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Exploring Technological Success Factors of Big Data in E-Learning Systems

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Abstract— Big data plays an important role in the development of e-learning systems. There are many factors affecting its implementation and success with e-learning systems. This study aims to identify the implementation success factors related to big data within e-learning systems. To identify these elements, a comprehensive examination of the literature was done by using exploratory and single-case research approaches, the study used Basrah University as the case study to assess the success factors of big data in their e-learning system. Additionally, survey and expert interviews were conducted to validate the literature review's conclusions and identify further factors. The collected data were analyzed using NVivo software to identify themes and sub-themes. To assess the quantitative survey data, machine learning methods are combined with qualitative analysis using a Random Forest Classifier. The finding showed that five factors should be considered which can aid in the creation of more efficient elearning systems namely: Positive Impact on Students, Faculty/Staff Support and Training, Effective Content Design, System Functionality and Usability, and Assessment and Feedback. The results of this study can be used to improve learning outcomes by developing more efficient big data analytics-integrated e-learning systems.

Keywords— Big data, E-learning, data analysis, machine learning.

I. INTRODUCTION

The use of big data analytics in e-learning systems has drawn a lot of attention recently because of its potential to enhance student learning results. There are massive amounts of data that need to be evaluated and interpreted to get relevant insights that can guide decision-making and enhance performance. This strategy can reveal priceless information that can be used to spur learning innovation and enable positive outcomes [1-2]. E-learning systems with big data analytics can provide teachers with crucial knowledge on the trajectory and patterns of student learning. This data can be utilized to tailor instruction and support to better meet the needs of the students. Big data analytics may rapidly reveal patterns and trends that would be impossible to find with traditional data management methods, resulting in better learning outcomes and increased student achievement [3]. Large data and analytics are growing into important tools for colleges and universities and will have a large impact on learning in the coming years [4].

Information and communications technology advancements have made it feasible to examine a significant amount of educational data and make decisions that will enhance the work atmosphere [5]. Big data analytics is becoming more popular in e-learning systems as mobile devices are utilized more frequently and data is easier to obtain [6]. Instructors can boost student engagement and inform the

curriculum by analyzing massive datasets to learn more about how students are interacting with the course materials. Additionally, incorporating big data analytics might open up possibilities for predictive modeling and in-the-moment feedback, which can aid students in making better decisions and enhancing their overall learning results [7]. The development of sensor-based e-learning systems as a result of recent technological advancements has the potential to improve the educational experience for students [1]. These systems use sensors to collect information on the learning environment's different components, including attendance, physical activity, and engagement, and they give students tailored feedback.

Recent studies have delved into incorporating big data analytics into e-learning systems and have highlighted its capacity to revolutionize the education industry. A study by Dietz and Hurn [8], highlighted the value of incorporating big data analytics into e-learning systems to improve student learning outcomes, increase retention rates, and provide customized learning experiences [9]. The e-learning sector may alter as a result of the application of big data analytics by providing instructors with important information about how students learn and perform. With this knowledge, they are more equipped to adapt their instruction and assistance to better meet the requirements of their pupils [10].

This study offers insightful information about the crucial success criteria that can help in the creation of more effective e-learning programs, ultimately enhancing educational outcomes for students. This work adds to the corpus of knowledge by merging cutting-edge machine-learning approaches and significant insights into the successful aspects of big data in e-learning systems.

II. MODELS OF BIG DATA IN E-LEARNING

In an intelligent e-learning system utilizing big data analytics, the technological models account for both the hardware and software prerequisites. Table I. presents a summary of pertinent research on technological models that incorporate big data analytics in e-learning systems.

TABLE I. TABLE TYPE STYLES

Ref.	Model	Results	Technological Issues Addressed
[1]	Big data-based personalized recommendation system for online learning	Personalized learning, improved learner engagement	Personalization, learner engagement
[2]	An innovative big data-based e-learning recommendation approach	Personalized recommendati ons	Learner performance, personalization

Ref.	Model	Results	Technological Issues Addressed
	Internet of Things and	Enhanced	IoT capabilities,
	Big Data Analytics in	fundamental	technology, and
[3]	E-Learning	principles	the problems
			associated with
			their deployment
	An e-learning system's	Improved	Decision-making,
[4]	big data analytics	decision-	personalization
	framework	making	
	Big Data Analytics for	More	Data management
	Learning in Education	accurate	or control
[5]		forecasts of	
		student	
		performance	
[6]	Data Analysis for e-	Increasing the	e-Learning
	Learning with	safety and	cybersecurity
	Intelligence	reliability of	based on reliability
		online	
		learning	
		systems	

Big data analytics integration with e-learning systems presents technical difficulties that must be addressed for successful adoption. One significant challenge is personalization, and several models strive to deliver customized experiences to learners. However, limited empirical evidence necessitates further research to investigate its effectiveness, and to determine the critical success factors that contribute to its success. For big data analytics to be successfully used in e-learning systems, several organizational and technological obstacles must be addressed [11-12].

III. ADVANTAGES OF BIG DATA ANALYTICS IN E-LEARNING SYSTEMS

Big data offers numerous advantages for e-learning professionals that could significantly impact the field's future and fundamentally change the way users perceive and evaluate the e-learning experience. An overview of the justification for e-learning advantages is given in Table II.

TABLE II. BIG DATA WITHIN E-LEARNING ADVANTAGES

Ref.	Impact	Description
[13]	Positive impact on student achievement	Using individualized learning based on big data analytics, learning results will be improved, and student happiness will rise
[14]	Positive impact on accurate prediction	Accurate forecasting of learners' academic achievement, enabling assistance and materials that are specifically targeted
[15]	Positive impact on the learning experience	personalization of advice based on big data analysis to enhance the educational process
[16]	Positive impact on Effective identification	Effectively identifying students' learning preferences and needs to produce personalized educational materials and tasks
[17]	Positive impact on student monitoring and support	Monitoring and feedback on student performance in real-time, allowing for prompt support and intervention

There is still a lack of actual evidence to prove the utility of big data analytics in e-learning, despite earlier studies highlighting its potential benefits [16].

IV. USAGE OF TECHNOLOGICAL SUCCESS FACTORS OF BIG DATA IN E-LEARNING SYSTEMS

Table III presents the statistical data regarding the extensive implementation of diverse technologies and methodologies in e-learning systems.

TABLE III. BIG DATA USAGE WITHIN E-LEARNING

Ref.	Factor	Usage Statistics	Effects
	Data	Incorporating tools for	As a result, learner
[18, 19]	Collectio	data collecting and	actions may be better
	n and	storage, like learning	tracked and analyzed,
	Storage	management systems	enabling individualized
		(LMS) and data	learning experiences
		warehouses, is	and data-driven
		something that about	decision-making for
		80% of e-learning	teachers and administrators
	Data	systems do The integration of data	Comprehensive student
	Integratio	from many sources,	profiles, cross-platform
	n and	such as learning	analytics, and
	Interoper	content, test results,	individualized
[20]	ability	and user profiles,	suggestions are made
		occurs in about 65% of	possible by the
		e-learning systems	seamless data exchange
			across many systems
	. ·	4 1 450/ 6	and platforms
	Processin	Approximately 45% of	This encourages
	g Data in Real	e-learning systems monitor student	improved learner engagement, flexible
	Time	activity and provide	learning opportunities,
[21]	111110	rapid feedback using	and prompt
		real-time data methods	intervention for
		of processing	students who might be
			having trouble
	Predictiv	Predictive analytics	This makes it possible
	e	algorithms are used by	to identify at-risk
	Analytics	around 60% of e-	students before it's too
[22]		learning platforms to foretell learner	late, develop individualized
		behavior.	intervention plans, and
		performance, and	distribute adaptive
		needs	content
	Machine	The delivery of	This leads to improved
	Learning	personalized material,	feedback systems,
	and AI	intelligent tutoring,	adaptive learning paths,
		and process automation are all	and content
[23]		made possible by the	recommendation systems
[23]		use of machine	systems
		learning and AI	
		algorithms in about	
		55% of e-learning	
		systems	
	Data	Data visualization	This improves data
	Visualiza	Data visualization tools are used by	comprehension, makes
		Data visualization tools are used by almost 70% of e-	comprehension, makes it possible to spot
[24]	Visualiza	Data visualization tools are used by almost 70% of e- learning platforms to	comprehension, makes it possible to spot patterns and trends, and
[24]	Visualiza	Data visualization tools are used by almost 70% of e- learning platforms to present complicated	comprehension, makes it possible to spot patterns and trends, and helps educators and
[24]	Visualiza	Data visualization tools are used by almost 70% of e- learning platforms to present complicated learner data in an	comprehension, makes it possible to spot patterns and trends, and
[24]	Visualiza	Data visualization tools are used by almost 70% of e- learning platforms to present complicated	comprehension, makes it possible to spot patterns and trends, and helps educators and administrators make
[24]	Visualiza	Data visualization tools are used by almost 70% of e- learning platforms to present complicated learner data in an aesthetically pleasing and understandable way	comprehension, makes it possible to spot patterns and trends, and helps educators and administrators make
[24]	Visualiza tion	Data visualization tools are used by almost 70% of e- learning platforms to present complicated learner data in an aesthetically pleasing and understandable way Most e-learning	comprehension, makes it possible to spot patterns and trends, and helps educators and administrators make wise decisions As a result, student
[24]	Visualiza tion Privacy and	Data visualization tools are used by almost 70% of e- learning platforms to present complicated learner data in an aesthetically pleasing and understandable way Most e-learning platforms use strong	comprehension, makes it possible to spot patterns and trends, and helps educators and administrators make wise decisions As a result, student privacy is protected,
[24]	Visualiza tion Privacy and Security	Data visualization tools are used by almost 70% of e- learning platforms to present complicated learner data in an aesthetically pleasing and understandable way Most e-learning platforms use strong privacy and security	comprehension, makes it possible to spot patterns and trends, and helps educators and administrators make wise decisions As a result, student privacy is protected, data integrity is
	Visualiza tion Privacy and	Data visualization tools are used by almost 70% of e- learning platforms to present complicated learner data in an aesthetically pleasing and understandable way Most e-learning platforms use strong privacy and security controls, such as	comprehension, makes it possible to spot patterns and trends, and helps educators and administrators make wise decisions As a result, student privacy is protected, data integrity is maintained, and data
[24]	Visualiza tion Privacy and Security	Data visualization tools are used by almost 70% of e- learning platforms to present complicated learner data in an aesthetically pleasing and understandable way Most e-learning platforms use strong privacy and security controls, such as encryption, access	comprehension, makes it possible to spot patterns and trends, and helps educators and administrators make wise decisions As a result, student privacy is protected, data integrity is maintained, and data protection laws are
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V. METHOD

This study employs a mixed-methods approach to examine the success factors of big data in e-learning systems. The research design combines various methods, including a literature review, survey, single case study, and expert interviews, to provide comprehensive insights into the effectiveness of big data analytics in e-learning and identify key contributing factors. The methodology commences with an extensive literature review to gather existing knowledge on the utilization of big data in e-learning systems, encompassing both success factors and challenges. This literature review forms the foundation for subsequent stages of the research.

Data collection involved the utilization of a structured questionnaire consisting of 18 inquiries that encompassed diverse facets related to big data in e-learning. The questionnaire is administered to students and lecturers at Basrah University which is the sample population used in this study. It focuses on capturing students' preferences, perceptions, and experiences about e-learning systems with the integration of big data analytics. A single case study approach is also used to increase the scope and depth of the investigation. To supplement the survey results, qualitative data is gathered by monitoring the e-learning system at Basrah University and interviewing experienced academics and professionals in e-learning platforms. Insights into operational practices, long-term objectives, faculty support and training, successful content design, system functionality, and usability, as well as assessment and feedback methods, are provided by the case study.

NVivo Software was used to analyze the data that had been obtained, particularly from the case study. NVivo is a potent qualitative data analysis tool that makes it easier to code and explore data systematically. NVivo was used in this study to find pertinent themes and sub-themes in the data. Initial codes, which are labels or classifications assigned to particular elements of the data depending on the research objectives, were created before the analytic process ever started. These codes played a key role in drawing attention to pertinent words or phrases in the dataset. The coding system was improved and broadened through an iterative coding process to include a wide variety of themes and sub-themes.

This study was able to build a full understanding of the success factors related to the application of big data analytics in e-learning systems by investigating patterns and linkages within and across these themes. NVivo offered a methodical and structured approach to data analysis, ensuring accuracy and dependability in the recognition and interpretation of the essential findings.

To assess the quantitative survey data, machine learning methods are combined with qualitative analysis using Python. The provided machine learning code is changed to incorporate more survey factors like teacher support and technological accessibility. Using training and testing sets of the survey data, a Random Forest Classifier is trained to predict technological aspects and evaluate the accuracy of these forecasts. The outcomes of the literature review, case study, expert interviews, surveys, machine learning analysis, and qualitative analysis are then merged and assessed. The success criteria for big data analytics in e-learning systems are determined using integrated insights from both qualitative and quantitative data.

VI. RESULTS AND DISCUSSION

Based on the methodology, to assess the efficiency of the various components of e-learning technology solutions, a single case study was carried out. The study focused on the technological components that were implemented at Basrah University Online Learning Management System using big data analytics. Data was collected through interviews with e-learning data analytics specialists. The findings from the interview along with the literature review confirmed that five success factors should be considered for an e-learning system. Fig. 1 shows five main success factors that have been identified from the qualitative analysis as main themes.

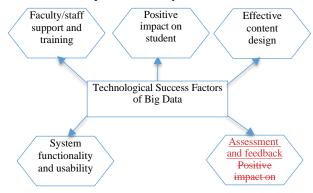


Fig. 1. Technological Success Factors of Big Data.

The newly developed concepts are then arranged according to the thematic analysis strategy employed in this study into themes and sub-themes. As the general findings of the qualitative data analysis that identifies the themes and sub-themes, Table IV. Summarizes the deployment success criteria, their respective components, and related sub-themes.

TABLE IV. SUCCESS FACTORS AND ELEMENTS

Factors	Success elements		
	Personalized learning approach		
Positive impact on student	Interactive multimedia content		
	Mobile learning access		
	Technical skills and expertise in technology service		
Faculty/staff support and	Faculty training and support programs		
training	IT infrastructure support		
	Collaborative faculty culture		
	Course quality and organization		
Effective	Learning objectives and outcomes alignment		
content design	High-quality course materials		
	Multimodal instructional design		
	Reliability and stability of the system		
System functionality	User-friendly interface and design		
and usability	Easy-to-use features and tools		
	Integration with other systems and applications		
	Multiple and diverse assessment methods		
Assessment and	Real-time feedback and support		
feedback	Rubrics and grading standards		
	Personalized feedback and progress tracking		

For the quantitative analysis, the questionnaires were distributed to lecturers and students at Basrah University, and 2034 replies were used in this study. Table V. Summarizes key findings and recommendations on the perceived success factors of big data in e-learning systems along with the recommendations. The most significant factor according to the respondents was the availability of relevant content, with 60% of the respondents highlighting it. Faculty support and engagement were ranked second with 22%, followed by access to technology and infrastructure with 12%, positive impact on student learning with 4%, and technical skills and expertise for technology service with 2%.

TABLE V. FINDINGS AND RECOMMENDATIONS

Key Findings	Implications	Recommendations
The availability of	To create and	Make sure that each
relevant	implement effective	student receives
information is	e-learning systems	individualized,
necessary for big	using big data	pertinent content from
data analytics in	analytics, relevant	e-learning platforms
e-learning	content must be	with big-data analytics
systems, based on	easily accessible	
60% of		
respondents.		
22% of	The involvement	Encourage faculty
respondents	and support of	members to engage
identify faculty	faculty members are	with and support the
support and	crucial for the	implementation of big
engagement as	effective integration	data
critical success	of big data analytics	
factors.	into e-learning	
	systems	
12% of	For big data	Make sure the
respondents	analytics to be used	technology and
identified access	effectively in e-	infrastructure are in
to technology and	learning systems,	place for big data
infrastructure as a	the right technology,	analytics-based e-
critical success	and infrastructure	learning systems to
factor.	are essential	function
4% of respondents	Big data may be	Further research is
believe big data	used to improve	required to
analytics has a	student learning	comprehend how big
positive impact on	outcomes in e-	data analytics can be
student learning.	learning systems.	incorporated into e-
		learning platforms to
		improve student
20/ -f1 /	E4	learning outcomes Ensure that technical
2% of respondents	For the successful	
believe technical skills and	deployment and	staff has the necessary
expertise for	operation of e-	skills and knowledge
technology	learning systems with big data	to effectively deploy and operate e-learning
services are	analytics, technical	systems with big data
critical.	competence, and	analytics
citucai.	understanding are	anarytics
	important.	
	широнаш.	

The findings of this study are in line with those of earlier investigations into the use of big data analytics in e-learning environments. Similar success elements were emphasized in the literature review, including faculty support, technology infrastructure, and content customization. Basrah University's case study provided useful details on the operational procedures and practical considerations for incorporating big data analytics into e-learning platforms. Big data analytics have been applied to e-learning systems, and effective content design has emerged as a key component, supporting the idea that relevant and tailored material improves student engagement and learning outcomes. Both the survey and the case study consistently recognized faculty participation and training as crucial success factors, highlighting the

significance of faculty assistance in promoting the efficient use of big data analytics. The case study also highlighted the significance of system usability and functioning, as well as the availability of methods for assessment and feedback, all of which are linked to infrastructure, technical know-how, and access to technology.

VII. MACHINE LEARNING AND STATISTICAL MODELING

By transforming the survey data into a pandas DataFrame and dividing it into features (factors) and the target variable (technological), this study uses machine learning and statistical modeling techniques to incorporate predictive analytics based on survey results in making suggestions. Using the scikit-learn train_test_split function, divide the data into training and testing sets. The data was used to train a Random Forest Classifier, which then used the test set's data to make predictions.

The endogenous latent variable's percentage R-squared variance on the exogenous variables reveals that the technological factor has a strong influence on students, with an R2 of 90%, while it has a stronger influence on faculty/staff support and training, with an R2 of 75%. As indicated in Table VI. effective content design had an R2 of 65%, system functioning and usability had an R2 of 60%, and assessment and feedback had an R2 of 60%.

TABLE VI. R2 VALUES AND P-VALUES FOR DIFFERENT FACTORS

Factors	R^2	p-VALUE
Positive impact on student	0.9	< 0.001
Faculty/staff support and training	0.75	< 0.001
Effective content design	0.65	< 0.001
System functionality and usability	0.6	< 0.001
Assessment and feedback	0.6	< 0.001

Table VI. Range of R-squared (R2) values shows a strong correlation between the components and the result. A higher R2 value indicates that the related component accounts for a larger proportion of the outcome's variability. The p-values, on the other hand, are all presented as "0.001," indicating a strong statistical relationship between the components and the result. The importance of the associations is increased by the fact that a p-value of less than 0.001 indicates that there is very little possibility that the observed results could have occurred by chance alone.

The factors (positive impact on student, faculty/staff support and training, effective content design, system functionality and usability, and assessment and feedback) are highly correlated with the outcome variable and have statistically significant p-values to substantiate their strong relationships. Additionally, by contrasting the predictions with the actual components from the test set, this study determines the forecasts' correctness. The survey data contained variables such as "faculty_support" and "technology_infrastructure" that are important to the success of big data analytics in e-learning systems. Table VII. Displays the outcomes of applying various classifiers to the test set in terms of the confusion matrix.

TABLE VII. CLASSIFICATION OF THE ALGORITHM.

	*Normal	0.9735	
Precision	**High	0.8664	
	Macro average	0.9199	
	Weighted average	0.9476	
Recall	Normal	0.9548	
	High	0.9185	
	Macro average	0.9366	
	Weighted average	0.946	
	Normal	0.964	
	High	0.8917	
F1-score	Macro average	0.9279	
	Weighted average	0.9465	
Accuracy	0.946	0.946	

A precision of 0.9735 for the "Normal" class indicates that around 97.35% of the predicted "Normal" instances are in fact "Normal". The "High" class's accuracy is 0.8664, meaning that around 86.64% of the projected "High" cases are actually "High". The macro average precision establishes the average precision across all classes by giving each class the same weight. In this circumstance, the macro average precision is 0.9199. The weighted average precision is used to calculate the average precision, taking into consideration the number of instances in each class. Precision as a weighted average is 0.9476.

Recall, also known as sensitivity or true positive rate, measures how accurately real positives are identified. The recall for this class is 0.9548, assuming that around 95.48% of the actual instances of the "Normal" class are correctly identified. Approximately 91.85% of the actual "High" cases are correctly identified with a recall of 0.9185 for the "High" class. The macro average recall determines the average recall across all classes by allocating the same weight to each class. The average recall is 0.9366. Utilizing a weighted average recall that accounts for the number of occurrences in each class, the average recall is calculated. When weighted, recall is 0.946.

The performance of the model is balanced indicated by the F1-score. The F1-score for the "Normal" class is 0.964. The "High" class's F1 score is 0.8917. The macro average F1-score establishes the average F1-score across all classes by allocating the same weight to each class. The macro average of the F1 score is 0.9279. The average F1-score is calculated using the weighted average F1-score, which accounts for the number of cases in each class. The average F1 score is 0.9465 when weighted. Accuracy serves as a barometer for how accurate the predictions are overall. Around 94.6% of the forecasts are accurate, according to the method's accuracy of 0.946. These metrics assess the overall effectiveness of the classification model and provide helpful details about how it performs on the specified dataset

A measurement model estimation was carried out to evaluate the validity, discriminant validity (containing indicators and outer loadings), and reliability consistency to study the effects of various elements on the e-learning system. Table VIII. Displays the reflecting measurement model's findings.

TABLE VIII. MEASUREMENT MODEL EVALUATION

Construct	Loadings	Average Variance Extracted (AVE)	Composite Reliability
Positive impact on student	0.885	0.918	0.856
Faculty/staff support and training:	0.742	0.719	0.843
Effective content design	0.648	0.942	0.917
System functionality and usability	0.690	0.616	0.781
Assessment and feedback	0.670	0.618	0.771

To evaluate the constructs, it was necessary to look at their loadings, average variance extracted (AVE), and composite reliability (CR). The loadings show how closely related the latent constructs are to the observed indicators. The AVE calculates the percentage of variation that the construct successfully captures in comparison to measurement error, suggesting convergent validity. The CR assesses the internal consistency reliability of the constructs. The analysis's findings showed that all of the constructs had satisfactory loadings, AVE values, and CR values. These results imply that the measurement model exhibits good validity and reliability and adequately depicts the components of the e-learning system.

VIII.CONCLUSION

The research's findings contribute to the body of knowledge on what makes big data analytics effective in elearning systems. The identified factors, including access to relevant content, faculty support, positive effects on student learning, technical skills, and access to infrastructure, serve as principles for organizations and decision-makers when building and putting into place efficient e-learning platforms. institutions may better assess Educational requirements, personalize instruction for each student, and offer timely support and interventions by utilizing the power of big data analytics. This may result in greater student motivation, engagement, and general learning results. Incorporating big data analytics into e-learning systems is significant, and this study underlines the significance of critical success elements for its successful implementation. The results pave the way for a more individualized and significant learning experience and support ongoing efforts to improve the caliber and efficacy of e-learning platforms. It is critical to recognize this study's constraints. The study was carried out at Basrah University, which can restrict how broadly the results can be applied to other settings or circumstances. To increase the findings' external validity, future studies should use a more varied sample population. The study also concentrated on particular success variables; therefore, more investigation into other elements and how they interact is necessary. Future research could use longitudinal evaluations or experimental designs to acquire a deeper understanding of how big data analytics affects student learning results.

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