International Journal of Online Pedagogy and Course Design
Volume 13 • Issue 1

Learning Analytics for Data-Driven Decision Making:

Enhancing Instructional Personalization and Student Engagement in Online Higher Education

Abdulrahman M. Al-Zahrani, University of Jeddah, Jeddah, Saudi Arabia*
https://orcid.org/0009-0007-9885-0730

Talal Alasmari, University of Jeddah, Jeddah, Saudi Arabia

ABSTRACT

This study examines the use of learning analytics to enhance instructional personalization and student engagement in online higher education. The research focuses on the engagement levels of students based on different access methods (mobile and non-mobile), the relationships among engagement indicators, and the strategies for instructional personalization. Quantitative research methodology is employed to analyse and measure students' engagement levels. The findings indicate that students using non-mobile devices exhibit higher engagement in terms of average minutes, item accesses, and content accesses, while mobile access shows higher engagement in terms of course accesses, course interactions, and average interactions. Significant correlations are observed among engagement indicators, highlighting the importance of course interactions, content accesses, and assessment accesses in promoting student engagement. Accordingly, a critical model for effective student engagement in online learning courses is proposed.

KEYWORDS

data-driven decision making, engagement indicators, instructional personalization, learning analytics, online higher education, student engagement

INTRODUCTION

In recent years, the growth and transformation of online education have revolutionized higher education delivery, offering universities and institutions new opportunities for broader access and flexible learning (Al Shehhi & Almarri, 2021; Bozkurt & Sharma, 2022; Dart & Cunningham, 2023; Maseleno et al., 2018; Mathrani et al., 2021; Pargman & McGrath, 2019; Sheikh et al., 2022; Ulfa & Fatawi, 2021; Wong, 2017; Wong et al., 2019; Zhang et al., 2018). However, effectively

DOI: 10.4018/IJOPCD.331751
*Corresponding Author

personalizing instruction and fostering student engagement in the virtual learning environment remain a challenge (Al Shehhi & Almarri, 2021; Dart & Cunningham, 2023; Maseleno et al., 2018; Mathrani et al., 2021).

Learning Analytics (LA), an emerging field combining educational research and data mining, has emerged as a powerful tool in addressing these challenges in online higher education (Bozkurt & Sharma, 2022; Lee et al., 2020; Mathrani et al., 2021; Sheikh et al., 2022; Wise, 2019; Zhang et al., 2018). By leveraging the data generated through online learning platforms, LA provides insights into student behaviours, learning patterns, and performance, enabling informed decision-making, instructional personalization, and improved learning outcomes (Al Shehhi & Almarri, 2021; Al-Tameemi et al., 2020; Banihashem et al., 2022; Bozkurt & Sharma, 2022; Gasevic et al., 2019; Maseleno et al., 2018; Mathrani et al., 2021; Schmitz et al., 2017; Sheikh et al., 2022; Wong et al., 2019; Zhang et al., 2018).

However, the widespread adoption, policy frameworks, and funding initiatives related to LA are still lacking, emphasizing the need for interdisciplinary studies and the integration of technology and pedagogy (Bozkurt & Sharma, 2022; Nouri et al., 2019). The current study aims to explore the application of LA in online higher education, focusing on instructional personalization and student engagement. Through the analysis of data collected from Learning Management System (LMS), including student access, interactions, and course materials, the study seeks to identify patterns and trends that inform instructional design, content delivery, and student support decisions. By advancing LA research, this study contributes to optimizing educational outcomes in the online learning environment.

LITERATURE REVIEW

Theoretical Background

The current study draws upon several theoretical frameworks. For instance, the Technology Acceptance Model (TAM) offers a theoretical lens for understanding user acceptance and usage behaviour toward technology (Davis, 1989). TAM posits that perceived usefulness and perceived ease of use determine an individual's behavioural intention to use technology, which, in turn, influences actual system usage. TAM has been widely applied in education to explain the adoption of learning technologies by students and teachers.

Additionally, the Community of Inquiry (CoI) framework conceptualizes the online educational experience through the interaction of social, cognitive, and teaching presences (Garrison et al., 1999). Social presence focuses on establishing a supportive community climate, cognitive presence deals with constructing meaning through communication and reflection, and teaching presence encompasses the design and facilitation of learning processes. CoI provides a holistic model that can be used to design and evaluate online learning environments.

Furthermore, Connectivism presents a theory of learning that emphasizes connecting specialized information sources and forming networks to continuously acquire new knowledge (Siemens, 2005). It proposes that learning resides in distributed databases and connections, emphasizing the role of networks, collaboration, diversity of opinions, and decision-making in networked environments. Connectivism provides a relevant framework for examining learning enabled through digital technologies and networks.

These three theoretical frameworks offer valuable perspectives for examining key issues in technology-enabled learning, including user adoption, multidimensional engagement, and networked knowledge construction. The current study incorporates elements of TAM, CoI, and Connectivism to enrich the investigation of LA for personalized and engaging online higher education.

LA in Online Higher Education

LA encompasses the development and application of data science methods specific to educational contexts for better understanding and supporting learning processes and outcomes (Wise, 2019). It involves measuring, collecting, analysing, and reporting data about learners and their context to optimize learning (Maseleno et al., 2018). LA software applications extract information from extensive log data generated by LMSs (Al Shehhi & Almarri, 2021; Ulfa & Fatawi, 2021; Wise, 2019), with the promise of understanding and optimizing learning and its environments (Bozkurt & Sharma, 2022).

LA finds application across diverse learning settings, from elementary to higher education, offering pedagogical and technological benefits (Lee et al., 2020; Nouri et al., 2019; Wise, 2019). It contributes to higher education at three levels: micro (improving teaching and learning, analysing student behaviours), meso (enhancing program performance), and macro (providing a broad view of institutional performance and accountability) (Daniel, 2017). What sets LA apart, according to Wise (2019), are three key aspects: 1) reliance on distinct data sources unique to LA, 2) utilization of specialized analytical techniques tailored to uncover insights, and 3) emphasis on practical application and utilization of findings to enhance learning processes and outcomes.

LA is an interdisciplinary concept drawing from fields such as computer science, learning science, statistics, data mining, psychology, and pedagogy, integrating their concepts and ideas (Al-Tameemi et al., 2020; Banihashem et al., 2022; Lee et al., 2020; Pargman & McGrath, 2019; Wong et al., 2019). Its primary objective is to transform learning data into meaningful knowledge (Al-Tameemi et al., 2020; Wong et al., 2019). LA focuses on interpreting learners' digital footprints to gain insights into their engagement patterns, including course navigation and content access at their own pace and preferred time (Ifenthaler et al., 2023; Mathrani et al., 2021; Nouri et al., 2019; Wong et al., 2019). The objectives of LA encompass monitoring, reflection, prediction, intervention, feedback, personalization, adaptation, and recommendation (Al-Tameemi et al., 2020; Chatti et al., 2012; Sahni, 2023).

The application of LA in online higher education holds significant promise. By tracking learners' digital traces and assessing their performance, institutions can identify valuable learning trends and improve instructional services (Blumenstein, 2020; Lee et al., 2020; Mathrani et al., 2021; Pargman & McGrath, 2019; Wong, 2017; Wong et al., 2019). LA allows analysis of student behaviour, engagement, and performance, leading to improved feedback practices in online learning environments (Al Shehhi & Almarri, 2021; Banihashem et al., 2022; Liu et al., 2017; Pargman & McGrath, 2019; Wong, 2017; Wong et al., 2019; Zhang et al., 2018). It helps enhance student retention rates, quality assurance practices, understanding of factors influencing academic achievement, and the promotion of self-regulated learning (Gasevic et al., 2019; Lee et al., 2020; Mathrani et al., 2021; Zhang et al., 2018).

Institutions, staff, and students can benefit from LA, including improved retention rates, informed decision making, cost-effectiveness, insights into learning behaviours, personalized assistance, timely feedback, and intervention (Gasevic et al., 2019). Additionally, LA contributes to innovative assessment methods by monitoring and analysing student data, providing automated feedback, making predictions, preventing issues, facilitating interventions, and introducing new assessment approaches (Caspari-Sadeghi, 2023).

Challenges to the Integration of LA

There are several challenges that hinder LA implementation. Mathrani et al. (2021) highlight several challenges in integrating LA in educational settings. First, there are generalizability challenges, as achieving a universal model solution applicable to various courses and learner groups is challenging in practice (Liu et al., 2017; Mathrani et al., 2021). Second, transparency challenges need to be addressed to ensure relevance, robustness, fairness, and social acceptance of LA (Corrin et al., 2019; Liu et al., 2017; Mathrani et al., 2021). Third, ethical challenges arise due to the use of educational datasets, requiring responsible handling of learners' data to protect privacy and confidentiality (Corrin et al., 2019; Dart & Cunningham, 2023; Mathrani et al., 2021).

Additional challenges include data management strategy, building a community of practice, ensuring IT support staff, resource constraints, ethical and security concerns, stakeholder commitment, and developing a long-term implementation strategy (Sheikh et al., 2022; Wise, 2019). The strategic value of LA necessitates significant investment in data infrastructure, analytics capabilities, staff training, and strategic planning (Liu et al., 2017; Sheikh et al., 2022; Wise, 2019). Universities should assess the strategic role of LA and allocate resources wisely, focusing on high-quality data, analytical tools, and skilled staff with knowledge of emerging technologies and data-driven opportunities (Liu et al., 2017; Sheikh et al., 2022). Bozkurt and Sharma (2022) caution against uncritically adopting data-centric LA strategies and emphasize the need for policies and strategies that prioritize data privacy and ethical considerations. Furthermore, the social dimensions of teaching and learning should not be overlooked in the context of LA (Bozkurt & Sharma, 2022).

Despite the availability of learning data, such as student interactions with LMSs, the contextualized nature of learning environments and instructional designs poses challenges for one-size-fits-all data-driven approaches (Liu et al., 2017). The unique characteristics and contexts of different learning settings highlight the limitations and potential risks of relying solely on standardized approaches. Gasevic et al. (2019) stress the importance of considering diverse factors and nuances within each learning environment to avoid potential drawbacks associated with a one-size-fits-all approach in LA. To ensure ethical practice in LA, Corrin et al. (2019) recommend that stakeholders should acknowledge the complexity of ethics in LA, establish clear principles and guidelines for data use, engage with multiple stakeholders, foster transparency and trust, learn from existing practices, stay proactive and adaptable, and implement processes for on-going practice review and improvement.

LA for Data-Driven Decision Making

In higher education, the significance of decision-making has become increasingly important to rely on evidence rather than intuition or experience alone (Daniel, 2017). With the rapid advancement of technology, a significant portion of decision-making now involves gathering information from diverse data sources (Al-Tameemi et al., 2020; Blumenstein, 2020; Caspari-Sadeghi, 2022; Daniel, 2017; Dart & Cunningham, 2023; Liu et al., 2017; Nouri et al., 2019; Schmitz et al., 2017; Wise, 2019). Researchers are actively working to build the field of data-driven education and research, leveraging the applications of big data through LA (Nouri et al., 2019).

Data-driven decision-making refers to the utilization of big data analysis to gain insights and enhance the performance of educational institutions (Al-Tameemi et al., 2020; Bozkurt & Sharma, 2022; Caspari-Sadeghi, 2022; Gasevic et al., 2019; Nouri et al., 2019; Sheikh et al., 2022; Ulfa & Fatawi, 2021; Wong, 2017). Although the use of analytics and data analysis is a relatively recent development in education, it has emerged primarily from the sector's need to facilitate data-driven decision-making and strategic planning (Baker & Yacef, 2009; Bozkurt & Sharma, 2022). The LA cycle, as outlined by Chatti and Muslim (2019), involves several stages, including learning activities, data recording, storage, data processing, analysis, representation, and action-taking. Similarly, LA encompasses capturing data, reporting on student progress, predicting outcomes, taking action based on insights, and refining the process for continuous improvement (Al-Tameemi et al., 2020).

Higher education institutions have utilized LA to inform decision-making related to instructional design, course development, and student support (Bozkurt & Sharma, 2022; Gasevic et al., 2019; Sahni, 2023; Schmitz et al., 2017; Sheikh et al., 2022; Wong, 2017). LA can identify undesirable learning behaviours and emotional states, enabling the timely detection of at-risk students (Bozkurt & Sharma, 2022; Dart & Cunningham, 2023; Liu et al., 2017; Pargman & McGrath, 2019; Wise, 2019; Wong, 2017). This information allows educational institutions to take prompt follow-up actions and provide appropriate assistance to effectively support these students (Bozkurt & Sharma, 2022; Gasevic et al., 2019; Sahni, 2023; Wong, 2017). Real-time tracking of student progress enables educators to address issues or concerns promptly and prevent students from falling behind (Bozkurt & Sharma, 2022; Sahni, 2023; Schmitz et al., 2017).

LA equips educational institutions with valuable information derived from vast amounts of data, enabling them to make informed decisions (Gasevic et al., 2019; Sheikh et al., 2022). This includes using data on course popularity and the types and frequency of materials reviewed by students to plan course development and allocate resources effectively (Gasevic et al., 2019; Wise, 2019). Thus, LA enhances decision-making abilities by facilitating convenient and dependable access to real-time data throughout the institution (Bozkurt & Sharma, 2022; Sheikh et al., 2022). Establishing an empowering framework that enables decision-making based on LA insights can generate value (Sheikh et al., 2022). Another approach is to incorporate automated decision models into institutional processes to further support informed decision-making (Sheikh et al., 2022). LA provides a new model for college and university leaders to improve teaching, learning, organizational efficiency, decision-making, and serve as a foundation for systemic change (Maseleno et al., 2018).

Current LA models for guiding interventions often adopt a standardized approach (Liu et al., 2017). Models derived from big data can be categorized into three main types: 1). Descriptive models that analyse data to identify trends and improve student learning, 2). Predictive models that forecast future outcomes, including identifying risky student behaviours, and 3). Prescriptive models that provide actionable insights for informed decision-making based on predictions (Daniel, 2015, 2017). To improve the accuracy of predictions, these models commonly gather extensive datasets from various courses or even multiple educational institutions to leverage a broader range of data (Liu et al., 2017). However, Wise (2019) argues that "more data do not necessarily mean more information," and crafting meaningful indicators from available data remains a challenge in LA (p. 124).

LA for Engagement and Instructional Personalization

There is a symbiotic relationship between instructional design and learning analytics (Blumenstein, 2020; Ifenthaler, 2017; Nguyen et al., 2021; Schmitz et al., 2017; Ulfa & Fatawi, 2021; Wise, 2019). Authentic student learning activities provide valuable data for LA, enabling real-time adjustments to the learning design during runtime (Schmitz et al., 2017; Wise, 2019). Instructional designers can leverage LA to assess the learning environment, materials, and tasks by analysing data on learners and their interactions within the learning environment (Ifenthaler, 2017; Nguyen et al., 2021; Wise, 2019; Wong et al., 2019). Conversely, LA relies on instructional design theories and principles to effectively translate data into actionable knowledge for instructional design (Ifenthaler, 2017; Wong et al., 2019).

LMSs have the capability to gather and store data and records of activities (Al Shehhi & Almarri, 2021; Dart & Cunningham, 2023). LMSs monitor students' patterns of involvement, including the locations they access different resources, the duration of their engagement, and the frequency of their utilization of content, quizzes, forums, and other tools (Al Shehhi & Almarri, 2021). LA can provide insightful data about students' engagement levels, learning characteristics, and patterns (Bozkurt & Sharma, 2022; Dart & Cunningham, 2023; Solé-Beteta et al., 2022; Wong, 2017; Zhang et al., 2018). It enables the personalization of online platforms based on interactions and data logs (Al Shehhi & Almarri, 2021). Traditional measurement of engagement relied on self-reported scales, interviews, or teacher observations (Caspari-Sadeghi, 2022; Solé-Beteta et al., 2022). However, LA offers the ability to automatically extract objective engagement features in a ubiquitous manner without disrupting the learning process (Caspari-Sadeghi, 2022; Solé-Beteta et al., 2022).

In the implementation of LA, Gasevic et al. (2019) identified three key themes: 1). The creation of predictors and indicators for factors such as academic performance, student engagement, and self-regulated learning; 2). The utilization of visualizations to analyse and interpret data and facilitate remedial actions; and 3). The development of interventions to shape the learning environment.

Engagement refers to the level of involvement and commitment that students demonstrate in their academic experiences and educational activities, including the effort, time, and energy they invest in achieving desired learning outcomes (Caspari-Sadeghi, 2022; Sahni, 2023; Solé-Beteta et al., 2022). Instructional personalized learning enhances engagement by empowering students to take ownership of and design learning experiences that are personally meaningful to them (Maseleno et al., 2018; Wise, 2019). LA is seen as a powerful force that can lead to more personalized learner experiences (Mathrani et al., 2021). By using LA, a more personalized, adaptive, and engaging learning environment can be created, enhancing teaching and learning effectiveness and the output of teachers and students (Al Shehhi & Almarri, 2021). Through recommendation systems, learners have the potential to receive personalized suggestions for appropriate educational materials, learning routes, or fellow classmates (Maseleno et al., 2018). LA plays a crucial role in supporting and enabling the implementation of personalized learning on a large scale within higher education institutions, providing the necessary scaffolding and integration across the institution to cater to the diverse needs of a large student population (Maseleno et al., 2018; Wise, 2019).

Practical Approaches in LA

Several studies have explored the application of LA in online higher education to enhance engagement, personalization, and instructional practices. For example, Liu et al. (2017) developed the Student Relationship Engagement System (SRES), which leverages LA to support teachers in utilizing data and implementing appropriate actions. Their study highlighted the positive impact of this human-centric approach on student engagement and outcomes, addressing cultural, pedagogical, and technical considerations. Zhang et al. (2018) investigated group behaviour among online learners and identified significant factors influencing individual learning processes and outcomes. Factors such as time management, resource utilization, social interaction, and support services emerged as crucial for learners. Teachers emphasized effective management, appropriate resources, intervention strategies, and accurate feedback. Bozkurt and Sharma (2022) conducted a study using text-mining and social network analysis, identifying themes including teaching enhancement through LA, data-driven teaching practices, multimodal LA, integrating analytics with learning design, formative assessment, analytics in social online learning spaces, and addressing privacy and ethical concerns. The study emphasized the importance of ethics, privacy, and social values in LA processes, cautioning against overreliance on algorithms.

In the context of LMS, Al Shehhi and Almarri (2021) found that LA plays a significant role in evaluating student data logs to customize system features. This enhances the learning experience, provides real-time feedback, improves information retrieval, ensures data security, streamlines administrative tasks, and enables personalized learning while optimizing resources. Ulfa and Fatawi (2021) explored non-human interactive activities, including concept mapping, and their impact on learning outcomes. Their research, conducted using LA data from an LMS, demonstrated the significant improvement in learning outcomes through exercises involving concept mapping. Similarly, Nguyen et al. (2021) developed and evaluated design principles for LA systems in higher education, providing a foundation for their implementation. Ifenthaler et al. (2023) investigated student engagement with self-assessments using LA and found a positive relationship with exam performance. Sahni (2023) assessed student engagement levels and their correlation with academic performance using LA tools, recommending the implementation of an analytics plug-in in the LMS for identifying at-risk students, and providing real-time feedback.

RESEARCH PROBLEM

Despite the growing popularity of online higher education, there is a need to effectively personalize instruction and foster student engagement in the online learning environment. While LA has emerged as a promising approach to address these issues, there is a lack of comprehensive research on how LA can be leveraged to enhance instructional personalization and improve student engagement in online higher education settings (Bozkurt & Sharma, 2022). Therefore, the research problem of this study is to investigate how LA can be effectively applied in online higher education to enable data-driven decision-making, enhance instructional personalization, and improve student engagement.

AIM AND SCOPE

This study explores the use of LA in online higher education to improve student engagement and instructional personalization. It focuses on the following:

1. **Engagement Levels Based on Access Methods:** Examining students' engagement levels in online courses using mobile and non-mobile access methods. Analysing differences in engagement indicators such as participation rates, completion rates, and interaction patterns between these methods.
2. **Relationships Among Engagement Indicators**: Exploring the connections and associations among various engagement indicators in online courses. Investigating if certain indicators are correlated, providing insights into students' engagement patterns.
3. **Strategies and Techniques for Instructional Personalization**: Investigating strategies and techniques for personalizing instruction in online higher education. Examining how LA can enhance these efforts by gathering and analysing learner data.

RESEARCH QUESTIONS

The current study aims to address the following research questions:

- **RQ1**: What are the engagement levels of students in online courses based on different access methods (mobile and non-mobile)?
- **RQ2**: What are the relationships and measure of association among students' engagement indicators in online courses?
- **RQ3**: What are the strategies and techniques for instructional personalization in online higher education, and how can LA support these efforts?

RESEARCH METHODOLOGY

The study adopts a quantitative method, which is used to analyse and measure students' engagement levels, relationships among engagement indicators, and the impact of different access methods (mobile and non-mobile) on engagement. This involves data collection in terms of students' interaction logs, time spent on course materials, and other relevant variables. Descriptive statistics and correlation analysis are employed to analyse the quantitative data and derive meaningful insights.

Research Design

The study employs quantitative methods, building upon the work of Chatti and Muslim (2019) and Al-Tameemi et al. (2020). To provide a deeper understanding of the context and methodology, the authors have expanded upon the research design as follows:

1. **Data Collection**: The targeted context is the University of Jeddah in Saudi Arabia. The data collection process involved capturing quantitative data from two primary sources: the University Blackboard Learning Management System (LMS) and the Pyramid dashboard for Learning Analytics (LA). The authors differentiated between mobile and non-mobile access based on whether students accessed the university LMS through the Blackboard mobile application or a web browser. This distinction was considered relevant due to potential differences in user experience and engagement patterns. The choice to differentiate between mobile and non-mobile access was rooted in the increasing reliance on mobile devices for online learning. Understanding how access method affects engagement can inform decisions related to platform optimization, content

delivery, and course design. Challenges related to data availability and technical constraints were minimal since data primarily came from the official source, the E-Learning and Distance Education Centre at the University of Jeddah. The authors' affiliation with the same university facilitated this process.

2. **Data Analysis**: The focus was on a range of engagement indicators, as shown in Table 1. Additionally, the authors compared engagement across different types of course items, such as multimedia materials, written content, and assessments. By comparing engagement with different course elements, the aim was to identify whether certain types of materials or activities were more effective in driving student participation. Furthermore, variations in course design among different courses were considered, and their potential impact on engagement outcomes is discussed.
3. **Integration of Findings**: The integration of findings was achieved through a rigorous synthesis of quantitative data using statistical analysis. This allowed the authors to provide a comprehensive understanding of the research questions, highlighting the relationships among engagement indicators and access methods.
4. **Conclusions**: The study generates evidence-based recommendations for instructional personalization, enhancing student engagement, and effectively utilizing LA in online higher education. These recommendations are grounded in data-driven insights derived from the analysis.

Research Data

To provide a clearer picture of the data sources and collection process, the authors offer the following insights:

1. **Data Sources**: The University Blackboard LMS is widely used in higher education, offering a platform for online course delivery, content management, student-teacher interactions, and assessments. Data collection involved accessing and aggregating student engagement data from this platform. The Pyramid dashboard provides a comprehensive view of LA data, enabling educators to monitor and analyse student progress, engagement, and performance. Data from these two sources were integrated for a more holistic view of student engagement.
2. **Data Collection Period**: The data analysed in this study were collected during the academic years 2021 and 2022. These years were selected to capture a recent timeframe and reflect the most up-to-date trends and practices in online higher education. Importantly, this period allowed the authors to account for any potential shifts in online learning behaviours and engagement strategies during this timeframe.

RESULTS

Students' Engagement Indicators in Online Courses

The indicators presented in Table 1 provide insights into the engagement levels of students in online courses based on different access methods (mobile and non-mobile).

Table 1 implies several findings and comparisons between students' access to educational resources through mobile devices and non-mobile devices, yielding the following observations:

1. **Distinct Users and Distinct Courses**: Non-mobile access has slightly more distinct users and courses, indicating broader participation.
2. **Course Accesses**: Mobile access shows higher frequency of course accesses.
3. **Course Interactions and Course Item Accesses**: Mobile access has more course interactions, while non-mobile access has more course item accesses.

Table 1. Summary of Student Engagement Indicators in Online Courses

Indicator	Mobile Access	Non-mobile Access
Distinct Users	27,875	28,407
Distinct Courses	6,927	7,120
Distinct User Course	176,282	170,948
Course Accesses	7,731,182	5,327,274
Course Interactions	40,241,421	29,565,822
Course Item Accesses	3,276,389	3,664,598
Tool Accesses	197	586
Content Accesses	2,517,920	2,906,435
Assessment Accesses	758,272	757,577
Average Minutes per Course Access	17.2	25.2
Average Interactions per Course Access	5.2	5.5
Average Items per Course Access	.4	.7
Average Content per Course Access	.3	.5
Average Assessments per Course Access	.1	.1
Average Minutes	753.6	786.3
Average Items	18.6	21.4
Average Interactions	228.3	173.0
Average Content Accesses	14.3	17.0
Average Assessment Accesses	4.3	4.4
Average Course Accesses	43.9	31.2

4. **Average Minutes per Course Access**: Non-mobile access has longer average time spent per course access.
5. **Average Interactions per Course Access**: Similar for both mobile and non-mobile access.
6. **Average Items per Course Access**: Non-mobile access involves accessing more course items per access.
7. **Average Content and Assessment Accesses**: Non-mobile access has slightly higher average content accesses, while both have similar assessment accesses.
8. **Overall Engagement**: Non-mobile access generally indicates higher engagement levels, with more time spent and higher item accesses.
9. **Average Course Accesses**: Mobile access has a higher average number of course accesses.

To identify relationships and measure of association among students' engagement indicators in online courses, Pearson correlations can be useful. The analysis of the dataset as shown in Table 2 (see Appendix 1) reveals statistically significant correlations among various variables related to user engagement in online courses. A Pearson correlation analysis was conducted, yielding significant results at varying levels of significance.

The findings indicate the presence of positive correlations between distinct users and distinct courses ($r = 1.000^{**}$, $p = 0.006$), suggesting that as the number of users increases, so does the diversity of courses accessed.

Course interactions exhibit a strong positive correlation with distinct courses ($r = 0.999^*$, $p = 0.032$), implying that courses with a higher number of interactions tend to offer a broader range of course options.

Tool accesses demonstrate positive correlations with both distinct users and distinct courses. The correlation coefficient between tool accesses and distinct users is ($r = 1.000^*$ $p = 0.014$), while the coefficient between tool accesses and distinct courses is ($r = 1.000^{**}$ $p = 0.008$), indicating that tool usage is positively associated with both a larger user base and a greater variety of courses.

Content accesses display a positive correlation with course item accesses ($r = 1.000^*$, $p = 0.017$), suggesting that users who access more course items also tend to access more content within the courses.

The average number of items per course access demonstrates a strong positive correlation with average interactions ($r = 1.000^{**}$, $p = 0.000$), indicating that courses with a higher average number of interactions per access tend to offer a greater number of items for users.

Average minutes spent on courses exhibits positive correlations with both course interactions ($r = 0.998^*$, $p = 0.036$) and course item accesses ($r = 0.999^*$, $p = 0.026$), suggesting that courses with more interactions and course item accesses also tend to have longer average durations.

Average items and average interactions demonstrate positive correlations with both course interactions and course item accesses. The correlation coefficient between average items and course interactions is ($r = 0.999^*$, $p = 0.023$), while the coefficient between average items and course item accesses is ($r = 1.000^{**}$, $p = 0.006$). The correlation coefficients between average interactions and course interactions ($r = 0.999^*$, $p = 0.034$) and course item accesses ($r = 1.000^{**}$, $p = 0.002$) are also significant. These findings suggest that courses with higher numbers of interactions and course item accesses tend to offer a greater number of average items and interactions.

Average content accesses and average assessment accesses demonstrate positive correlations with course item accesses, average minutes, and average content accesses. The correlation coefficients between average content accesses and course item accesses, average minutes, and average assessment accesses are ($r = 0.998^*$, $p = 0.043$), ($r = 0.999^*$, $p = 0.026$), and ($r = 1.000^*$, $p = 0.020$), respectively. These results imply that courses with more course item accesses, longer average durations, and more average assessment accesses tend to have a higher average number of content accesses.

There is a significant positive correlation between the average number of content accesses and the average number of course item accesses ($r = 0.998^*$, $p = 0.043$). This means that as the number of content accesses increases, the number of course item accesses also tends to increase. There is also a significant positive correlation between the average number of content accesses and the total number of content accesses ($r = 0.999^*$, $p = 0.026$). This means that as the total number of content accesses increases, the average number of content accesses also tends to increase. Further, There is a significant positive correlation between the average number of content accesses and the average number of items ($r = 1.000^*$, $p = 0.020$). This means that as the number of content accesses increases, the number of items also tends to increase.

There is a significant positive correlation between the average number of assessment accesses and the average number of course item accesses ($r = 0.997^*$, $p = 0.048$). This means that as the number of assessment accesses increases, the number of course item accesses also tends to increase. Also, there is a significant positive correlation between the average number of assessment accesses and the total number of assessment accesses ($r = 1.000^*$, $p = 0.014$). This means that as the total number of assessment accesses increases, the average number of assessment accesses also tends to increase. Moreover, there is also a significant positive correlation between the average number of assessment accesses and the average number of minutes ($r = 1.000^*$, $p = 0.012$). This means that as the number of assessment accesses increases, the amount of time spent in the course also tends to increase.

There is a significant positive correlation between the average number of course accesses and the total number of course accesses ($r = 1.000^{**}$, $p = 0.001$). This means that as the total number of course accesses increases, the average number of course accesses also tends to increase. There is also a significant positive correlation between the average number of course accesses and the average number of course interactions ($r = 0.999^*$, $p = 0.033$). This means that as the number of course accesses increases, the number of course interactions also tend to increase. Similarly, there is also a significant positive correlation between the average number of course accesses and the average number of interactions ($r = 0.998^*$, $p = 0.035$). This means that as the number of course accesses increases, the number of interactions also tends to increase.

DISCUSSION

The utilization of LA in online learning platforms offers valuable insights into student behaviours, learning patterns, and performance. These insights contribute to informed decision-making, personalized instruction, and enhanced learning outcomes (Al Shehhi & Almarri, 2021; Al-Tameemi et al., 2020; Banihashem et al., 2022; Bozkurt & Sharma, 2022; Gasevic et al., 2019; Maseleno et al., 2018; Mathrani et al., 2021; Schmitz et al., 2017; Sheikh et al., 2022; Wong et al., 2019; Zhang et al., 2018).

The findings regarding mobile and non-mobile access and their engagement indicators highlight distinct student behaviours based on the type of device used. Students using non-mobile devices tend to exhibit higher levels of engagement, spending more time on average, and accessing more course items and content. In contrast, mobile access indicates higher course accesses, course interactions, and average interactions, suggesting more frequent, but potentially shorter, engagement. These variations may be influenced by factors such as device capabilities, user preferences, and the convenience of accessing courses on different devices.

Analysing user engagement in online courses reveals noteworthy correlations. Firstly, there is a positive correlation between the number of distinct users and the diversity of courses accessed, indicating that as the user base expands, a wider variety of courses are explored. Similarly, course interactions show a strong positive correlation with distinct courses, suggesting that courses with more interactions offer a broader range of options.

Tool accesses demonstrate positive correlations with both the number of distinct users and distinct courses, indicating that increased tool usage is associated with a larger user base and a greater variety of courses being accessed.

Content accesses display a positive correlation with course item accesses, implying that users who access more course items also tend to access more content within the courses.

The average number of items per course access shows a strong positive correlation with average interactions, suggesting that courses with more interactions per access tend to offer a greater number of items for users.

Average minutes spent on courses exhibit positive correlations with both course interactions and course item accesses, indicating that courses with more interactions and course item accesses tend to have longer average durations.

Average items and average interactions show positive correlations with both course interactions and course item accesses. These findings suggest that courses with a higher number of interactions and course item accesses tend to offer a greater number of average items and interactions.

Average content accesses and average assessment accesses demonstrate positive correlations with course item accesses, average minutes, and average content accesses, indicating that courses with more course item accesses, longer average durations, and more average assessment accesses tend to have a higher average number of content accesses.

Significant positive correlations were also found between the average number of content accesses and the average number of course item accesses, content accesses, and items, as well as between the average number of assessment accesses and the average number of course item accesses, assessment accesses, and minutes. These correlations suggest that as the number of content accesses and assessment accesses increases, the corresponding variables also tend to increase.

Lastly, there are significant positive correlations between the average number of course accesses and the average number of course interactions and total number of interactions, indicating that as the average number of course accesses increases, the total number of course interactions and total interactions also tend to increase.

These findings align with previous studies on the role of LA in online higher education and its impact on engagement, personalization, and instructional practices. Liu et al. (2017) highlight the positive impact of the student relationship engagement system in supporting teachers with data utilization and targeted support for students. Zhang et al. (2018) emphasize the importance of factors like time management, resource utilization, social interaction, and support services for individual learning processes.

Bozkurt and Sharma (2022) stress the need for ethics, privacy, and social values in LA processes, cautioning against overreliance on algorithms. Al Shehhi and Almarri (2021) demonstrate the significant role of LA in customizing system features and enhancing the learning experience in LMSs. Ulfa and Fatawi (2021) and Nguyen et al. (2021) show the positive impact of LA on learning outcomes, particularly through non-human interactive activities like concept mapping. Ifenthaler et al. (2023) and Sahni (2023) find positive correlations between student engagement, self-assessments, and exam performance, highlighting the potential of LA in identifying at-risk students and providing real-time feedback. Together with the current study findings, these studies emphasize the importance of leveraging LA to enhance engagement, personalize instruction, and improve learning outcomes in online higher education. The findings on engagement indicators and correlations shed light on the relationship between student behaviours, system features, and the learning experience, providing valuable insights for educators and instructional designers.

Drawing upon existing theoretical frameworks, the variations in engagement levels between mobile and non-mobile access can be understood through the lens of TAM (Davis, 1989). The findings suggest that non-mobile platforms have greater perceived usefulness and ease of use, leading to higher engagement. In contrast, the limitations of mobile platforms regarding interface, features, and technical issues may negatively impact acceptance and usage intentions, resulting in lower engagement. These results validate core TAM principles regarding how acceptance drives actual system use.

As such, the significant correlations discovered between engagement indicators, such as course interactions, content access, and assessment access, reinforce key components of the CoI framework (Garrison et al., 1999). These interrelationships reflect the dynamic interplay between cognitive, social, and teaching presences emphasized in CoI. For instance, the correlation between course interactions and content access underscores the linkage between social and cognitive presence. Similarly, the correlation between assessment access and minutes spent validates the role of teaching presence in supporting cognitive engagement. Overall, the findings empirically demonstrate the interconnectivity of presences in the educational transaction.

The proposed student engagement model embodies core CoI principles regarding purposeful community interaction, applied learning tasks, and teacher presence. The emphasis on monitoring course access aligns with teaching presence functions. From a connectivist perspective, the use of analytics to extract patterns from digital networks mirrors the theory's focus on knowledge derivation through network connections (Siemens, 2005). The results generally affirm key assumptions within TAM, CoI, and connectivism about technology acceptance, multidimensional engagement, and networked learning. Targeted studies can further test the efficacy of interventions guided by these models in improving mobile access, presence, and data-driven personalization.

CONCLUSION AND IMPLICATIONS

The findings indicate that students using non-mobile devices show higher average minutes, item accesses, and content accesses, while mobile access indicates higher course accesses, course interactions, and average interactions. Several significant correlations were found among engagement indicators, highlighting the importance of course interactions, content accesses, and assessment accesses in promoting student engagement. The results suggest that engaging and interactive courses with ample content tend to attract higher levels of user engagement. Based on the study results, a critical model for effective student engagement in online learning courses emerged taking into account the following factors:

1. **Device Considerations**: Recognize the differences in engagement indicators between mobile and non-mobile access. Design courses to cater to different access modes based on device capabilities and user preferences.
2. **Encourage Diverse Courses**: Offer a wide variety of courses to cater to diverse interests and needs, ensuring a balance between popular and niche options.
3. **Promote active course interactions**: Foster meaningful interactions within courses through discussion forums, collaborative projects, and live sessions.
4. **Encourage Utilization of Effective Learning Tools**: Promote the use of tools that enhance the learning experience and contribute to engagement.
5. **Design Comprehensive Course Content**: Incorporate multimedia resources, interactive modules, and supplementary materials to cater to different learning styles.
6. **Promote Longer Duration of Engagement**: Structure courses to promote longer average durations of student engagement through engaging and well-paced content.
7. **Offer Rich Course Materials**: Provide a diverse range of resources, activities, and assessments to stimulate curiosity and active participation.
8. **Integrate Meaningful Assessments**: Design assessments that encourage higher order thinking and application of knowledge.
9. **Monitor and Analyse Course Access Patterns**: Use analytics to identify patterns, assess student progress, and provide timely feedback and support.

LIMITATIONS AND FUTURE DIRECTIONS

There are some limitations associated with the current study. Firstly, the findings of this study are based on data collected from a specific university's Blackboard and Pyramid dashboard for LA. The generalizability of the results may be limited to similar online higher education settings or institutions using similar LMSs. Secondly, the study relies on data collected from the 2021 and 2022 academic years. As technology and learning environments continue to evolve, the findings may not fully capture the current landscape of online education. Thirdly, the study focuses on a specific set of engagement indicators and access methods (mobile and non-mobile). Other factors that may influence student engagement, such as personal characteristics, course design, or pedagogical approaches, are not extensively explored.

Based on these limitations, it is suggested that researchers conduct longitudinal studies over multiple academic years, as this would provide a more comprehensive understanding of how student engagement and access methods evolve over time. Also, it is recommended that the research be extended to include comparative analysis between different online higher education institutions or LMSs, which would help validate the generalizability of the findings. Finally, it is critical to conduct intervention studies that implement specific instructional personalization techniques or LA interventions can assess the effectiveness of these strategies in improving student engagement.

AUTHOR NOTE

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

The authors declared no financial support for the research, authorship, and/or publication of this article.

Correspondence concerning this article should be addressed to Abdulrahman M. Al-Zahrani, Dept. of Educational Technology, University of Jeddah, Jeddah, Saudi Arabia.. Email: ammzahrani@uj.edu.sa

REFERENCES

Al Shehhi, K., & Almarri, K. (2021). Using a hybrid approach of game design, blockchain technology and learning analytics in higher education institutions: A case study of the British University in Dubai. In *European, Mediterranean, and Middle Eastern Conference on Information Systems* (pp. 180-193). Cham: Springer International Publishing. doi:10.1007/978-3-030-95947-0_13

Al-Tameemi, G., Xue, J., Ajit, S., Kanakis, T., & Hadi, I. (2020, June). Predictive learning analytics in higher education: Factors, methods and challenges. In *2020 International Conference on Advances in Computing and Communication Engineering (ICACCE)* (pp. 109). IEEE. https://doi.org/ doi:10.1109/ICACCE49060.2020.9154946

Baker, R. S., & Yacef, K. (2009). The state of educational data mining in 2009: A review and future visions. *Journal of Educational Data Mining*, *1*(1), 3–17. doi:10.5281/zenodo.3554657

Banihashem, S. K., Noroozi, O., van Ginkel, S., Macfadyen, L. P., & Biemans, H. J. (2022). A systematic review of the role of learning analytics in enhancing feedback practices in higher education. *Educational Research Review*, *37*, 100489. doi:10.1016/j.edurev.2022.100489

Blumenstein, M. (2020). Synergies of learning analytics and learning design: A systematic review of student outcomes. *Journal of Learning Analytics*, *7*(3), 13–32. doi:10.18608/jla.2020.73.3

Bozkurt, A., & Sharma, R. C. (2022). Exploring the learning analytics equation: What about the carpe diem of teaching and learning? *Asian Journal of Distance Education*, *17*(2). http://www.asianjde.com/ojs/index.php/AsianJDE/article/view/689

Caspari-Sadeghi, S. (2022, January). Applying learning analytics in online environments: Measuring learners' engagement unobtrusively. In *Frontiers in Education* (Vol. 7, p. 840847). Frontiers. doi:10.3389/feduc.2022.840947

Caspari-Sadeghi, S. (2023). Learning assessment in the age of big data: Learning analytics in higher education. *Cogent Education*, *10*(1), 2162697. doi:10.1080/2331186X.2022.2162697

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning*, *4*(5-6), 318–331. doi:10.1504/IJTEL.2012.051815

Chatti, M. A., & Muslim, A. (2019). The PERLA framework: Blending personalization and learning analytics. *International Review of Research in Open and Distance Learning*, *20*(1). doi:10.19173/irrodl.v20i1.3936

Corrin, L., Kennedy, G., French, S., Buckingham Shum, S., Kitto, K., Pardo, A., West, D., Mirriahi, N., & Colvin, C. (2019). *The Ethics of Learning Analytics in Australian Higher Education. A Discussion Paper*. Melbourne Center for the Study of Higher Education. https://melbourne-cshe.unimelb.edu.au/__data/assets/pdf_file/0004/3035047/LA_Ethics_Discussion_Paper.pdf

Daniel, B. (2015). Big data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology*, *46*(5), 904–920. doi:10.1111/bjet.12230

Daniel, B. K. (2017). Overview of big data and analytics in higher education. *Big data and learning analytics in higher education: Current theory and practice,* 1–4. 10.1007/978-3-319-06520-5_1

Dart, S., & Cunningham, S. (2023). Using institutional data to drive quality, improvement, and innovation. In *Technology-Enhanced Learning and the Virtual University* (pp. 1–24). Springer Nature Singapore., doi:10.1007/978-981-19-9438-8_29-1

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Management Information Systems Quarterly*, *13*(3), 319–340. doi:10.2307/249008

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. doi:10.1016/S1096-7516(00)00016-6

Gasevic, D., Tsai, Y. S., Dawson, S., & Pardo, A. (2019). How do we start? An approach to learning analytics adoption in higher education. *The International Journal of Information and Learning Technology*, *36*(4), 342–353. doi:10.1108/IJILT-02-2019-0024

Ifenthaler, D. (2017). *Learning analytics design. The Sciences of Learning and Instructional Design: Constructive Articulation Between Communities, 202–211*. Routledge., doi:10.4324/9781315684444

Ifenthaler, D., Schumacher, C., & Kuzilek, J. (2023). Investigating students' use of self-assessments in higher education using learning analytics. *Journal of Computer Assisted Learning*, *39*(1), 255–268. doi:10.1111/jcal.12744

Lee, L. K., Cheung, S. K., & Kwok, L. F. (2020). Learning analytics: Current trends and innovative practices. *Journal of Computers in Education*, *7*(1), 1–6. doi:10.1007/s40692-020-00155-8

Liu, D. Y. T., Bartimote-Aufflick, K., Pardo, A., & Bridgeman, A. J. (2017). Data-driven personalization of student learning support in higher education. In Learning Analytics: Fundaments, Applications, and Trends: A View of the Current State of the Art to Enhance e-Learning, 143–169. https://doi.org/ doi:10.1007/978-3-319-52977-6_5

Maseleno, A., Sabani, N., Huda, M., Ahmad, R., Jasmi, K. A., & Basiron, B. (2018). Demystifying learning analytics in personalised learning. *International Journal of Engineering and Technology (UAE)*, *7*(3), 1124–1129. doi:10.14419/ijet.v7i3.9789

Mathrani, A., Susnjak, T., Ramaswami, G., & Barczak, A. (2021). Perspectives on the challenges of generalizability, transparency and ethics in predictive learning analytics. *Computers and Education Open*, *2*, 100060. doi:10.1016/j.caeo.2021.100060

Nguyen, A., Tuunanen, T., Gardner, L., & Sheridan, D. (2021). Design principles for learning analytics information systems in higher education. *European Journal of Information Systems*, *30*(5), 541–568. doi:10.1080/0960085X.2020.1816144

Nouri, J., Ebner, M., Ifenthaler, D., Sqr, M., Malmberg, J., Khalil, M., Bruun, J., Viberg, O., & Conde González, M. (2019). Efforts in Europe for data-driven improvement of education—A Review of learning analytics research in seven countries. *International Journal of Learning Analytics and Artificial Intelligence for Education*, *1*(1), 8–27. doi:10.3991/ijai.v1i1.11053

Pargman, C. T., & McGrath, C. (2019). Be careful what you wish for! Learning analytics and the emergence of data-driven practices in higher education. *Technology*, *50*(6), 2839–2854. doi:10.16993/bbk.i

Sahni, J. (2023). Is learning analytics the future of online education? Assessing student engagement and academic performance in the online learning environment. *International Journal of Emerging Technologies in Learning*, *18*(02), 33–49. doi:10.3991/ijet.v18i02.32167

Schmitz, M., Van Limbeek, E., Greller, W., Sloep, P., & Drachsler, H. (2017). Opportunities and challenges in using learning analytics in learning design. In *Data Driven Approaches in Digital Education: 12th European Conference on Technology Enhanced Learning, EC-TEL 2017, Tallinn, Estonia, September 12–15, 2017, Proceedings 12* (pp. 209-223). Springer International Publishing. doi:10.1007/978-3-319-66610-5_16

Sheikh, R. A., Bhatia, S., Metre, S. G., & Faqihi, A. Y. A. (2022). Strategic value realization framework from learning analytics: A practical approach. *Journal of Applied Research in Higher Education*, *14*(2), 693–713. doi:10.1108/JARHE-10-2020-0379

Siemens, G. (2005). Connectivism: A learning theory for the digital age. *International Journal of Instructional Technology and Distance Learning*, *2*(1), 3–10. http://www.itdl.org/Journal/Jan_05/article01.htm

Solé-Beteta, X., Navarro, J., Gajšek, B., Guadagni, A., & Zaballos, A. (2022). A data-driven approach to quantify and measure students' engagement in synchronous virtual learning environments. *Sensors (Basel)*, *22*(9), 3294. doi:10.3390/s22093294 PMID:35590984

Ulfa, S., & Fatawi, I. (2021). Predicting factors that influence students' learning outcomes using learning analytics in online learning environment. *International Journal of Emerging Technologies in Learning*, *16*(1), 4–17. doi:10.3991/ijet.v16i01.16325

Wise, A. F. (2019). *Learning analytics: Using data-informed decision-making to improve teaching and learning. Contemporary Technologies in Education: Maximizing Student Engagement, Motivation, and Learning, 119–143*. Springer International Publishing. doi:10.1007/978-3-319-89680-9_7

Wong, B. T. M. (2017). Learning analytics in higher education: An analysis of case studies. *Asian Association of Open Universities Journal*, *12*(1), 21–40. doi:10.1108/AAOUJ-01-2017-0009

Wong, J., Baars, M., de Koning, B. B., van der Zee, T., Davis, D., Khalil, M., Houben, G.-J., & Paas, F. (2019). Educational theories and learning analytics: From data to knowledge: The whole is greater than the sum of its parts. In Utilizing Learning Analytics to Support Study Success (pp. 3-25). doi:10.1007/978-3-319-64792-0_1

Zhang, J. H., Zhang, Y. X., Zou, Q., & Huang, S. (2018). What learning analytics tells us: Group behavior analysis and individual learning diagnosis based on long-term and large-scale data. *Journal of Educational Technology & Society*, *21*(2), 245–258. https://www.jstor.org/stable/26388404

APPENDIX 1

Table 2. Pearson Correlations Among Engagement Indicators in Online Courses (Sig. 2-Tailed)

	Distinct Users	Distinct Courses	Course Accesses	Course Interactions	Course Item Accesses	Content Accesses	Assessment Accesses	Average Interaction Per Course Access	Average Minutes	Average Items	Average Interactions
Distinct Courses	1.000**										
	0.006										
Course Interactions			0.999*								
			0.032								
Tool Accesses	1.000*	1.000**									
	0.014	0.008									
Content Accesses					1.000*						
					0.017						
Average Items per Course Access								1.000**			
								0.000			
Average Minutes					0.998*		0.999*				
					0.036		0.026				
Average Items					0.999*	1.000**					
					0.023	0.006					
Average Interactions			0.999*	1.000**							
			0.034	0.002							
Average Content Accesses					0.998*	0.999*				1.000*	
					0.043	0.026				0.020	
Average Assessment Accesses					0.997*		1.000*		1.000*		
					0.048		0.014		0.012		
Average Course Accesses			1.000**	0.999*							0.998*
			0.001	0.033							0.035

Talal Alasmari is an associate professor professor of educational technology at University of Jeddah. He served as the director of eLearning and distance education. His areas of interests are ubiquitous learning, AI empowered learning, and learning analytics.