each other than to objects in other clusters (Han et al., 2012).

As in many fields, clustering methods provide meaningful insights in education as well. Students' online activities can lead to the identification of subgroups exhibiting similar behaviour patterns. Researchers emphasise that the careful analysis of large educational datasets can yield valuable information beneficial to educational institutions, students, instructors, and experts. These benefits include course selection, curriculum development, understanding student learning outcomes and behaviours, personalised learning, improved instructor performance, post-education employment opportunities, and overall enhancements in education (Avella et al., 2016).

The learning analytics recorded within LMSs contain the big data structures necessary for EDM. Researchers have applied numerous machine learning and statistical methods to these datasets. Existing studies show that learning analytics have been employed for classifying learning outcomes (Huang et al., 2020; Romero et al., 2013; Shahiri et al., 2015) and clustering student behaviours (Bharara et al., 2018; Bogarín et al., 2014; Eryilmaz, 2019). Additionally, some studies have utilised natural language processing (NLP) methods on learning analytics to extract qualitative data on students and conduct sentiment analysis (Dessì et al., 2019; Hew et al., 2020).

In alignment with these objectives, this study applies clustering approaches to learning analytics in synchronous courses and evaluates the academic performance of students within different interaction clusters.

Learning Analytics and Clustering Approaches

Students' behavioural patterns in online learning environments may exhibit similarities or differences. Individual variations in behaviour can categorise students into distinct profiles, such as "engaged" versus "disengaged" or "active participant" versus "passive listener." Learning analytics derived from these behavioural characteristics can be analysed using various clustering methods. Studies in the literature have demonstrated that student behaviours can be sharply clustered and that these clusters contain significant insights into students' cognitive and behavioural states (Antonenko et al., 2012; Bharara et al., 2018; Bogarín et al., 2014; Chen et al., 2009; Eryilmaz, 2019; Ghorbani & Montazer, 2012; Khalil & Ebner, 2016; Tie et al., 2010). Research has further shown that clustered learning analytics can be compared with academic achievement, motivation, attitudes, and other variables, providing valuable perspectives on students' behavioural and cognitive structures. The existing literature predominantly focuses on asynchronous learning analytics, such as system logins and logouts, assignment submissions, and forum activities (Moubayed et al. 2020). However, directing attention to learning analytics within synchronous education could provide a novel perspective to the academic discourse.

On the other hand, several studies have focused on evaluating the performance of clustering algorithms when applied to learning analytics datasets (Battaglia et al., 2017; Luis Cavalcanti Ramos et al., 2016; Valsamidis et al., 2012). These studies argue that before using clustering methods to assess students' academic performance, the effectiveness of the clustering approaches must first be evaluated. They also suggest that the performance of clustering algorithms may vary depending on the dynamics of the data in learning analytics. There is no consensus on which clustering method is most suitable for a given dataset; thus, comparing multiple methods across various scenarios is crucial (Rodriguez et al., 2019). When clustering learning analytics, different clustering approaches should be assessed and compared to determine their effectiveness (DeFreitas & Bernard, 2015).

In the field of education, clustering approaches are utilised for three main purposes: (1) categorisation studies, where analytics are used for classification in future research; (2) behavioural analysis, where student behaviours are evaluated; and (3) exploratory studies, which focus on comparing the performance of different clustering techniques (DeFreitas & Bernard, 2015).

A review of the literature reveals that researchers have employed various clustering algorithms, including Expectation Maximisation (EM), K-Means, Hierarchical Clustering (HC), Non-Hierarchical Clustering (NHC), Fuzzy Clustering (FC), C-Means, Particle Swarm Optimisation (PSO), Markov Clustering (MC), and Latent Class Analysis (LCA). While clustering algorithms do not follow a strict classification, they generally adopt specific grouping strategies based on their inherent characteristics (Berkhin, 2006). Broadly, clustering approaches can be classified into agglomerative and divisive hierarchical clustering methods, partition-based methods such as K-Means and DBSCAN, and probability-based methods, which are frequently applied in research (Berkhin, 2006).

As noted by DeFreitas & Bernard (2015), learning analytics serve purposes such as classification, assessment, and exploration. Additionally, a significant portion of existing learning analytics research has focused on asynchronous learning analytics, while clustering studies addressing synchronous teaching and learning activities remain relatively scarce. The literature highlights a gap in studies examining synchronous course data, suggesting a need for further research in this area. Furthermore, comparisons between hierarchical and non-hierarchical clustering methods have also been explored. Among these, the K-Means algorithm has been identified as the most used clustering technique in learning analytics studies.

Method

Research Design

This study adopts a causal-comparative research design. Causal-comparative designs typically involve the use of pre-existing or derived groups to investigate differences between them concerning an outcome or dependent variable. In many cases, variables examined in causal research cannot be experimentally manipulated due to practical or ethical constraints (Schenker & Rumrill, 2004).

A causal-comparative design is a type of non-experimental quantitative research in which the researcher compares two or more groups based on a prior cause (or independent variable) that has already occurred (Creswell & Creswell, 2022). In this study, learning analytics data collected during a semester of synchronous distance education were clustered based on students' interaction levels, and the causal effects of these interaction groups on academic achievement were analysed quantitatively.

Sample

In this study, learning analytics data from synchronous distance education during the COVID-19 pandemic were clustered based on interaction levels, and the relationship between these interaction clusters and academic achievement was investigated.

The sample consists of undergraduate and associate degree students who participated in synchronous distance education via Microsoft Teams at a public university during the 2020–2021 autumn and spring semesters. The Learning Management System recorded each student's data in the database using a unique anonymised ID.

- Autumn semester sample: 10386 undergraduate and 5918 associate degree students, totalling 16304 students.
- Spring semester sample: 9307 undergraduate and 4735 associate degree students, totalling 14042 students (Table 1).

In the autumn semester, the total number of students enrolled in undergraduate and associate degree programmes was 17,878. However, this figure declined to 17,365 in the spring semester due to factors such as graduation and student withdrawals. When constructing the research sample, students who were enrolled in the programmes but did not participate in any online courses were excluded from the dataset. Consequently, the learning analytics of 16,304 students in the autumn semester and 14,042 students in the spring semester were included in the analyses.

Table 1. Demographic characteristics of students

	Autumn Semester		
Gender	**Undergraduate Degree**	**Associate degree**	**Total**
Male	4756	2929	7685
Female	5630	2989	8619
Total	10386	5918	16304
	Spring Semester		
Gender	**Undergraduate Degree**	**Associate degree**	**Total**
Male	4101	2220	6321
Female	5206	2515	7721
Total	9307	4735	14042

In the autumn semester, 7685 students in undergraduate and associate degree programmes were male, while 8619 were female. In the spring semester, 6321 students were male, and 7721 were female in undergraduate and associate degree programmes.

Data Collection Tools and Procedures

The data consist of learning analytics from live lessons conducted via Microsoft Teams during the 2020–2021 autumn semester. These analytics include:

- Number of live session attendances (LSA)
- Duration of webcam usage (DWU)
- Duration of microphone usage (DMU)

Live lessons were conducted between 12 October 2020 and 28 May 2021. During this period, reports of all student activities in live sessions on Microsoft Teams were retrieved from the LMS databases. Students who did not attend any live sessions were excluded from the dataset. At the end of the semester, instructors entered students' grades into the automation system. Learning analytics and semester grade point averages (SGPA) were obtained from the LMS database, where they were represented using anonymised unique IDs. These data did not contain personally identifiable information such as student names or other sensitive details. The research adhered to institutional data protection policies, ensuring confidentiality and anonymity in all stages of data processing and analysis.

Data Analysis

The data were analysed using IBM SPSS Statistics, and the normality of distribution was assessed based on skewness and kurtosis values. The skewness and kurtosis values were within the ±1.5 range, indicating that the data followed a normal distribution (Tabachnick & Fidell, 2013). Students' live session attendance (LSA), duration of webcam usage in seconds (DWU), and duration of microphone usage in seconds (DMU) were clustered using the K-Means algorithm. The objective of the K-Means clustering algorithm is to partition m data points in an N-dimensional space into K clusters while minimising the within-cluster sum of squares (Hartigan & Wong, 1979). In K-Means clustering, the number of clusters (K) is predefined and introduced into the algorithm at the beginning. The sum of squared errors (SSE) is calculated as the first step in the clustering process. The K-Means algorithm operates in four primary steps:

1. Randomly selecting K initial cluster centroids (m_1, m_2, … m_k).
2. Calculating the Euclidean distance between each data point (x_i) and every cluster centroid (Equation 1).

$$d(x_i, m_i) = \sqrt{\sum_{j=1}^{d} (x_{i1} - m_{j1})^2}, i = 1 \ldots . . N; j = 1 \ldots k; \quad \text{(Equation 1)}$$

In the equation, d (x_i, m_j) represents the distance between data point i and cluster j.

3. The new cluster centroids are calculated as the mean of the data points within each cluster (Equation 2).

$$m_i = \frac{1}{N_i} \sum_{J=1}^{N_{\dot{\mathrm{I}}}} X_{\dot{\mathrm{I}}J}\,; \dot{\mathrm{I}} = 1,2 \ldots . K;\ N_i \quad \text{(Equation 2)}$$

The number of elements in the current i-th cluster.

4. Steps 2 and 3 are repeated until there is no change in the cluster centroids.

The results obtained using the K-Means algorithm formed the cluster centres in the learning analytics dataset, providing findings relevant to the first research question. To address the second research question, differences in students' semester grade point averages (SGPA) on a 4.0 scale across interaction clusters were analysed. For the third research question, differences in SGPA among students in different academic programmes within the interaction clusters were examined. In this context, one-way ANOVA and 3×2 factorial ANOVA analyses were conducted.

Findings

The descriptive statistics, including mean, standard deviation, skewness, and kurtosis, are presented in Table 2.

Table 2 shows that LSA data indicate students attended an average of 60 live sessions over 14 weeks during the 2020–2021 autumn semester, meaning an average student participated in four sessions per week. DWU data show that, on average, a student turned on their webcam for 33 minutes throughout the semester, while DMU data indicate that they used their microphone for 50 minutes. The average SGPA was 2.64, corresponding to 66 points on a 100-point scale. In the spring semester, students attended an average of 36 live sessions, suggesting that they had higher absenteeism compared to the autumn semester. This decrease in attendance also led to a decline in webcam and microphone usage durations. In the spring semester, students turned on their webcam for an average of 19 minutes and their microphone for 30 minutes. The SGPA increased by 0.01 points compared to the autumn semester.

Findings Related to RQ1

To determine the distribution of learning analytics cluster centres, LSA, DWU, and DMU data were clustered using the K-Means algorithm. The number of clusters was set to three to classify students into high, moderate, and low interaction groups. The cluster centres for the autumn and spring semesters are presented in Table 3.

The table presents student interaction levels (live session attendance, webcam usage, and microphone usage) across three clusters for the autumn and spring semesters. In the spring semester, interaction levels decreased across all clusters. Even students in the high interaction cluster became less active. The low interaction cluster is the largest group and experienced the most significant decline in interaction levels. The distribution of interaction clusters among undergraduate and associate degree students is shown in Table 4.

Table 2. Descriptive Statistics of the data

Semester	Variable	Min	Max	Mean	Std Dev	Skewness	Kurtosis
Autumn	LSA	1	219	59.28	37.22	0.23	-0.47
	DWU (sec)	0	11558	2021.49	1716.35	1	0.89
	DMU (sec)	0	14131	3027.26	2172.01	0.46	-0.29
	SGPA	0	4	2.64	0.91	-1.22	1.36
Spring	LSA	1	165	36.47	29.33	0.59	-0.49
	DWU (sec)	0	5998	1140.47	1278.71	1.37	1.32
	DMU (sec)	0	10409	1848.76	1697.32	0.84	-0.03
	SGPA	0	4	2.65	0.9	-1.20	1.31

Table 3. Cluster centres for high, moderate, and low interaction levels by variables

	Autumn Semester Interaction Level Cluster Centres			Spring Semester Interaction Level Cluster Centres		
Cluster / Variable	High (N=2461)	Moderate (N=6763)	Low (N=7080)	High (N=1973)	Moderate (N=4420)	Low (N=7649)
LSA	106.02	77.79	25.36	79.38	55.67	14.32
DWU	5001.45	2431.38	594.12	3617.68	1501.25	292.02
DMU	6457.16	3905.28	996.33	4809.10	2768.39	553.77

Table 4. Distribution of interaction clusters in undergraduate and associate degree programmes during the autumn and spring semesters

		High Interaction Cluster		Moderate Interaction Cluster		Low Interaction Cluster		Total	
Semester	Programme Type	N	%	N	%	N	%	N	%
Autumn	Undergraduate	2150	13.1%	4545	27.9%	3691	22.6%	10386	63.7%
	Associate degree	311	1.9%	2218	13.6%	3389	20.8%	5918	36.3%
	Total	2461	15%	6763	41.5%	7080	43.4%	16304	100%
Spring	Undergraduate	1736	12.4%	3228	23.0%	4343	30.9%	9307	66.3%
	Associate degree	237	1.7%	1192	8.5%	3306	23.5%	4735	33.7%
	Total	1973	14.1%	4420	31.5%	7649	54.4%	14042	100%

Table 5. ANOVA table showing the difference in SGPA among interaction level groups in the autumn and spring semesters

Semester	Group	Mean	Std Dev	s	SS	df	MS	F	p
Autumn	High	2.83	0.92	Between Groups	1194	2	597	777	0.001*
	Moderate	2.89	0.72	Within Groups	12516	16301	0.76		
	Low	2.33	0.98	Total	13711	16303			
	Total	2.64	0.91						
Spring	High	2.84	0.89	Between Group	480	2	240	302	0.001*
	Moderate	2.86	0.79	Within Groups	11146	14039	0.79		
	Low	2.48	0.94	Total	11626	14041			
	Total	2.65	0.90						

Table 6. Post-Hoc analysis showing differences among interaction groups

Semester	(i) Group	(j) Group	Difference(i-j)	Std Dev	p
Autumn	High	Moderate	-0.06	0.02	0.004*
		Low	0.49	0.02	0.001*
	Moderate	High	0.06	0.02	0.004*
		Low	0.56	0.01	0.001*
	Low	High	-0.49	0.21	0.001*
		Moderate	-0.56	0.01	0.001*
Spring	High	Moderate	-0.01	0.02	0.711
		Low	0.35	0.02	0.001*
	Moderate	High	0.01	0.02	0.711
		Low	0.37	0.01	0.001*
	Low	High	-0.35	0.02	0.001*
		Moderate	-0.37	0.01	0.001*

There is no significant difference in the percentage distribution of students in the high interaction cluster between the autumn and spring semesters. However, the low interaction cluster increased from 43.4% in the autumn semester to 54.4% in the spring semester. The moderate interaction cluster accounted for 41.5% of students in the autumn semester, whereas in the spring semester, this group decreased to 31.5%. Across all interaction clusters, associate degree students have a lower percentage compared to undergraduate students.

Findings Related to RQ2

To determine whether there was a significant difference in SGPA among the high, moderate, and low interaction clusters in the autumn and spring semesters, an ANOVA analysis was conducted. The findings are presented in Table 5.

The ANOVA results indicate that there is a significant difference among interaction groups in both the autumn and spring semesters ($p < 0.05$). To determine which groups, differ significantly, a post-Hoc analysis was conducted (Table 6). The Games-Howell test was selected for the post-Hoc analysis.

In both the autumn and spring semesters, students in the low interaction cluster had lower SGPA compared to those in the high and moderate interaction clusters. This was an expected finding. However, the post-Hoc analysis revealed a striking result. In the autumn semester, students in the moderate interaction cluster had a higher SGPA than those in the high interaction cluster. In contrast, in the spring semester, there was no significant difference in SGPA between the moderate and high interaction clusters. This notable finding suggests that higher interaction in synchronous education does not necessarily lead to higher academic success. Students who exhibited moderate interaction performed as well as those in the high interaction cluster and were even more successful in the autumn semester. On the other hand, low interaction, as expected, was associated with lower academic performance.

Findings Related to RQ3

To determine whether there was a significant difference in SGPA among undergraduate and associate degree students in the high, moderate, and low interaction clusters during the autumn and spring semesters, a 3×2 factorial ANOVA was conducted. The findings are presented in Table 7.

Table 7. Two-Factor ANOVA results showing significant differences in SGPA among students in different academic programmes within interaction clusters

Semester	Source	SS	df	MS	F	p	η^2
Autumn	Interaction Group	1135	2	567	740	**0.000***	0.083
	Programme Type	2.32	1	2.32	3.02	0.082	0.000
	Interaction Group * Programme Type	17.3	2	8.65	11.28	**0.001***	0.001
	Error	12499	16298	0.767			
	Total	127639	16304				
	Corrected Total	13711	16303				
Spring	Interaction Group	449	2	224	283	**0.001***	0.039
	Programme Type	9.04	1	9.04	11.4	**0.001***	0.001
	Interaction Group * Programme Type	15.2	2	7.61	9.6	**0.001***	0.001
	Error	11130	14036	0.79			
	Total	110771	14042				
	Corrected Total	11626	14041				

Table 8. Post-Hoc analysis showing differences in SGPA among different academic programmes within interaction clusters for the autumn and spring semesters

Semester	Interaction Group	(i) Programme Type	(j) Programme Type	Difference (i-j)	Std Dev	p
Autumn	High Interaction	Undergraduate	Associate degree	-0.14	0.53	**0.007***
		Associate degree	Undergraduate	0.14	0.53	**0.007***
	Moderate Interaction	Undergraduate	Associate degree	-0.39	0.02	0.086
		Associate degree	Undergraduate	0.39	0.02	0.086
	Low Interaction	Undergraduate	Associate degree	0.07	0.02	**0.001***
		Associate degree	Undergraduate	-0.07	0.02	**0.001***
Spring	High Interaction	Undergraduate	Associate degree	-0.2	0.06	**0.001***
		Associate degree	Undergraduate	0.2	0.06	**0.001***
	Moderate Interaction	Undergraduate	Associate degree	-0.07	0.03	**0.016***
		Associate degree	Undergraduate	0.07	0.03	**0,016***
	Low Interaction	Undergraduate	Associate degree	0.03	0.02	0.083
		Associate degree	Undergraduate	-0.03	0.02	0.083

The two-way ANOVA results evaluate the effect of both the interaction group (high, moderate, and low) and the programme type (undergraduate and associate degree) on the dependent variable within the framework of seasonal differences. In the autumn semester, the interaction group had a significant effect on the dependent variable ($p < 0.05$, $\eta^2 = 0.083$), whereas the programme type did not show a statistically significant effect ($p = 0.082$). However, the interaction between these two variables was significant ($p < 0.05$), indicating that the effect of the programme type varies depending on the interaction group. In the spring semester, both main effects were significant, with the interaction group ($p < 0.05$, $\eta^2 = 0.039$) and the programme type ($p < 0.05$, $\eta^2 = 0.001$) causing significant differences in the dependent variable. Additionally, the interaction between these two variables was significant ($p < 0.05$), but the effect size was low. The results suggest that the effect of programme type on the dependent variable becomes significant only in certain groups, and seasonal differences influence this interaction. The post-Hoc analyses, which identify the groups where these significant differences occurred in the autumn and spring semesters, are presented in Table 8.

The post-Hoc analysis results presented in Table 8 illustrate the differences in SGPA among students in different academic programmes (undergraduate and associate degree) within various interaction clusters during the autumn and spring semesters. In the autumn semester, a significant difference was observed between undergraduate and associate degree students in the high interaction group ($p < 0.05$), whereas in the moderate interaction group, this difference was not statistically significant ($p = 0.086$). However, in the low interaction group, the difference between undergraduate and associate degree students was significant ($p < 0.05$). In the spring semester, significant differences were found across all interaction groups, except in the low interaction group, where the difference between undergraduate and associate degree students was not statistically significant ($p = 0.083$). Overall, while differences between academic programmes were significant in the high and moderate interaction groups, they lost significance in the low interaction group. This finding suggests that interaction levels impact students' academic success differently depending on their academic programme. The detailed distribution of these differences for the autumn and spring semesters is presented in Figure 1.

Figure 1 illustrates the differences in SGPA among students in undergraduate and associate degree programmes within high, moderate, and low interaction clusters for the autumn and spring semesters. In both semesters, undergraduate students in the moderate interaction cluster had higher SGPA compared to those in both the high and low interaction clusters. However, among associate degree students, those in the high interaction cluster had higher SGPA than those in the moderate and low interaction clusters. In other words, at the undergraduate level, high interaction does not necessarily lead to higher academic success. In fact, the moderate and high interaction clusters showed similar academic performance among undergraduate students. However, this pattern does not hold for associate degree students, where high interaction was associated with higher academic success. Nevertheless, this does not imply that associate degree students outperform undergraduate students. The yellow lines in Figure 1 represent the overall trend, indicating that undergraduate students generally perform better than associate degree students. Although this study does not aim to compare undergraduate and associate degree students, this distinction is highlighted in the total line in Figure 1 to prevent potential misinterpretations. The primary objective of this research was to examine academic success within interaction clusters, and the findings provide significant contributions to the literature.

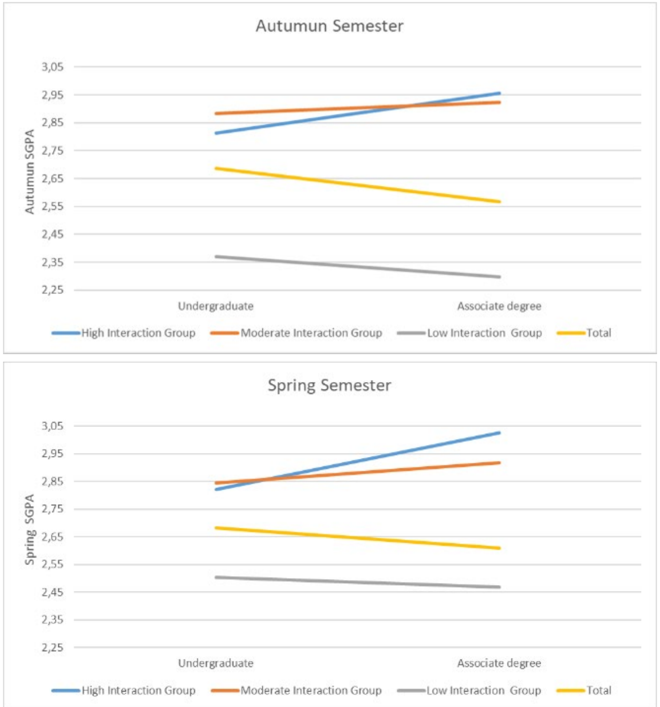

Figure 1. Differences in SGPA among different academic programmes within interaction clusters for the autumn and spring semesters

Discussion and Conclusion

This study clustered learning analytics from synchronous online lessons during the pandemic based on interaction levels and examined their relationship with academic achievement. Naturally, various factors influence interaction levels and academic success, including students' motivation, self-regulation, and attitudes towards courses. However, this research focused on key learning analytics, shedding light on underlying patterns. Previous studies argue that students with high interaction levels tend to achieve higher academic success (Cerezo et al., 2016; Roski et al., 2024; Yoon et al., 2021). While this claim is valid, a closer examination of the data reveals a more nuanced picture. If students are divided into high vs. low interaction or active vs. passive groups, it is expected that those putting in more effort will perform better. However, by clustering learning analytics with the right number of groups, intermediate interaction groups reveal distinct behavioural patterns.

In this study, K-Means clustering was applied to live session attendance, webcam usage, and microphone usage data from synchronous online education during the 2020–2021 autumn and spring semesters, resulting in three clusters: high, moderate, and low interaction levels. The cluster centres for learning analytics in the spring semester were lower than in the autumn semester, indicating a decline in interaction. When examining the academic success of students in these interaction clusters, an unexpected result emerged: in the autumn semester, students in the moderate interaction group achieved higher SGPA than those in the high interaction group. In the spring semester, no significant difference was observed between high and moderate interaction groups, while the low interaction group consistently showed significantly lower SGPA in both semesters. A two-factor ANOVA was conducted to explore how these differences varied across academic programmes. In this study, the lack of a significant difference in academic achievement between the moderate and high interaction groups during the spring term is noteworthy. This finding suggests that students' interaction levels may not have a direct impact on academic performance beyond a certain threshold. Similarly, Weidlich and Bastiaens (2017) and Wut and Xu (2021) highlight that social presence has a limited contribution to learning outcomes after reaching a particular level, and an increase in interaction does not necessarily enhance academic success. From the perspective of Transactional Distance Theory (Moore, 2013), this may be attributed to students developing independent study habits at a certain stage and requiring less direct interaction in the learning process. Furthermore, while undergraduate students performed better with moderate interaction, associate degree students achieved higher success with high interaction, indicating that the effects of interaction strategies may vary depending on academic level. Therefore, future research should explore the relationship between interaction types and academic achievement in greater detail. The results showed that in both autumn and spring semesters, undergraduate students in the moderate interaction group performed better than those in the high interaction group, whereas associate degree students in the high interaction group were the most successful. Overall, undergraduate students outperformed associate degree students.

In synchronous lessons, student participation, webcam usage, and microphone usage primarily support student-teacher interaction. The variables analysed in this study reflect student-teacher interactions, which, according to Moore (1991), help instructors deepen and enhance the learning process. Teachers who guide students, provide feedback, respond to questions, and maintain student motivation significantly impact their academic success. In this study, all students were required to attend synchronous online lessons, but webcam and microphone usage was not mandatory. However, some instructors insisted on webcam usage, encouraged discussions, and promoted an interactive online learning environment, which may have led to the emergence of high interaction clusters. On the other hand, students in the moderate interaction group may have participated voluntarily, engaging in lessons through webcam and microphone use at their own discretion, which could explain their higher success rates compared to both the high and low interaction groups. Using a webcam and microphone in online learning is often associated with academic success, yet concerns related to home environments, personal appearance, and self-consciousness often discourage students from turning on their webcams (Mirza & Samen, 2022). Students in the high interaction group also tend to have higher social presence, which encourages participation in discussions and group activities, enhancing understanding and engagement with learning materials (Richardson et al., 2017). However, excessive social interaction can lead to distractions, shifting focus away from academic content. Some students prefer individual learning, and despite having low social presence, they may still achieve high academic performance (Kreijns et al., 2003). Students in the low interaction group, who rarely participated in lessons or used webcams and microphones, had lower SGPA. However, the moderate interaction group demonstrated higher academic success than both high and low interaction groups, suggesting that both excessive and minimal interaction may not necessarily yield the best learning outcomes in synchronous online education. Nonetheless, interaction levels influence students' engagement with lessons, and low-interaction students should be encouraged to participate actively by using webcams and microphones.

This study is unique in that it focuses on synchronous learning analytics during the COVID-19 period. Research on asynchronous learning analytics has consistently shown that high-interaction students outperform those in moderate and low interaction clusters (Bogarín et al., 2014; Ghorbani & Montazer, 2012; Moubayed et al., 2020). Social presence plays a crucial role in online group learning, as students feel more motivated and engaged when they perceive others as "real" participants. However, excessive social presence can become distracting. Overly high levels of social interaction may disrupt the learning process and shift discussions away from academic content (Kreijns et al., 2022). As transactional distance increases, various types of interactions—especially student-teacher interaction—may weaken (Moore, 2013). Therefore, educators must encourage students to participate in synchronous lessons through verbal and visual interactions. Students with low social presence tend to fall into the low interaction cluster, which negatively affects their sense of belonging and academic performance. However, excessive social presence does not necessarily lead to better academic outcomes. To optimise student engagement, concerns about webcam and microphone use should be addressed, and a supportive learning environment should be provided. When examining the impact of students' interaction levels on academic achievement, it is crucial to consider the factor of social presence. According to social presence theory, students' interaction levels and social perceptions in online environments directly influence their learning experiences (Weidlich et al., 2023). Indeed, some studies in the literature suggest that the relationship between social interaction and academic achievement encompasses not only a quantitative but also a qualitative component (Orhan Göksün, 2020). The processes through which students establish a social space can shape their academic success and perceived learning outcomes (Weidlich & Bastiaens, 2017). Therefore, when designing interaction strategies, not only the frequency but also the content and quality of interaction should be considered.

Author Contributions

The author declares that no other author has contributed to the study and that he has read and approved the final version of the study.

Ethical Declaration

This study did not require formal ethical approval as it utilised data with unique anonymised IDs, ensuring no personally identifiable information was collected. No direct participant involvement was required, and all data processing adhered to institutional confidentiality and ethical standards. The researcher declares full compliance with the Higher Education Institutions Scientific Research and Publication Ethics Directive and Committee on Publication Ethics (COPE) guidelines.

Conflict of Interest

The author declares that there is no conflict of interest with any institution or person within the scope of the study.

References

Al-Samarraie, H. (2019). A Scoping Review of Videoconferencing Systems in Higher Education: Learning Paradigms, Opportunities, and Challenges. *The International Review of Research in Open and Distributed Learning*, *20*(3). https://doi.org/10.19173/IRRODL.V20I4.4037

Antonenko, P. D., Toy, S., & Niederhauser, D. S. (2012). Using cluster analysis for data mining in educational technology research. *Educational Technology Research and Development*, *60*(3), 383-398. https://doi.org/10.1007/s11423-012-9235-8

Avella, J. T., Kebritchi, M., Nunn, S. G., & Kanai, T. (2016). Learning Analytics Methods, Benefits, and Challenges in Higher Education: A Systematic Literature Review. *Online Learning*, *20*(2), 13-29. https://eric.ed.gov/?id=EJ1105911

Battaglia, O. R., Di Paola, B., & Fazio, C. (2017). A quantitative analysis of Educational Data through the Comparison between Hierarchical and Not-Hierarchical Clustering. *EURASIA Journal of Mathematics, Science and Technology Education*, *13*(8). https://doi.org/10.12973/eurasia.2017.00943a

Berkhin, P. (2006). A Survey of Clustering Data Mining Techniques. Içinde J. Kogan, C. Nicholas, & M. Teboulle (Ed.), *Grouping Multidimensional Data* (25-71). Springer. https://doi.org/https://doi.org/10.1007/3-540-28349-8_2

Bharara, S., Sabitha, S., & Bansal, A. (2018). Application of learning analytics using clustering data Mining for Students' disposition analysis. *Education and Information Technologies*, *23*(2), 957-984. https://doi.org/10.1007/s10639-017-9645-7

Bogarín, A., Romero, C., Cerezo, R., & Sánchez-Santillán, M. (2014). Clustering for improving Educational Process Mining. *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge*, 11-15. https://doi.org/https://doi.org/10.1145/2567574.256760

Bonk, C. J. (2020). Pandemic ponderings, 30 years to today: synchronous signals, saviors, or survivors? *Distance Education*, *41*(4), 589-599. https://doi.org/10.1080/01587919.2020.1821610

Burnham, B. R., & Walden, B. (1997). Interactions in distance education: A report from the other side. *Annual Adult Education Research Conference Proceedings*, 49-54. https://newprairiepress.org/aerc/1997/papers/9

Cerezo, R., Sánchez-Santillán, M., Paule-Ruiz, M. P., & Núñez, J. C. (2016). Students' LMS interaction patterns and their relationship with achievement: A case study in higher education. *Computers & Education*, *96*, 42-54. https://doi.org/10.1016/J.COMPEDU.2016.02.006

Chen, J., Huang, K., Wang, F., & Wang, H. (2009). E-learning Behavior Analysis Based on Fuzzy Clustering. *2009 Third International Conference on Genetic and Evolutionary Computing*, 863-866. https://doi.org/10.1109/WGEC.2009.214

Clow, D. (2013). An overview of learning analytics. *Teaching in Higher Education*, *18*(6), 683-695. https://doi.org/10.1080/13562517.2013.827653

Creswell, J. W., & Creswell, J. D. (2022). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches, 5th Edition. *Journal of Electronic Resources in Medical Libraries*, *19*(1-2), 54-55. https://doi.org/10.1080/15424065.2022.2046231

DeFreitas, K., & Bernard, M. (2015). Comparative Performance Analysis of Clustering Techniques in Educational Data Mining. *International journal on computer science & Information systems*, *10*(2), 14.

Dessì, D., Fenu, G., Marras, M., & Reforgiato Recupero, D. (2019). Bridging learning analytics and Cognitive Computing for Big Data classification in micro-learning video collections. *Computers in Human Behavior*, *92*, 468-477. https://doi.org/10.1016/j.chb.2018.03.004

Elton, L. (1996). Strategies to enhance student motivation: A conceptual analysis. *Studies in Higher Education*, *21*(1), 57-68. https://doi.org/10.1080/03075079612331381457

Eryilmaz, M. (2019). Sanal Öğrenme Ortamlarındaki Öğrenci Davranışlarının Kümeleme Yöntemi ile Analiz Edilmesi. *Yüzüncü Yıl Üniversitesi Eğitim Fakültesi Dergisi*, *16*(1), 725-743. https://doi.org/10.23891/efdyyu.2019.139

Fang, Y., Shubeck, K., Lippert, A., Cheng, Q., Shi, G., Feng, S., Chen, S., Cai, Z., Pavlik, P., Frijters, J., Greenberg, D., & Graesser, A. (2018). Clustering the Learning Patterns of Adults with Low Literacy Skills Interacting with an Intelligent Tutoring System. *International Conference on Educational Data Mining*, 7.

Garrison, D. R. (2007). Online Community of Inquiry Review: Social, Cognitive, and Teaching Presence Issues. *Journal of Asynchronous Learning Networks*, *11*(1), 61-72.

Garrison, D. R., Anderson, T., & Archer, W. (1999). Critical Inquiry in a Text-Based Environment: Computer Conferencing in Higher Education. *The Internet and Higher Education*, *2*(2-3), 87-105. https://doi.org/10.1016/S1096-7516(00)00016-6

Ghorbani, F., & Montazer, G. A. (2012). Learners grouping improvement in e-learning environment using fuzzy inspired PSO method. *6Th National And 3Rd International Conference Of E -Learning And E -Teaching*, 65-70. https://doi.org/10.1109/ICELET.2012.6333367

Giesbers, B., Rienties, B., Tempelaar, D., & Gijselaers, W. (2013). Investigating the relations between motivation, tool use, participation, and performance in an e-learning course using web-videoconferencing. *Computers in Human Behavior*, *29*(1), 285-292. https://doi.org/10.1016/J.CHB.2012.09.005

Gillies, D. (2008). Student perspectives on videoconferencing in teacher education at a distance. *Distance Education*, *29*(1), 107-118. https://doi.org/10.1080/01587910802004878

Han, J., Kamber, M., & Pei, J. (2012). Cluster Analysis: Basic Concepts and Methods. Içinde *Data Mining Concepts and Techniques* (s. 443). Elsevier Inc.

Händel, M., Bedenlier, S., Kopp, B., Gläser-Zikuda, M., Kammerl, R., & Ziegler, A. (2022). The webcam and student engagement in synchronous online learning: visually or verbally? *Education and Information Technologies*, *27*(7), 10405-10428. https://doi.org/10.1007/S10639-022-11050-3/FIGURES/1

Hartigan, J. A., & Wong, M. A. (1979). Algorithm AS 136: A K-Means Clustering Algorithm. *Applied Statistics*, *28*(1), 100. https://doi.org/10.2307/2346830

Hew, K. F., Hu, X., Qiao, C., & Tang, Y. (2020). What predicts student satisfaction with MOOCs: A gradient boosting trees supervised machine learning and sentiment analysis approach. *Computers & Education*, *145*, 103724. https://doi.org/10.1016/J.COMPEDU.2019.103724

Huang, A. Y. Q., Lu, O. H. T., Huang, J. C. H., Yin, C. J., & Yang, S. J. H. (2020). Predicting students' academic performance by using educational big data and learning analytics: evaluation of classification methods and learning logs. *Interactive Learning Environments*, *28*(2), 206-230. https://doi.org/10.1080/10494820.2019.1636086

Joksimović, S., Gašević, D., Kovanović, V., Riecke, B. E., & Hatala, M. (2015). Social presence in online discussions as a process predictor of academic performance. *Journal of Computer Assisted Learning*, *31*(6), 638-654. https://doi.org/10.1111/JCAL.12107

Khalil, M., & Ebner, M. (2016). Clustering patterns of engagement in Massive Open Online Courses (MOOCs): the use of learning analytics to reveal student categories. *Journal of Computing in Higher Education* , *29*(1), 1-19. https://doi.org/10.1007/S12528-016-9126-9

Kreijns, K., Kirschner, P. A., & Jochems, W. (2003). Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: a review of the research. *Computers in Human Behavior*, *19*(3), 335-353. https://doi.org/10.1016/S0747-5632(02)00057-2

Kreijns, K., Kirschner, P. A., & Vermeulen, M. (2013). Social aspects of CSCL environments: A research framework. *Educational Psychologist*, *48*(4), 229-242. https://doi.org/10.1080/00461520.2012.750225

Kreijns, K., Xu, K., & Weidlich, J. (2022). Social Presence: Conceptualization and Measurement. *Educational Psychology Review*, *34*(1), 139-170. https://doi.org/10.1007/S10648-021-09623-8/TABLES/2

Lowenthal, P. R., & Snelson, C. (2017). In search of a better understanding of social presence: an investigation into how researchers define social presence. *Distance Education*, *38*(2), 141-159. https://doi.org/10.1080/01587919.2017.1324727

Luis Cavalcanti Ramos, J., e Silva, R., Carlos Sedraz Silva, J., Lins Rodrigues, R., & Sandro Gomes, A. (2016). A Comparative Study between Clustering Methods in Educational Data Mining. *IEEE Latin America Transactions*, *14*(8), 3755-3761. https://doi.org/10.1109/TLA.2016.7786360

Mirza, E., & Samen, K. (2022). Web Kamerayı Açmak ya da Açmamak: Uzaktan Senkron Eğitimde Derse Giren Lisans Öğrencileri Web Kameraya Nasıl Bir Anlam Yüklüyorlar? *Uluslararası Medya ve İletişim Araştırmaları Hakemli Dergisi*, *5*(2), 206-235. https://doi.org/10.33464/MEDIAJ.1130565

Moore, M. G. (1991). Editorial: Distance Education Theory. *American Journal of Distance Education*, *5*(3), 1-6. https://doi.org/10.1080/08923649109526758/ASSET//CMS/ASSET/F4D64AE0-1D1D-4FF7-A974-9931E3498F02/08923649109526758.FP.PNG

Moore, M. G. (2013). The Theory of Transactional Distance. Içinde *Handbook of Distance Education* (C. 14, Sayı 304, ss. 66-85). Routledge. https://doi.org/10.4324/9780203803738-10

Moore, M. G., & Kearsley, G. (2012). *Distance Education: A Systems View of Online Learning*. Wadsworth Cengage Learning.

Moubayed, A., Injadat, M., Shami, A., & Lutfiyya, H. (2020). Student Engagement Level in an e-Learning Environment: Clustering Using K-means. *American Journal of Distance Education*, *34*(2), 137-156. https://doi.org/10.1080/08923647.2020.1696140

Orhan Göksün, D. (2020). Predictors of perceived learning in a distance learning environment from the perspective of SIPS model. *International Journal of Human–Computer Interaction*, *36*(10), 941-952. https://doi.org/10.1080/10447318.2019.1700643

Oviedo, B., Moral, S., & Puris, A. (2016). A hierarchical clustering method: Applications to educational data. *Intelligent Data Analysis*, *20*(4), 933-951. https://doi.org/10.3233/IDA-160839

Pahl, C., & Donnellan, D. (2002). Data Mining Technology for the Evaluation of Web-based Teaching and Learning Systems. *ELearn: World Conference on EdTech*, 6.

Retalis, S., Papasalouros, A., Psaromiligkos, Y., Siscos, S., & Kargidis, T. (2006). Towards Networked Learning Analytics – A concept and a tool. *Networked Learning*, 8.

Richardson, J. C., Maeda, Y., Lv, J., & Caskurlu, S. (2017). Social presence in relation to students' satisfaction and learning in the online environment: A meta-analysis. *Computers in Human Behavior*, *71*, 402-417. https://doi.org/10.1016/J.CHB.2017.02.001

Rodriguez, M. Z., Comin, C. H., Casanova, D., Bruno, O. M., Amancio, D. R., Costa, L. da F., & Rodrigues, F. A. (2019). Clustering algorithms: A comparative approach. *PLOS ONE*, *14*(1), e0210236. https://doi.org/10.1371/journal.pone.0210236

Romero, C., López, M.-I., Luna, J.-M., & Ventura, S. (2013). Predicting students' final performance from participation in on-line discussion forums. *Computers & Education*, *68*, 458-472. https://doi.org/10.1016/j.compedu.2013.06.009

Romero, C., & Ventura, S. (2007). Educational data mining: A survey from 1995 to 2005. *Expert Systems with Applications*, *33*(1), 135-146. https://doi.org/10.1016/j.eswa.2006.04.005

Romero, C., & Ventura, S. (2010). Educational Data Mining: A Review of the State of the Art. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, *40*(6), 601-618. https://doi.org/10.1109/TSMCC.2010.2053532

Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *10*(3), e1355. https://doi.org/10.1002/WIDM.1355

Roski, M., Sebastian, R., Ewerth, R., Hoppe, A., & Nehring, A. (2024). Learning analytics and the Universal Design for Learning (UDL): A clustering approach. *Computers & Education*, *214*, 105028. https://doi.org/10.1016/J.COMPEDU.2024.105028

Schenker, J. D., & Rumrill, Jr. , P. D. (2004). Causal-comparative research designs. *Journal of Vocational Rehabilitation*, *21*(3), 117-121.

Shahiri, A. M., Husain, W., & Rashid, N. A. (2015). A Review on Predicting Student's Performance Using Data Mining Techniques. *Procedia Computer Science*, *72*, 414-422. https://doi.org/10.1016/j.procs.2015.12.157

Siemens, G. (2011). Penetrating the Fog: Analytics in Learning and Education. *EDUCAUSE Review*, *46*(5), 30. https://eric.ed.gov/?id=EJ950794

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics.* (6. ed). Pearson.

Tie, Z., Jin, R., Zhuang, H., & Wang, Z. (2010). The Research on Teaching Method of Basics Course of Computer based on Cluster Analysis. *2010 10th IEEE International Conference on Computer and Information Technology*, 2001-2004. https://doi.org/10.1109/CIT.2010.338

Valsamidis, S., Kontogiannis, S., Kazanidis, I., Theodosiou, T., & Karakos, A. (2012). A Clustering Methodology of Web Log Data for Learning Management Systems. *Educational Technology & Society*, *15*(2), 154-167. https://eric.ed.gov/?id=EJ988458

Weidlich, J., & Bastiaens, T. J. (2017). Explaining social presence and the quality of online learning with the SIPS model. *Computers in Human Behavior*, *72*, 479-487. https://doi.org/10.1016/j.chb.2017.03.016

Weidlich, J., Göksün, D. O., & Kreijns, K. (2023). Extending social presence theory: Social presence divergence and interaction integration in online distance learning. *Journal of Computing in Higher Education*, *35*(3), 391-412. https://doi.org/10.1007/s12528-022-09325-2

Wut, T. M., & Xu, J. (2021). Person-to-person interactions in online classroom settings under the impact of COVID-19: a social presence theory perspective. *Asia Pacific Education Review*, *22*(3), 371-383. https://doi.org/10.1007/s12564-021-09673-1

YÖK. (2020). *Koronavirüs (Covid-19) Bilgilendirme Notu: 1*. https://covid19.yok.gov.tr/Documents/alinan-kararlar/02-coronavirus-bilgilendirme-notu-1.pdf Accessed on 03/02/2025.

Yudhanegara, M. R., & Lestari, K. E. (2019). Clustering for multi-dimensional data set: a case study on educational data. *Journal of Physics: Conference Series*, *1280*(4), 42025. https://doi.org/10.1088/1742-6596/1280/4/042025

Zaiane, O. R., & Luo, J. (2001). Towards evaluating learners' behaviour in a Web-based distance learning environment. *Proceedings IEEE International Conference on Advanced Learning Technologies*, 357-360. https://doi.org/10.1109/ICALT.2001.943944