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Utilizing Big Data Analytics Tools in E-learning Environments to Improve Personalized Learning Experience

Jawaher Alghamdi and Maryam Alhaykan*
Department of Educational Technology
College of Education, Imam Abdulrahman Bin Faisal University,
Dammam, Saudi Arabia

Abstract. Higher education often underestimates the value of data in decision-making, resulting in a lack of use of big data generated from e-learning (electronic learning) activities to improve the quality of online courses and redesign teaching and learning experiences. Big data play a pivotal role in improving the quality of content and resources, accessibility, automated assessment, and understanding the impact of e-learning courses on student engagement and participation. The aim of this study was to explore students' engagement with online learning environments to improve learners' personalized learning experience. The research tools used were the business analytics platform "Pyramid" as a tool for analyzing student interactions within e-learning environments, and the e-learning system "Blackboard" as a tool for collecting interaction data within the e-learning environment. The data were collected through learner engagement online in the learning management system of Blackboard. A descriptive analysis approach was used to analyze the data. A total of 20,000 students from a Saudi university undertook one of the main courses during the academic year 2022--2023. Using the convenience sampling method, which is a type of nonprobability sampling strategy that allows the selection of a study sample that can be easily reached during the course of the study, the study sample of 2,600 students was selected. The results revealed significant variations in interaction rates within the Blackboard e-learning environment, along with distinct fluctuations in the duration of learner engagement on the platform. Among the four daily time periods, the morning consistently emerged as the peak time for educational activity. Mobile application access in the morning demonstrated the highest level of engagement with the course elements and content. The interaction rates gradually declined throughout the day, reaching their lowest point in the afternoon. The results also revealed that students have a high level of academic achievement. Some learning strategies have been suggested to improve

*Corresponding author: Maryam Alhaykan; *maalhaikan@gmail.com*

students' participation rates during low-activity periods. This study highlights the importance of using learning analytics to provide exploratory insights into learner activity and develop data-driven strategies to meet individual learner needs and improve personalized learning experiences.

Keywords: big data analytics; e-learning environments; higher education; personalized learning experience

1. Introduction

The Fourth Industrial Revolution has ushered in an era of vast and diverse datasets, which are invaluable for acquiring the knowledge and skills required for future science markets and informed decision-making across societal institutions, impacting the future labor market. This is achieved through meticulous data collection, analysis, and interpretation, enabling a focus on future challenges, strategic planning, and building deeper organizational insights (Ajani et al., 2024; Ajani et al., 2023). Analyzing big data requires advanced technologies to manage its massive volume and uncover hidden correlations.

Abdullah and Ibrahim (2022) reported that data are indispensable for decision-makers to initiate action and drive sustainable development. Crucially, this includes analyzing current conditions, identifying trends and vulnerabilities post intervention, and ensuring strategic alignment. Nations that successfully leverage data collection, processing, and integration into high-value solutions are poised to gain significant short-term and long-term advantages.

The Kingdom of Saudi Arabia is committed to data excellence through the National Strategy for Data and Artificial Intelligence (AI), developed by the Saudi Data and Artificial Intelligence Authority (SDAIA, 2020). This phased strategy aims to realize the Saudi Arabia's Vision 2030, prioritizing national imperatives by 2025 and building competitive advantages in specialized domains by 2030. The Kingdom aspires to achieve global leadership in data and AI utilization and exports beyond 2030 (SDAIA, 2020).

Vision 2030 drives a balanced approach to empowering citizens through human development. Recognizing the pivotal role of education across life stages, the Kingdom aims to create a sustainable system adaptable to future advancements, aligning educational outcomes with labor market needs and future professions, enhancing core values and skills, fostering creativity, supporting a culture of innovation, and entrepreneurship (Abdullateef et al., 2023; Al-Zahrani & Rajab, 2017).

Daniel (2017) argued that education is essential to societal prosperity and the advancement of civilization. Information technology is reshaping education and expanding its scope beyond traditional lecture halls and classrooms, accommodating learners who require flexibility in time and distance through virtual and online learning systems. Many academic institutions are moving toward cloud architectures. With the increasing use of digital devices, data collection and analysis within these institutions has become imperative, as it enhances decision-making within these institutions. Universities must utilize big data analytics to provide the best learning environments, link research to teaching, and access best research practices within educational institutions (Capurro et al., 2022; Marsh et al., 2014).

According to the National Strategy for Data and Artificial Intelligence (SDAIA, 2020), big data are defined as large datasets necessitating scalable technologies for storage, processing, management, and analysis owing to their inherent volume, variety, velocity, and variability.

Krumm et al. (2018) highlighted digital and administrative environments as a primary source of educational big data. Digital environments provide process data (log data related to interaction, real-time learning behaviors, habits, preferences, and teaching quality) and outcome data (test scores and dropout rates). Big data analytics enable a more accurate understanding of students' skills and their alignment with evolving professional trajectories (Kvartanlyi, 2023), understanding students' needs and analyzing their future skill and knowledge requirements.

These are essential for sustained engagement (Pandey, 2022), optimizing learning experiences and identifying students' preferences for content that enhances engagement, developing learning content through behavioral analysis, and adapting learning on the basis of skill levels and experience (Sulanto, 2018). Hajjaj (2020) highlighted the promising role of big data analytics in improving decision-making processes, reducing student dropout from school, and developing effective educational technologies.

Although Belkabir and Sedkawi (2023) emphasized the pivotal role of big data in the future of e-learning (electronic learning), improving the quality of content and resources, accessibility, and automated assessment, and emphasized the importance of continuing to explore big data in e-learning to ensure student support, Al-Dihani et al. (2021) noted the low investment in big data and the moderate challenges it faces. Al-Alwani (2016) noted that higher education often underestimates the value of data in decision-making, treating it as mere numbers from databases that lack practical application in e-learning. Adam and Bakar (2018) noted the underutilization of big data generated from e-learning activities in learning management systems (LMS) at educational institutions.

This research aimed to extract student interaction data from e-learning environments to support decision-making and enhance personalized learning experiences, identify academic needs and priorities, leverage big data analytics, improve the quality of e-courses, and assist decision-makers and e-learning developers in redesigning teaching and learning experiences.

This research answers the following main research question:
How can big data analysis results inform decision-making to enhance personalized learning experiences?

This question is expanded further into the following sub-questions:
1. How can big data analytics reveal students' interactions in e-learning environments?
2. What is the impact of student interactions in e-learning environments on academic achievement?

2. Theoretical Frameworks and Previous Studies

This section explores big data analysis and e-learning environments, examining their theoretical foundations, as well as relevant previous studies.

2.1 Big Data Analysis

2.1.1 Defining Big Data

Big data encompass vast, diverse, and rapidly generated datasets that hold immense potential for knowledge, including structured, partially structured, and unstructured data (Kumar et al., 2024; Sivarajah et al., 2017; Kaplan & Haenlein, 2010). Big data are characterized by four characteristics: volume, variety, velocity, and veracity (Kumar et al., 2024). In education, big data refer to unique, complex, and vast datasets derived from student interactions within learning platforms (Gerges, 2022). These datasets can be stored in private databases, such as social media platforms and search engines, to provide valuable insights that improve learning environments and enhance student achievement (Hajjaj, 2020).

Rahmani et al. (2021) emphasized the importance of powerful technologies and advanced algorithms for effectively processing big data. The development of various types of educational data mining applications (apps) using big data can help develop smarter schools and universities on the basis of the extracted knowledge. Hajjaj (2020) noted that education is one of the most prominent fields that has undergone radical changes following the adoption of big data, which is evident in the unprecedented speed, ease, and ease of data acquisition, use, and exchange.

Khan and Alqahtani (2020) noted that educational big data provide diverse opportunities for educational research and offers insights into enhancing student engagement. Fischer et al. (2020) noted that the emergence of big data in education has enhanced the digitization of institutional data in traditional settings, enabling the creation of vast, standardized student information repositories and the tracking of learning behaviors, which were previously difficult to monitor in traditional settings.

Zhao et al. (2022) indicated that big data and learning analytics in LMSs help predict online learning behavior, allowing timely feedback, analyzing student progress in the learning process, identifying teaching issues, and enhancing teaching and learning efficiency. Abdul Majeed (2022) also indicated that the intelligent use of big data recorded in LMSs helps analyze learning behavior and provides instructors with information to improve student learning and e-course design. Zhao et al. (2022) also indicated that the data available in LMS repositories help determine learning duration, task completion rates, discussion forum interactions, and test scores. Ibañez et al. (2020) also indicated that big data help determine the degree of teacher–student communication, student contributions, and collective learning.

2.1.2 Importance of Big Data Analysis

Big data analysis provides organizations with a competitive advantage (Al-AKlabi, 2019). Effective analysis of big data yields deeper insights into individuals and organizations, aiding effective decision-making and enhancing efficiency, profitability, and loss reduction (Hajjaj, 2020). Fischer et al. (2020) confirmed the broader impact of big data analysis on education. The availability of student data and their analysis empower institutions to improve outcomes, predict timely graduation, and forecast performance on the basis of progress tracking via an LMS. Karabtsev et al. (2023) reported that faculty data filtering in work planning systems reduces workload. Abdul Majeed (2022) emphasized the need to provide diverse learning opportunities to improve student learning through qualitative or competency-based approaches. Monitoring progress, understanding student behaviors and challenges, supporting high achievers, and refining e-learning environments are key benefits.

Diverse learning methods, such as exploratory, project-based, or research-oriented approaches, can be offered to advanced learners, whereas targeted resources, such as educational videos, software, or audio guidance, can benefit beginners. Adapting assessments to accommodate diverse experiences enhances the learning ecosystem and allows timely feedback on updated content and methods (Zhao et al., 2022). Students who are struggling can be redirected or the content and methods can be adjusted to ensure goal attainment, transforming traditional teaching into a collaborative process that supports student growth through optimized teaching and learning integration (Zhao et al., 2022).

2.1.3 Challenges of Big Data Analysis

The World Wide Web currently generates large volumes of data through rapid internet traffic, originating from distributed and heterogeneous sources (Oussous et al., 2018). These sources are characterized by high velocity, massive volume, and heterogeneous data formats, often marked by incompleteness or inconsistency. Processing these data deluge poses significant challenges (Sivarajah et al., 2017; Akerkar, 2014; Zicari, 2014). Some of the primary obstacles in big data analysis include limited device capabilities, a lack of expert mechanisms tailored to organizational needs, security concerns, access complexities, and gaps in researcher skills (Belkbir & Suriya, 2023).

Processing such vast datasets exceeds the capacity of traditional data processing methods for storage and analysis (Sunny et al., 2023; Rahmani et al., 2021). Despite advancements in context-aware applications and mobile computing (Sunny et al., 2023; Schilit et al., 1994), Karabtsev et al. (2023) and Tsai et al. (2015) noted that big data analysis is extremely complex because of limited availability of appropriate hardware and specialized automated systems specifically designed to meet the needs of organizations, coupled with their weak deployment and development capabilities and flexibility. Furthermore, these data are in electronic formats and scattered across disparate operational sources, including electronic resources, databases, and multimedia, resulting in isolated databases or data sources being unable to quickly provide integrated and graphically valuable information.

Security challenges are among the most prominent concerns related to big data analytics. Rahmani et al. (2021) noted that the collection of private data via personal smart devices poses critical issues such as the absence of robust data security laws, ethical dilemmas surrounding the use of user data, and the lack of secure methodologies for managing big data collected from diverse systems and environments. These issues undermine the reliability of big data analytics systems. Mohammad et al. (2024) and Atoum and Keshta (2021) noted that addressing security vulnerabilities in big data analytics across various domains requires multifaceted strategies, including robust protection of Internet of Things devices from attacks, secure AI technologies, and secure connectivity to external systems.

Fisher et al. (2020) highlighted the difficulties inherent in accessing educational data. These include the availability of educational data in diverse formats and environments, which poses significant obstacles to accessing research and investments aimed at improving educational environments, limited powers for researchers to publish and share data, and a lack of awareness and growing resistance to adopting educational technologies to leverage big data. Hajjaj (2020) added that developing countries face a critical challenge due to the scarcity of data and statistics, which form the basis for educational system planning. Decision makers rely on databases, information, and analytical documents based on educational information systems, institutional mapping, and complementary information systems.

Another challenge is the limited skills of education researchers, such as poor proficiency in basic programming languages such as Python, which are essential for data science (Alanazi et al., 2025). Furthermore, graduate programs in education rarely provide adequate training in data collection, modelling, and forecasting techniques, which are vital for big data analysis (Haben et al., 2023; Zhao et al., 2022). To address these challenges, Al-Subhi (2023) proposed several strategies, including continuous training in data collection, statistical methods, analytical techniques, and interpretation; incentivizing faculty adoption of educational technologies; and increasing awareness of the importance of big data analysis findings in educational settings.

2.2 E-Learning Environments

Zhao et al. (2022) defined a smart learning environment as a student-centered, intelligent, advanced, flexible, and humanistic learning environment built on big data and cloud computing and equipped it with advanced facilities and technical resources, such as large data centers and a cloud computing infrastructure. Al-Subhi (2023) defined e-learning environments as integrated online systems designed to manage the educational process in terms of recording and managing student data, providing academic content, training, assignments, activities, and electronic tests, and monitoring student performance, communication, and continuous interactions throughout the learning process.

Ibanez et al. (2020) described the LMS Blackboard as one of the most popular e-learning environments in higher education, known as a central platform for teaching and learning activities. Blackboard enhances access to essential course statistics, such as student access to the virtual campus, forum interactions, and resource usage. It represents a revolution in traditional teaching methods, creating an effective form of educational information management, enabling seamless communication between students and instructors through podcast conversations, discussion boards, file sharing, and shared access to the virtual learning environment (VLE) (Almufarreh et al., 2021).

Darko (2021) and Lang (2022) noted that Blackboard is a superior e-learning software capable of managing curricula, enhancing student engagement and interaction, facilitating online assessments and discussions, and delivering high-quality training and educational content. It includes various blended learning capabilities and content authoring tools designed to enhance e-learning content and learner engagement, as well as presentation slides, supplemental notes, and lecture materials.

2.2.1 Student Interaction in the E-Learning Environment

The proliferation of e-learning tools and interactive programs has led to a massive increase in the volume of data, which varies in quality and depth. Educational data are now considered big data due to their volume and diversity, with vast amounts of data being generated daily about students and their interactions with learning systems and platforms; information about courses and learning portfolios; peer learning experiences; and detailed records of learning activities from text, media, and video sources (Al-Subhi, 2023; Khan & Alqahtani, 2020).

This heightened interaction within diverse e-learning systems has resulted in massive data accumulation (Nayak & Walton, 2024; Sadowski, 2019). Analyzing these data is crucial to improve teaching and learning methods and enhance learning opportunities, extracting potential value and transforming it into practical insights that improve student achievement, increase success rates, optimize resource allocation, foster valuable partnerships, improve the management of academic institutions, and facilitate effective faculty recruitment, thus contributing to the development of robust educational institutions (Mossavi et al., 2020; Brynjolfsson et al., 2011).

Zhao et al. (2022) affirmed that remote independent learning fosters systematic, self-directed, interactive learning. These interactions are categorized into cooperation, communication, and evaluation, with instructors selecting or creating resources and uploading them to the e-learning system. Zhao et al. (2022) highlighted that social networks and online learning platforms have broadened student interactions and diversified teaching methods, leading to rich data repositories. These platforms generate data on learning durations, task completion rates, interaction frequencies, discussion topics, and test results. Using these rich datasets, students can be grouped according to their learning styles and interests, fostering enhanced collaborative learning experiences. Consequently, educational institutions can provide customized instructional support to specific student groups, optimizing student learning management. Darko (2021) reported a correlation between increased time spent on the Blackboard LMS and students' reprocessing of information, which increased their potential for improved grades. A robust LMS with strong functionality can positively influence students' moods, encouraging further exploration and knowledge development.

Considering big data analytics, a new development in the field of educational intelligence, known as educational analytics, has emerged. This focus is on collecting, analyzing, and reporting data related to student performance and learning contexts to understand and improve learning environments, analyzing student behaviors and social engagement rates, predicting performance, suggesting appropriate educational resources, identifying strengths and weaknesses in performance, and identifying appropriate educational interventions (Al-Subhi, 2023).

Ibañez et al. (2020) affirmed that the analysis of data obtained from e-learning management environments informs organizational and institutional management, enabling data-driven decisions that enhance student experience. Studies have indicated the importance of analyzing student interactions, which is evident in providing diverse opportunities and options to improve student learning through:

- Customizing learner paths toward content mastery through competency-based education.
- Assessing students' knowledge bases and systematic thinking, collaboration, and problem-solving skills in in-depth contexts.
- Identifying targeted interventions to improve student success and reduce costs.
- Leveraging existing environments and complex information to make informed decisions and develop informed policies.
- Designing learning environments according to specific student needs.
- Measuring social interactions within educational settings to enhance problem-solving and collaboration skills.
- Exploring student interactions in online or blended courses to gather baseline data for making decisions about educational program design.
- Identifying areas for improving student experiences by analyzing their activities on virtual campuses and their impact on educational institutions (Lang, 2022; Hajjaj, 2020; Ibañez et al., 2020).

2.3 Personalized Learning Experience

Walkington and Bernacki (2020) defined personalized learning experience as an innovative instructional design methodology that involves personalizing education to individual learner needs and goals. This approach emphasizes students' strengths and preferences, delivering holistic learning experiences that broaden access to diverse disciplines and help students cultivate skills essential for 21st century employment. Personalized learning provides students with flexibility and support regarding learning content, methods, time, and settings, enabling opportunities to demonstrate mastery of knowledge and skills.

Schmid et al. (2022) demonstrated that practical application influences technology-supported personalized learning, significantly shifting pedagogy toward learner-centered methods compared with traditional teacher-centered approaches. This shift provides greater self-direction for learners, cognitively engaging them in the classroom. It also empowers learners to determine the content, materials, and timelines of their learning process via technological tools, enhancing perceived individual support and increasing learning motivation.

Previous research has demonstrated the crucial role of technology in enhancing personalized learning experiences. Zhao et al. (2022) indicated that an interactive interface design is fundamental to effective personalized learning environments. Smart learning systems, powered by big data, can integrate with systems utilized for conducting exams, performing grade analysis, managing student cases, and planning students' careers. This integration enables precise data extraction for continuously improving student databases and updating personal information through ongoing data collection and analysis.

Ibañez et al. (2020) underscored the importance of learning analytics as a tool for developing technology-enabled, personalized learning experiences. Learning analytics offers exploratory insights into students' learning activities, facilitating tailored strategies to enhance their learning experiences. This represents progress toward more comprehensive learning analytics projects aimed at customizing data-driven learning strategies to individual learner needs. Hajjaj (2020) suggested that these data can also provide modern and effective tools for measuring student performance in educational tasks, which can improve the relevance and accuracy of outcomes related to student learning methods.

It can also aid in designing learning environments customized to specific student needs and provide clear analyses of individual and collective responses to various educational issues. Therefore, technology-supported personalized learning significantly enhances educational quality by providing students with flexible, interactive, and supportive learning environments, boosting their engagement in and motivation to achieve educational goals.

2.4 Enhancing the Learning Experience with E-Learning Environments

Ibañez et al. (2020) proposed three approaches for integration into e-learning environments to enhance learning: adaptive learning, predictive analytics, and customer relationship management.

- Adaptive Learning: Organizations are increasingly adopting adaptive learning to provide personalized education. This approach tailors' educational content to individual students' responses. Adaptive learning relies on extensive learning data and pedagogical responses derived from algorithms within the learning environment (Ibañez et al., 2020). Karabtsev et al. (2023) corroborated this, asserting that higher education institutions process and store vast datasets within their information systems, encompassing students' academic performance, faculty workload, research activities, financial costs, and organizational budget planning. Recognizing the value of analytical data processing, which supports informed decision-making, has shifted perspectives on data. Once viewed as a byproduct of operations, data are now recognized as a vital organizational asset that is central to management and profitability. Hajjaj (2020) added that adaptive learning enhances learning by enabling faster and deeper assessments of individual learning needs and challenges. This includes evaluating skills such as structured thinking, collaboration, and problem-solving in complex contexts; authentic assessment of knowledge domains; targeted interventions for student success; cost reduction; and leveraging existing environments and complex information for strategic decision-making and policy development.

- Predictive Analytics: Predictive analysis involves developing analytical models from diverse data sources to predict future behaviors or outcomes (Ibañez et al., 2020). Higher education administrators consider predictive analytics crucial for strategies aimed at improving student success. Hajjaj (2020) further suggested that developing advanced learning process models could ensure efficient, high-quality, and high-volume productivity, while also aiding in predicting future trends such as course enrollment patterns. Through data collection and analysis of student profiles from their institution's Blackboard VLE and other sources, Lang (2022) reported that various participation indicators significantly influence academic performance, as evidenced by course costs, assignment scores, and end-of-term exam results.
- Customer Relationship Management (CRM): In education, CRM tools help manage relationships with current and prospective students, families, businesses, and other stakeholders. CRM implementation serves two primary goals: automating and improving student-centered processes and collecting data to generate analytics for enhanced institutional decision-making (Ibañez et al., 2020).

Analyzing educational big data supports monitoring student progress, understanding student behaviors and challenges during e-courses, and facilitating problem resolution. It also enables providing support and enrichment for high-achieving students, improving course design by identifying underperforming content, and enhancing the overall learning environment (Abdul Majeed, 2022).

Khan and Alqahtani (2020) reported that collecting educational data from diverse sources can enhance learning experiences by providing intelligent feedback. This includes feedback on optimizing learning efficiency, organizing course resources, and informing appropriate decision-making. Ibañez et al. (2020) supported this view, noting that feedback facilitates the discovery of novel and insightful patterns within data, supporting the educational process. Furthermore, students can receive personalized recommendations on the basis of their activities, visit links, and view upcoming tasks, enabling customized content, interfaces, and activities for each student.

Integrating technological tools, such as Blackboard Ally, into VLEs to create more accessible content for interactive classes helps organizations foster a more balanced teaching and learning experience. Almufarreh et al. (2022) described Blackboard Ally as a unique approach seamlessly integrated with the VLE, operating directly within existing student and instructor workflows. This approach offers diverse teaching methods that can augment self-directed pedagogy. E-learning environments, such as Blackboard, are now widely adopted by educational organizations globally as an integral part of their educational activities, demonstrating the effective application of e-learning tools. Consequently, machine knowledge significantly impacts faculty practices (Almufarreh et al., 2022).

Zhao et al. (2022) noted that multimedia learning environments help analyze relationships among students, multimedia technology, and instructors. The convergence of modern communication technology and multimedia has led to the creation of robust learning environments that are compatible with:

- Educational content.
- Design of realistic tasks within realistic scenarios using multimedia to stimulate student engagement and enhance the sense of social value in acquiring information.
- Use of modern teaching methods that support student interaction with the teacher and the learning content in e-learning environments.
- Use of problem-based learning, the support of information technology.
- Development of students' cognitive abilities.
- Design of an active learning interface that enables the extraction of valuable data and the improvement of student information databases. The continuous updating of student profiles through data mining and learning analytics (Aparicio-Gómez et al., 2024; Comesaña-Comesaña et al., 2022; Maina, 2014; Olawuyi & Mgbole).

3. Research Methodology

This research employed a quantitative design, utilizing a descriptive analytical approach to provide quantitative descriptions and structured graphic visualizations. This approach was selected to extract data on higher education student interactions within e-learning environments to inform decisions aimed at enhancing personalized learning experiences in these settings.

3.1 Research Population and Sample

The study included students enrolled at a Saudi university during the 2022—2023 academic year. The study focused on one course, entrepreneurship, a university requirement taught in an integrated manner across all majors via the Blackboard e-learning environment. The student body included 39 male and 40 female sections, for a total of 79 academic sections with over 20,000 students. The university was selected on the basis of the researchers' affiliation. Using convenience sampling to select all the students, the study sample consisted of 2,600 students. According to Etikan et al. (2016), convenience sampling is a type of nonprobability sampling strategy that allows a researcher to select the majority of a target population, easily accessed during the study.

3.2 Research Tools

This research utilized Pyramid, a business analytics platform, to analyze student interactions within e-learning environments. Pyramid is an integrated, user-friendly platform powered by AI that supports data preparation, data science, and business analytics. Its intuitive design enables users to access multiple data sources directly within their e-learning environment, creating personalized experiences. The platform simplifies advanced data analytics, which reduces complexity and material costs.

Pyramid analytics was selected for its ability to operate directly on diverse datasets, offering self-service capabilities in a code-free environment. It eliminates the need for data extraction, ingestion, and replication and allows seamless integration with Blackboard to learn course analytics. Furthermore, the university relies on Pyramid for extracting analytics and key performance indicators (Pyramid, 2024).

Blackboard, the e-learning system adopted by the university, was also used. The university has received international recognition, earning awards such as the Blackboard Catalyst Award and the Anthology Together Middle East 2022 Award for teaching and learning. Blackboard was instrumental in collecting interaction data within the e-learning environment. This system records student activities, such as enrollment in the learning environment, duration of content viewing, dates of last access to specific content, number of views and downloads of learning materials, contributions to discussion forums, and other interactions.

3.3 Learning Material

3.3.1 Course Description

The entrepreneurship course is a university requirement for all undergraduate students across all disciplines. It covers the foundational principles for transforming ideas and innovations into viable business projects, adhering to sound business venture creation practices. The course explores various aspects of establishing, nurturing, and developing new ventures, both individually and corporately. It equips students with the essential skills required to initiate projects, encompassing the fundamentals of entrepreneurship, project planning, organization, marketing strategies, funding acquisition, and project management execution.

The course covers the following topics: creativity and innovation; introduction to entrepreneurship, entrepreneurs and entrepreneurial opportunities; identifying and creating creative opportunities; creative decisions and their importance; the role of technology in innovation and entrepreneurship; implementing entrepreneurial ideas and funding sources; and feasibility studies.

3.3.2 Course Delivery Mechanism

The course is offered annually in the second semester for over 18 weeks, including three weeks of official holidays for Foundation Day, the mid-term, and Eid Al-Fitr. It employs a blended synchronous and asynchronous remote learning approach via the Blackboard e-learning environment, utilizing virtual classrooms and e-learning resources. Teaching is delivered throughout the academic weeks, with 30% of instruction using synchronous virtual classroom methods and 70% via asynchronous engagement with the learning environment.

3.3.3 Course assignments

Student engagement in the course is facilitated through the following assignments: attendance at synchronous and asynchronous remote lectures, completion of 10 short quizzes, participation in three collaborative activities, completion of three group assignments, and a collaborative innovative final project.

3.3.4 Course Objectives

The course aimed at enabling students to:

1. Develop a comprehensive understanding of the entrepreneurial process and its components:

- Opportunity identification and evaluation.

-Key personal, psychological, organizational, industrial, and environmental factors.

-Business growth challenges.

2. Develop the capacity to generate and evaluate innovative project ideas.

3. Apply the theoretical frameworks, concepts, and insights acquired in class to their own business concepts.

4. Understand the practical aspects of operating a small business, including licensing requirements and legal business ownership structures.

3.4 Data collection and analysis procedures

To collect student interaction data in e-learning environments, the model proposed by Ibañez et al. (2020) was adopted, comprising four stages:

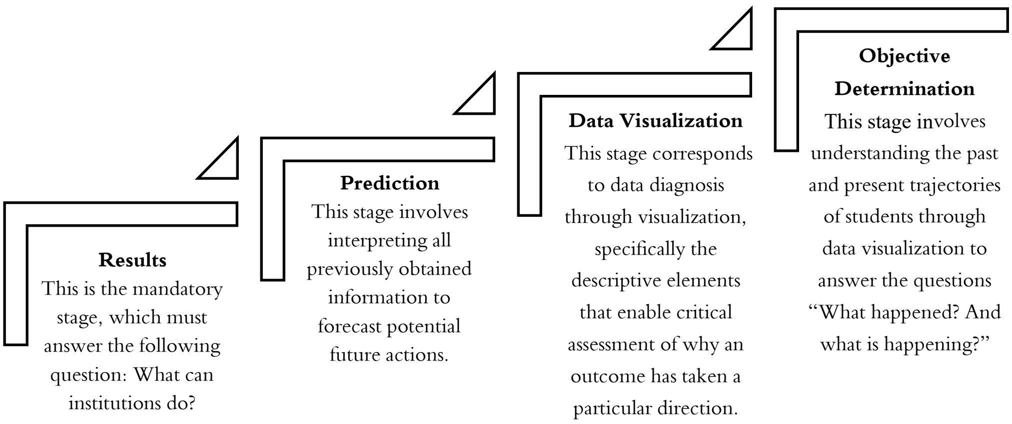

Figure 1: Ibañez et al. (2020) model

Data extraction was performed by importing records of past student activity in the Blackboard LMS e-learning environment from 2022–2023. This was facilitated by the e-learning system information technology team, following communication with the Deanship of E-Learning to gain access to the analytical system within Blackboard Learn.

Stage 1: After determining the objective for data extraction—to improve personalized learning experiences—the initial descriptive phase of the research focused on visualizing and describing data from the Pyramid system. The data, which included the averages of diverse student interactions during the entrepreneurship course on Blackboard Learn, along with students' academic performance, were extracted as tables and graphs and then exported to Excel. Data visualization was subsequently performed to compare access methods to the e-learning platform, differentiating between web and mobile app usage.

Stage 2: The data visualization stage involves diagnosing and describing visualizations to enable critical evaluation via Pyramid. Categories for data provision were defined as:

- Student interaction data with main course content.
- Student interaction data with instructor-added course elements.
- Student-instructor interactions within the course.
- Student interaction data accessing learning elements.
- Student interaction data with learning content. Student interaction data via the web (https://vle.iau.edu.sa/).
- Student interaction data via the Blackboard mobile app.
- Student interaction data in discussion forums.
- Student academic performance data in the e-course.

Stage 3: All the data, correlations, and comparisons derived from the student interactions within the e-learning environment were interpreted in this stage to guide future actions focused on enhancing personalized learning experiences.

Stage 4 (Results): The final stage addresses the core research question: How can big data analysis results inform decision-making to enhance personalized learning experiences?

3.5 Data Analysis

The data were statistically extracted from the e-learning environment and are presented in tables showing average values. Pyramid was used to analyze and process the data, creating comparisons and correlations across tables to generate graphs. These visualizations aimed to illustrate student interactions within e-learning environments. The resulting analysis informed decisions for improving personalized learning experiences.

3.6 Ethical Considerations

This study was approved by the University Review Board (IRB) of the NCBE Registration No. HAP-05-D-003 and the IRB No. IRB-2024-15-651.

4. Results

This section presents the findings of the research questions.

4.1. Results of the First Question: How Can Big Data Analytics Reveal Student Interactions In E-Learning Environments?

4.4.1 Learner interaction with the course over time

Figures 1 through 4 illustrate the student interaction patterns within the entrepreneurship course on Blackboard from the 2022–2023 academic year, with the data categorized by time of day: morning, noon, evening, and outside working hours.

4.4.2 Student interaction throughout the day

Figure 2 presents the average student activity derived from the interaction patterns of the students enrolled in the course, indicating the rate of student engagement across different times of day during the 2022–2023 academic year. Examples of these interactions include learners entering the learning platform, students registering to access the course, and downloading course elements. The average number of student interactions ranged from 3 to 5 per session. The analysis of the student interactions throughout the day, presented in Figure 1, revealed that the morning period had the highest average interaction rate, with approximately 4.5 interactions per session. This average gradually declined throughout the day, reaching approximately 3.5 interactions per session outside working hours.

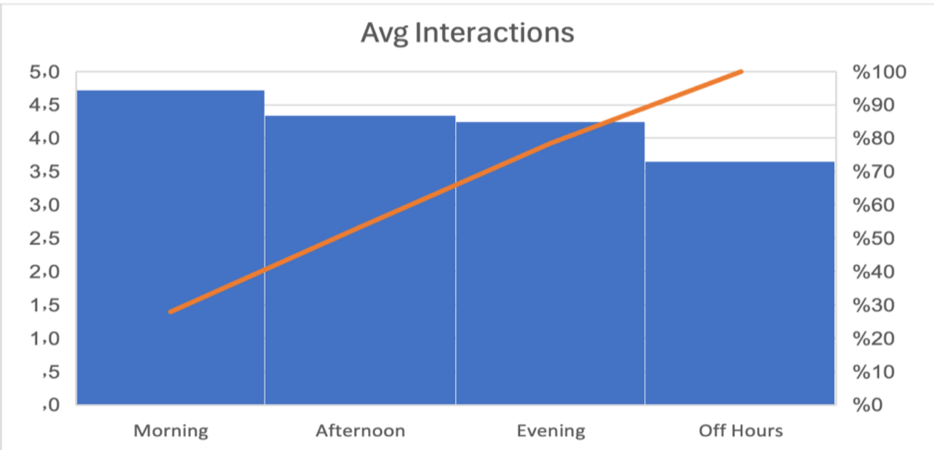

Figure 2: Average student activity derived from the student interactions within the course

Figure 2 indicates the number of times the students interacted with the course during the 2022–2023 academic year, categorized by time of day.

4.4.3 Learner Interaction with Course Elements

Figure 3 depicts the average number of interactions with the course elements—annexes, sections, and interactive lectures—per user, separated by time of day. Overall, the data indicated positive engagement with the various course elements. The figure depicts a gradual decrease in the average interaction rates over time after the peak periods, with noticeable variations between morning, evening, and outside working hours. Examples of these interactions include exploring learning topics through learning platforms and watching presentations related to the content elements.

The student interaction data in Figure 3 also indicates that the highest average interaction rate was recorded in the evenings, with approximately 1.8 interactions per session, highlighting peak activity during this time. In contrast, similar averages, slightly more than 1.6 interactions per session, were observed in the mornings and afternoons, suggesting relatively consistent activity. The lowest average interaction rate, approximately 1.4 interactions per session, was observed outside working hours.

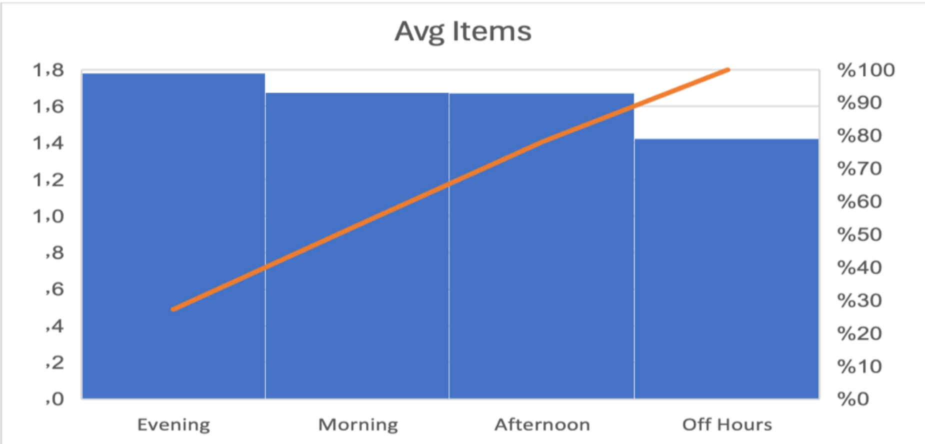

Figure 3: Average number of interactions with the course items for each user, categorized by time of day

An analysis of the data presented in Figure 4 revealed the average student interaction frequency for accessing educational items via the official website during the 2022–2023 academic year, categorized by time of day. The analysis indicated a distinct temporal distribution of educational activity within the entrepreneurship course, with the interaction rates varying significantly across the different times of the school day.

The data indicated that the highest access rate for the educational items was recorded in the evenings, with an average of 1.1 items per session. A decreasing trend in the average number of items accessed was observed across the other time periods. An average of 1.0 items per session was recorded outside working hours, followed by an average of 1.0 items in the mornings and an average of 0.9 items in the afternoons.

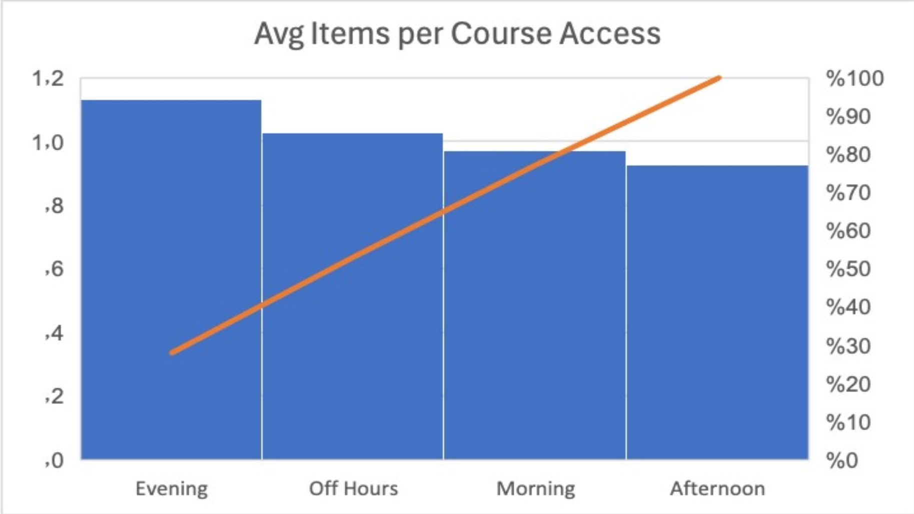

Figure 4: Average student interactions with the educational items via the official website during the 2022–2023 academic year categorized by time of day

The figure illustrates a distinct temporal distribution of educational activity.

4.4.4 Student Engagement with the Learning Content

Figure 5 provides a comprehensive analysis of the student interaction patterns with the educational content of the entrepreneurship course during the 2022–2023 academic year, categorized by time of day. The horizontal axis represents the time periods (morning, afternoon, evening, and outside working hours), whereas the left vertical axis indicates the average number of items accessed, from 0--1.7.

According to the data, the morning period recorded the highest content access rate, averaging approximately 1.7 items per session, reflecting the start of the students' daily activities and peak engagement with educational materials. This was followed by the afternoon and evening periods, which had similar average access rates of approximately 1.6 items per session, indicating continued educational activity. The lowest average access rate, approximately 1.4 items per session, was recorded outside working hours, reflecting decreased educational activity during this period.

These interactions include, for example, learning course content; solving exercises and questions related to the content; performing thought-provoking activities; group discussions about course elements; asking questions with the instructor and colleagues; exchanging knowledge with the instructor and colleagues through chat rooms; and searching for new knowledge and linking it to course elements.

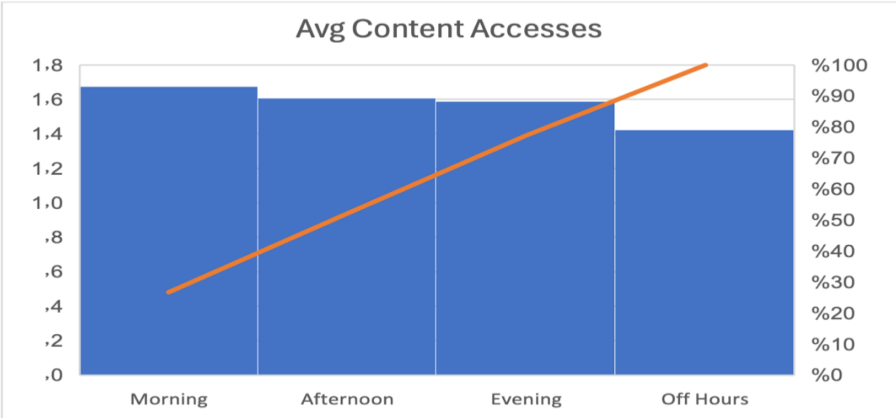

Figure 5: Comprehensive analysis of student interaction patterns with educational content in the entrepreneurship course during the 2022–2023 academic year, categorized by time of day

4.4.5 Learner Interaction Via the Mobile App Over Time

Figures 6 and 7 illustrate the student interaction patterns with the entrepreneurship course using the Blackboard mobile app, highlighting mobile device usage trends. Figure 6 shows the average student activity derived from the student interactions with the course via the Blackboard mobile app. It reflects the frequency of mobile device interactions during the 2022–2023 academic year, categorized by time of day. The results revealed the interaction rates for each course across the different times of day.

The data indicated a distinct user behavior pattern, with the maximum user activity and engagement occurring in the morning, averaging 2.8 interactions per session. This reflected the high levels of concentration and cognitive activity typically observed at the beginning of the school day. The data further reflected a gradual decline in the interaction rates as the day progressed. An average of 2.5 interactions per session were observed outside working hours, followed by 2.4 interactions per session in the afternoons and 2.3 interactions per session in the evenings.

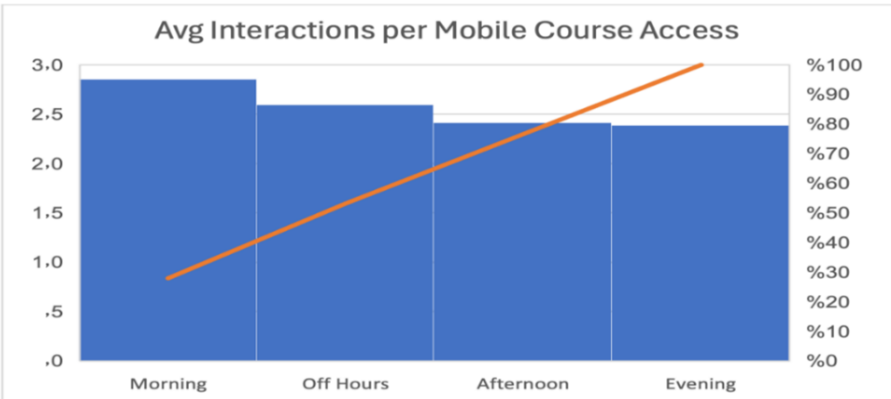

Figure 6: Average student activity data derived from the student interactions with the course via the Blackboard mobile application

Figure 7 provides a detailed analysis of the average number of items accessed per session for the Entrepreneurship course via the Blackboard mobile app during the 2022–2023 academic year, categorized by time of day. The horizontal axis represents the time periods (morning, noon, evening, and outside working hours). The data revealed an interesting pattern that mornings, afternoons, and evenings presented a relatively consistent average of approximately 1.1 items accessed per session, indicating stable student usage patterns during core working hours. Outside working hours, the average decreased to 0.9 items per session. This pattern highlighted student behavior in accessing educational content, suggesting a tendency for increased engagement in the evening while maintaining a consistent level of activity during traditional working hours.

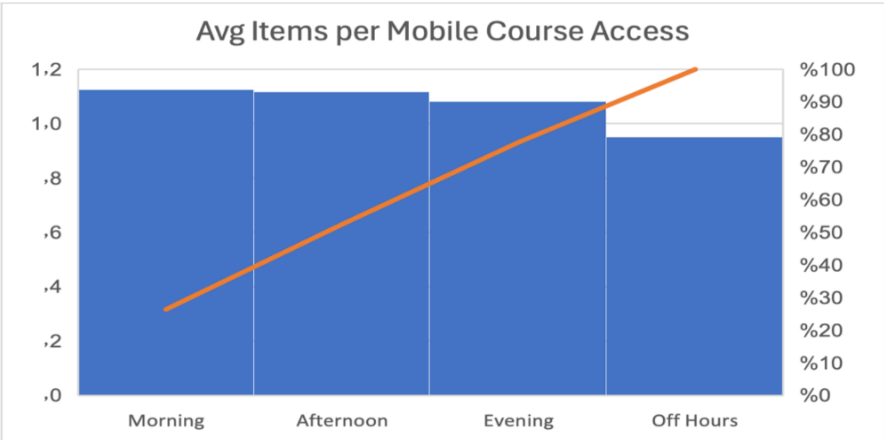

Figure 7: Detailed analysis of the average number of items accessed per course session via the Blackboard mobile app during the 2022–2023 academic year, categorized by time of day

4.4.6 Time Spent Interacting With the E-Learning Environment

Figure 8 illustrates the time the learners spent on the educational platform during the different periods (morning, noon, evening, and outside working hours). This figure represents the average time spent per platform session, segmented by the access medium, such as the mobile app versus web browser. When the mobile app was used, the highest average session duration was 7.2 minutes in the afternoon, whereas the lowest duration was 4 minutes outside working hours. When a web browser was used, the highest average session duration was 6.4 minutes in the afternoon, whereas the lowest duration was 4 minutes outside working hours.

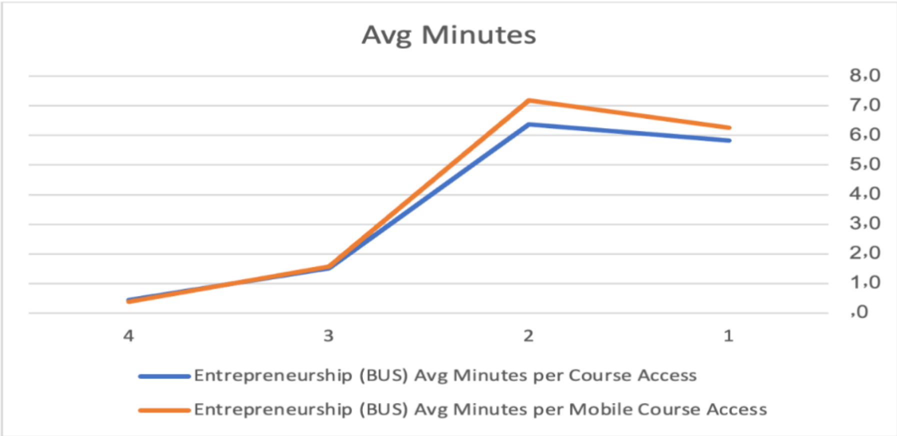

Figure 8: Time spent by the learners on the educational platform across different time periods

4.4.7 Learner Interaction in Discussion Forums

Table 1 presents the student interaction data from the discussion forums. The results indicated that the number of forums created in the entrepreneurship course ranged from 19--31, with student participation ranging from 87--251 posts. The number of student comments ranged from 12--61.

Table 1: Student interaction data in discussion forums

Term	Student Posts	Threads	Student Threads
2022 Acad Year 2022-2023 Term 1	251	61	61
2022 Acad Year 2022-2023 Term 2	87	12	12
2022 Acad Year 2022-2023 Term 3	186	1	1
2022 Acad Year 2022-2023 Summer	1	1	1

4.2 Results of the Second Question: What Is the Impact of Student Interactions In E-Learning Environments on Academic Achievement?

Figure 9 illustrates the distribution of the students' grades in the entrepreneurship course, revealing a distinct pattern in the frequency distribution along with cumulative percentages. The analysis revealed that the highest frequency of grades was at the Grade A+ level, with approximately 1,058 students achieving this grade. This was followed by Grade A, with approximately 479 students, and Grade A-, with approximately 459 students.

The grade distribution pattern demonstrated a positive skew toward higher scores, with most grades concentrated in the upper range of the scale. The number of students gradually decreases as the grades decline. For example, approximately 440 students achieved a Grade B+, whereas lower grades such as C-, D-, and D- were significantly less frequent.

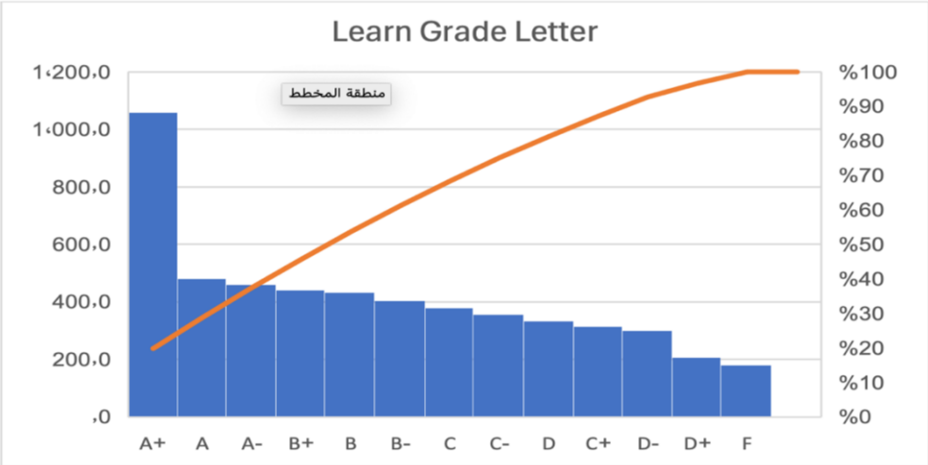

Figure 9: Distribution of the students' grades in the course, demonstrating a distinct pattern in the frequency distribution along with cumulative percentages

5. Discussion

This study aimed to leverage student engagement data from e-learning environments to support informed decision-making, ultimately enhancing personalized learning experiences. The research population comprised more than 20,000 students enrolled in an entrepreneurship course at a Saudi university during the 2022--2023 academic year. A total of 2,600 students were selected via a convenience sampling method. Data extraction and analysis were conducted via Pyramid and Blackboard, which employ the model proposed by Ibañez et al. (2020) for collecting student interaction data in higher education within e-learning environments.

The analysis conducted in this study revealed significant variations in interaction rates within the Blackboard e-learning environment, along with distinct fluctuations in the duration of learner engagement on the platform. These variations were contingent upon the access methods used at different times of the school day and across academic semesters, effectively reflecting important user experience metrics (Krumm et al., 2018).

Among the four daily time periods, the morning consistently emerged as the peak time for educational activity. Mobile app access in the morning demonstrated the highest level of engagement with the course elements and content. The interaction rates gradually declined throughout the day, reaching their lowest point in the afternoon. These findings align with those of Ibañez et al. (2020), who observed an increase in user activity from 8:00 a.m., which plateaued between 12:00 p.m. and 8:00 p.m., showing a stable distribution of active users, and subsequently declined.

These patterns likely mirror typical user behavior, which is correlated with daily energy and concentration cycles. The peak morning activity may be attributed to users starting fresh and benefiting from heightened focus, productivity, and fewer daytime commitments such as homework and social engagements. Reduced afternoon activity could stem from fatigue, engagement in other tasks, scheduled breaks, socializing, or a combination thereof. This afternoon decline could also indicate a need for more varied content or novel instructional methods. Stable activity during evenings and outside working hours reflects user flexibility in choosing study times, which is consistent with the course's blended learning approach.

With respect to engagement with course elements, the students showed significant engagement with multimedia elements, such as short videos and quick tasks, which significantly impact knowledge acquisition processes (Almufarreh et al., 2022) and learning activities (Al-Subhi, 2023; Khan and Alqahtani, 2020), with peak engagement occurring in the evening. This correlates with the scheduling of interactive lectures in blended courses, allowing students to participate after work or off-campus study commitments. The consistent interaction levels observed across the other periods suggest students' ongoing engagement with traditional on-campus classes (Fabian et al., 2024; Chen et al., 2024; Owston et al., 2013).

This observation concurs with that of Ibañez et al. (2020), who identified peak e-learning activity between 5:00 p.m. and 8:00 p.m., highlighting the blended intensity of such programs and fostering a humanized approach to distance learning. It also aligns with Al-Mufarreh and Arshad (2021), who reported that faculty members commonly use Blackboard two to three times weekly to provide course elements, including lecture notes, presentation slides, online assessments, and assignments.

The analysis of mobile app usage highlighted its significance as a robust, adaptable, and technologically relevant educational tool. The data revealed consistent interaction rates and access to items across different times of the school day, underscoring the app's flexibility in meeting the students' educational needs and its efficiency in facilitating access to course content. However, the study identified variations in learner engagement duration when the app was used, with learners spending the most time in the afternoon, suggesting peak content interaction. This may be because of lunch breaks or reduced morning pressure, which facilitates concentration (Javid et al., 2023; Rocque, 2022; Hwang & Chang, 2011).

Conversely, the lowest app usage was recorded outside working hours, reflecting decreased engagement with e-learning apps outside formal academic hours. These results confirm the app's technical reliability and successful integration into the educational process as a key tool supporting flexible and independent learning, enhancing creativity and learning in a variety of settings, both formal and informal, promoting comprehensive learning, increasing learning speed, engaging in a positive thinking process, and building a deep understanding of the content (Rocque, 2022; Henriksen et al., 2021; Almufarreh et al., 2021; Darko, 2021; Lang, 2022).

Consequently, app utilization can be further optimized by enhancing the user experience through dynamic instructional design and digital interaction strategies (Walkington & Bernacki, 2020). The development of additional features that promote sustained engagement and motivate students to leverage their potential fully is crucial, ultimately improving the overall e-learning experience (Pandey, 2022). This research advocates providing supplementary resources adapted to the diverse learning styles of students to increase their degree of participation (Krumm et al., 2018; Sulanto, 2018). In addition, it advocates the development of predictive models to identify students at risk of low engagement.

Zhao et al. (2022) supported this study's findings, demonstrating that learners' personal information and learning activity records serve as attributes in resource models, with learning resources acting as target data for recommending suitable learning materials. Their model emphasized ubiquitous learning, enabling students to learn anytime, anywhere, and on any device. Therefore, recommendation systems for ubiquitous learning resources must accommodate diverse mobile and desktop devices.

With respect to access to web-based courses across different times of the day, the afternoon period had the greatest average engagement duration. This suggests that the students preferred to access the platform via the web during the afternoon, possibly because of high concentration levels or increased task requirements during this time. The data also indicated a pronounced decrease in the time spent outside working hours, representing the lowest level of platform engagement. This reflects a consistent user interaction pattern during this period.

These findings highlight the importance of timing in both educational content delivery and user interaction requirements (Sokołowski et al., 2024). Mullens and Glorieux (2023), Hobbes et al. (2011), and Vickery (1977) indicated that time is influential in the learning process and that freely available time is the best measure of how much time an individual has left to pursue future investment commitments (such as learning). Educational institutions can capitalize on the afternoon peak by scheduling important tasks or content that require high concentration.

This finding confirms what Xavier et al. (2022) indicated: time management is an important element in continuing the online learning process. This finding also indicates that students' time management online may be key to their success (Xavier et al., 2022; Zheng et al., 2022). This was confirmed by Zheng et al. (2022), Wladis et al. (2022), and Burston (2017), who stated that the ability to manage time effectively helped students complete their online courses.

Regarding the impact of the students' interaction with the course on their academic achievement, the results indicated that the course was successful in fostering high levels of academic achievement. This finding is consistent with that of Darko (2021) and Lang (2022), who also noted high student achievement in courses. Darko's research suggested that some students prioritize achieving high grades over participating in seminars and meetings, indicating a focus on grade attainment. A positive correlation between students' login frequency and their final grades suggests that greater interaction with the LMS is associated with improved academic outcomes. The reasons for high achievement may include increased reliance on instructor feedback, the use of Blackboard, face-to-face discussions, and instructor-provided graduate support and coursework. This finding reinforces the positive impact of student interactions on academic achievement by enhancing learning motivation, promoting deeper learning skills, and improving overall academic performance.

With respect to the enhancement of personalized learning experiences, the findings offered significant insights into user interaction with Blackboard. This knowledge could facilitate the design improvement and delivery of flexible learning content that is compatible with diverse mobile operating systems and suitable for shorter learning sessions (Al-Subhi, 2023; Lang, 2022; Darko, 2021; Almufarreh, 2021; Ibañez et al., 2020; Krumm, 2018). The findings also highlighted the importance of timing in planning learning activities and allocating academic tasks, the diversity of students' activity patterns, interaction styles, media preferences, and duration of engagement to achieve learning goals and maintain continuous engagement requirements (Sokołowski et al., 2024; Mullens & Glorieux, 2023; Hobbes et al., 2011).

However, insights into the importance of timing in online learning enable educational institutions to improve e-learning experiences, develop policies to enhance learning, foster engagement through innovative learning activities, and predict the causes of student declines in engagement throughout the semester (Xavier et al., 2022; Zheng et al., 2022; Wladis et al., 2022; Burston, 2017). A cyclical pattern of intense morning activity, a gradual decline during the day, and relative stability during the evening and outside of work hours was observed. This observed pattern could contribute to adjusting educational activity scheduling, redesigning class schedules and assignments to align with student engagement patterns, and improving educational processes based on peak periods.

Strategies to improve student engagement during periods of low activity include providing incentives for participation, such as points, rewards, and recognition; engaging students and enriching their learning experiences; designing interactive activities tailored to students' needs and preferences and aligning with different times of the day; providing ongoing technical and academic support, including AI-powered personal assistants to personalize learning experiences; designing personalized learning experiences; and continuously updating content via innovative methods to ensure continued engagement and enhance the effectiveness of personalized learning (Sokołowski et al., 2024; Mullens & Glorieux, 2023; Zheng et al., 2022; Xavier et al., 2022; Hobbes et al., 2011).

This analysis can inform the design of personalized learning experiences with continuous content updates, employing innovative methods to ensure sustained engagement and enhance the effectiveness of personalized learning. This suggestion aligns with that of Ibañez et al. (2020), who recommended that learning analytics offer exploratory insights into learner activity, enabling customized strategies that improve learning experiences. This represents a move toward more comprehensive learning analytics projects aimed at personalizing data-driven strategies to individual learner needs. Zeng et al. (2024) further explored mechanisms for addressing diverse learning styles, advocating for dedicated resources for each style on the basis of specific learning requirements and recommending personalized learning tools or platforms. For students with extensive prior knowledge, the authors suggested more exploratory, project-based, or research-oriented learning methods, whereas beginners may benefit more from guided learning resources such as instructional videos, tutorials, or personalized guidance. They also emphasized the importance of aligning assessment methodologies with diverse student experiences and learning styles.

6. Conclusion

This study focused on the importance of big data in the era of the Fourth Industrial Revolution and its implications for university education policymakers. It also explored the role of big data analytics in improving the quality of online courses, which helps decision-makers and e-learning program developers redesign their teaching and learning experiences. This study examined the use of big data analytics tools in e-learning environments to improve personalized learning experiences.

The results revealed significant differences in engagement rates within the Blackboard e-learning environment, along with significant fluctuations in the duration of learner engagement on the platform. These differences are linked to the access methods used at different times of the school day and across semesters. The morning period is the peak period for students' learning activity and the use of mobile apps to interact with course elements and content. This can be attributed to increased focus and productivity, along with fewer daytime commitments such as homework and social activities.

It has also been shown that engagement rates with course elements and content gradually decline throughout the day, reaching their lowest point in the afternoon. Therefore, it is important to use learning strategies to improve student engagement during periods of low activity and to provide more diverse content or innovative teaching methods. The results also revealed that students demonstrate engagement with course elements and multimedia elements, such as short videos and quick assignments, which significantly impact knowledge acquisition and academic achievement.

The study concluded that using mobile apps as effective, adaptable, and technologically relevant educational tools is important for promoting comprehensive learning, increasing learning speed, engaging in positive reflection, and building a deep understanding of content. The authors also concluded that user interaction with the Blackboard system enhances personalized learning experiences. Additionally, the study found that personalized learning experiences are enhanced by the timing of planning educational activities and distributing academic tasks, the diversity of educational activities and assignments, interaction styles, media preferences, and engagement duration.

Overall, the results revealed the importance of big data in providing valuable insights into the behaviors of users (students), their interactions with course content, and their engagement with learning tasks, which enhances their personalized learning experiences and enables more personalized services. Big data are therefore viewed as effective tools capable of revealing the reality of teaching and learning processes, improving the quality of educational services, enhancing teaching and learning processes, improving services, enhancing personal learning experiences, and enhancing decision-making.

7. Recommendations for Policymakers

On the basis of these findings, this study recommends the integration of AI technologies to personalize learning experiences and develop educational strategies tailored to specific engagement patterns. It also recommends considering the timing and variety of learning activities, the distribution and learning of academic tasks, the quality of content, interaction methods, media preferences, and engagement duration to achieve learning objectives, maintain continuous engagement, and enhance engagement through innovative learning activities.

Furthermore, improving e-learning experiences and optimizing educational processes on the basis of peak periods should be considered. It also recommends enhancing the user experience during periods of low engagement through various strategies, such as offering simple interactive activities, reviewing content, and developing features that encourage increased engagement in the mobile learning environment. The study also recommends providing supplementary resources designed to suit students' diverse learning styles to enhance their engagement, as well as developing predictive models to identify students at risk of low engagement.

Higher education policymakers should encourage and support the integration of big data solutions into teaching and learning processes and educational decision-making. Policymakers can facilitate this process by allocating funding, resources, and incentives to launch pilot research projects that highlight the benefits of using and analyzing big data in teaching and learning processes and enhancing personalized learning experiences. Policymakers should also allocate resources for comprehensive training in data management and analysis, provide funding for the purchase of data analysis tools and technologies, and acquire the skills and tools needed to effectively harness the potential of big data.

By analyzing big data, educational institutions can improve outcomes; predict performance on the basis of progress tracking via a LMS; provide diverse learning opportunities to enhance student learning through competency-based curricula; consider optimal learning timing; understand student behaviors and learning challenges; improve e-learning environments; and provide diverse learning tasks, activities, and methods on the basis of discovery, scientific research, and projects.

8. Suggestions for Future Studies

Considering these findings and recommendations, the following research proposals are proposed:

- Use big data analytics tools in digital e-learning environments to promote sustainable development goals.
- Use big data analytics tools in light of digital transformation to improve digital learning environments and enhance decision-making capacity
- Design an educational website based on big data analytics and its impact on developing digital citizenship skills, problem-solving ability, and cultural intelligence among college of education students
- Study the relationship between big data applications and self-regulated learning skills and future thinking among teachers
- Enhance the effectiveness of a smart training environment in developing big data analytics skills for e-courses and the trend toward using the Internet of Things among college of education students.
- Build learner-based e-learning environments and big data analytics to enhance academic achievement and engagement in learning.

9. Limitations

The current study is not without limitations. Because this study used the Pyramid business analytics platform to analyze student interactions within e-learning environments, other tools that can be used with the Pyramid platform, such as Apache Hadoop, Apache Spark, Tableau, and IBM Watson Analytics, would provide a more comprehensive picture of student interactions within e-learning environments. The study included a single "entrepreneurship" course; it would have been preferable to examine more than one course. Additionally, the study used course access data from a LMS (Blackboard). The LMS does not collect any demographic data in its reports; it only collects access records by student name.

This study included a sample of students from Imam Abdulrahman bin Faisal University in Saudi Arabia, so the study's findings are unlikely to apply to other Saudi universities. The current study also did not consider differences between students enrolled in online classes and those enrolled in online programs, as these demographics may differ and were not measured here.

Among the limitations that should be noted are that, first, the participants in this study were higher education students. Future studies should expand to include pre-university students and analyze student interactions within e-learning environments, especially during times of crisis. Second, the convenience sampling method was used within a target population, and third, the study was conducted at a public university where the researchers work.

Therefore, the study's findings cannot be generalized. Fourth, the research design, while informative, may not be considered rigorous enough to generate generalizable results across Saudi, Arab, or international universities. However, it serves as a "preliminary study," primarily aimed at using big data analytics tools in e-learning environments to improve the personalized learning experience, informing future research endeavors.

Statement and Declarations

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The authors have no relevant financial or nonfinancial interests to disclose.

Author contributions
All the authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Jawaher Alghamdi and Maryam Alhaykan. The first draft of the manuscript was written by Maryam Alhaykan, and Jawaher Alghamdi commented on previous versions of the manuscript. All the authors read and approved the final manuscript.

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