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Data Analysis Skills in Teaching Leadership: A Strategic Study to Improve Student Learning Outcomes and Digital Literacy

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Abstract
This study examines the impact of incorporating data analysis skills—specifically, data interpretation, predictive analytics, and data-driven decision-making—on student learning outcomes and digital literacy. As technology and data increasingly influence education, it is essential for educators to possess the analytical expertise necessary to adapt their teaching methods effectively. A quantitative approach was employed, gathering data from 251 participants (100 educators and 151 students) through a structured questionnaire survey. Stratified random sampling ensured diverse representation across various educational levels. The data analysis utilised SPSS software, incorporating descriptive statistics, correlation analysis, and regression techniques. The results revealed a strong positive correlation between the proficient application of data analysis in educational contexts and enhanced student performance and capabilities. Predictive analytics emerged as the most significant factor in forecasting student success, with instruction in data interpretation and data-driven decision-making also yielding substantial improvements in learning outcomes. The study highlights the critical need for teacher training in data literacy and advocates for the integration of digital tools to effectively monitor student progress. The findings underscore the importance of educational leadership in utilising data to create

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technology-enhanced environments that support personalised learning. By offering recommendations for data-informed teaching practices, this research contributes to the development of educational policies aimed at improving academic performance and digital literacy.

Keywords: Data Analysis Skills, Predictive Analytics, Teaching Leadership, Digital literacy, Student Learning Outcomes

Introduction

Background

Data analysis has increasingly become a critical factor in the success of teaching leadership and student learning in modern education. Viberg et al. (2018) highlighted that, with the integration of technology into various aspects of learning, data has emerged as a vital resource for decision-making and enhancing teaching practices. Traditionally, teaching leadership was understood as the process of imparting knowledge, skills, and character, alongside classroom management. However, this concept has now evolved to include data analysis capabilities, aimed at providing recommendations that serve the best interests of both teachers and students. Additionally, Day et al. (2016) explained that this shift aligns with current educational discourse, which emphasises the use of data and digital technology to improve student performance and equip learners with the skills necessary for the future. Educational data analytics involves the collection, measurement, and evaluation of student information related to academic performance, attendance, and learning, with the goal of informing instructional strategies and leadership decisions. Furthermore, Ingersoll et al. (2018) noted that, given the growing availability of educational data, it has become essential for leaders to be proficient in analysing and interpreting this information. This is particularly important in a context where schools are expected to deliver results for students, often being evaluated through standardised tests and other methods of school improvement. In essence, by applying data to decision-making processes, educators and leaders can implement targeted interventions that more effectively support student learning and achievement.

Another advantage of integrating data analysis into teaching leadership is the opportunity to enhance the quality of education by making lesson delivery more student-centred, using individualised approaches. Sottilare et al. (2018) emphasised that when teachers conduct a detailed analysis of student data, they can identify specific areas where students are struggling, allowing them to adjust instructional methods accordingly. For example, if data reveals that a class is underperforming in mathematics, teachers may respond by offering additional lessons or altering the pace of instruction. Furthermore, Zeide (2017) argued that data analysis enables educators to move beyond generic teaching practices, providing tailored learning solutions that can significantly improve students' educational experiences. In addition, it promotes

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staff development by encouraging critical self-reflection and continuous scholarly engagement in the domains of learning, teaching, and academic scholarship. Preparing educators today also involves equipping them for success both in the classroom and in post-secondary life, particularly in the digital age. Avella et al. (2016) further noted that digital literacy—the ability to use digital tools to retrieve, analyse, and generate information—has become a crucial learning area. With the increasing reliance on technology in education, both teachers and students must master technological skills for learning purposes. For teachers, this entails incorporating technology into their teaching practices, while also using data analysis to track student progress and enhance learning outcomes.

Problem Statement

Advances in technology and its integration into teaching leadership have created a growing need for data utilisation; however, many educators lack the necessary data analytical skills to capitalise on this opportunity. With an increasing emphasis on data to inform academic decision-making and improve student outcomes, data literacy—along with the ability to apply and integrate analytical tools for accurate data analysis and informed decision-making—has become essential. Despite this, there remains a lack of empirical research that links these skills to improvements in student learning outcomes and digital literacy. This gap presents a challenge for educators, as they require data to tailor instruction and prepare students for a technology-dependent world (Marsh & Farrell, 2015). Accordingly, the aim of this study is to explore teaching leadership and evaluate the impact of data interpretation, predictive analytics, and data-driven decision-making on students' learning achievements and the enhancement of their digital competencies.

Research Objectives

- To investigate the impact of teaching data interpretation skills on enhancing student learning outcomes and digital literacy.
- To assess the influence of incorporating predictive analytics into teaching strategies on improving student learning outcomes and digital literacy.
- To explore the effect of teaching data-driven decision-making on the enhancement of student learning outcomes and digital literacy.

Research Questions

- In what ways do teaching data interpretation skills impact student learning outcomes and digital literacy?
- What is the effect of integrating predictive analytics into teaching strategies on improving student learning outcomes and digital literacy?
- How does teaching data-driven decision-making contribute to enhancing student learning outcomes and digital literacy?

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Significance of the Research

The significance of this research lies in its ability to address a crucial gap in the education system by exploring the role of data analysis skills in both teaching leadership and the technological literacy of students. In light of this, the study provides valuable insights into the effectiveness of data interpretation, predictive analytics, and data-driven decision-making in personalising learning and preparing students for future educational demands. The findings will be instrumental in enhancing instructional strategies and shaping educational policies that incorporate information and communication technologies, ultimately improving academic performance and fostering digital literacy.

Literature Review

Overview

This chapter synthesises the current findings on the impact of teaching data interpretation, predictive analytics, and evidence-based decision-making on students' learning achievements and technological competence. It explores how these skills enhance students' abilities in critical evaluation, differentiation, and the effective use of technology within the context of the digital environment.

Impact of Teaching Data Interpretation on Student Outcomes and Digital Literacy

The utilisation of data interpretation skills in enhancing student learning outcomes and their competency in understanding data is a crucial aspect that should not be overlooked. This is supported by Mohammadyari and Singh (2015), who argue that in a world inundated with vast amounts of information daily, the ability to analyse and derive meaning from it is essential. By equipping students with these skills, educators help prepare them for decision-making processes that involve analytical data, which in turn contributes to improved achievement rates and overall employability. First and foremost, teaching data interpretation fosters critical thinking skills. Specifically, students learn to differentiate between relevant and irrelevant information, identify patterns, and draw accurate conclusions. Falloon (2020) further contends that this analytical approach enhances problem-solving abilities, leading to better academic outcomes across various subjects such as science, mathematics, and social studies. For instance, in subjects like mathematics, social studies, and business, interpreting graphs, charts, and data sets strengthens students’ problem-solving skills, resulting in improved performance in assessments. It empowers students to critically evaluate the information they obtain from diverse sources, assessing its validity and credibility.

While learning data interpretation skills through various tools, students become familiar with the ways in which information is presented and shared within the digital

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environment. Moreover, data interpretation training involves linking academic content to real-world scenarios. For instance, students may engage with data on topics such as climate change, public health, or economic trends, thereby connecting classroom learning to contemporary issues (Chan et al., 2017). This approach not only reinforces the understanding of specific concepts but also helps students develop research skills, thereby enhancing their digital competencies. Effective training in data interpretation directly improves learning outcomes by fostering critical thinking, problem-solving, and practical application (Alsaleh, 2020). Given the integral role of data in today's society, it is essential for students to cultivate strong skills in data comprehension and analysis, which will benefit their academic performance and future career prospects.

Integrating Predictive Analytics in Teaching Strategies

The integration of predictive analytics into teaching strategies can positively impact student learning outcomes and enhance the use of technology. According to Romero and Ventura (2020), predictive analytics involves applying data, statistical models, and machine learning to forecast future events based on past data. In education, it helps instructors make informed decisions about instruction, interventions, and curriculum improvements for better student outcomes. Predictive analytics personalises learning by identifying patterns and predicting which students may struggle, allowing teachers to provide tailored support for low achievers and enrichment for high achievers (Williamson, 2016). Additionally, it improves real-time monitoring of student progress through data dashboards, enabling teachers to track participation, attendance, and performance to intervene proactively.

Predictive models that identify students at risk of poor performance, based on previous test scores and study habits, allow teachers to provide targeted support, such as extra tutoring or learning materials, increasing the likelihood of student success and improving learning outcomes. Predictive analytics also contribute to the sociotechnical construction of students' digital literacy as they engage with large sets of data, enhancing their understanding of data analysis and its applications (Gasevic et al., 2017). This exposure fosters digital skills relevant to the modern workforce, where data and technology are increasingly important. By integrating predictive analytics, teachers can offer more targeted learning solutions, real-time monitoring, and early interventions, thereby strengthening students' digital literacy and decision-making abilities (Alshanqiti & Namoun, 2020).

Teaching Data-Driven Decision-Making for Better Learning and Digital Literacy

Educating learners on data-driven decision-making is a significant advancement in education that enhances student performance and imparts valuable technological skills. As Wise (2019) noted, in a data-driven world, preparing students to work with data analysis equips them for both college and employment. Decision-making

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involves collecting facts or statistics and using this information to make informed choices, rather than relying on speculation. Walker and Moran (2019) emphasized that teaching this skill in education enables students to approach problems systematically and objectively, improving their academic performance and fostering critical thinking and problem-solving skills, ultimately enhancing the efficiency of the learning process. Improving problem-solving with data also enhances digital competency by integrating various devices and technologies. To make data-driven decisions, students must develop skills in using digital tools, such as spreadsheets, statistical software, and other analytical tools (Datnow & Hubbard, 2016). By utilizing tools like Microsoft Excel or Google Sheets for data analysis, students learn essential technical skills, including algorithms and data interpretation (Cunningham-Nelson et al., 2018). These practical experiences not only boost ICT proficiency but also prepare students for a data-driven work environment.

Theoretical Framework

The theoretical framework for this research draws on two key theories: Constructivist Learning Theory and the Technology Acceptance Model (TAM).

Constructivist Learning Theory

Constructivist learning theory suggests that learning occurs individually as learners create new knowledge through interactions with their environment and reflection on past experiences. This theory is applied through strategies like teaching data interpretation, predictive analytics, and data-driven decision-making, as students use critical thinking and problem-solving skills to analyse real data (Matriano, 2020). By adopting a constructivist approach, students become active participants in their learning, enhancing their learning outcomes and digital competencies.

Technology Acceptance Model (TAM)

The TAM is a framework that seeks to explain technology use based on perceived usefulness and perceived ease of use. This model is particularly relevant in the context of adopting predictive analytics and utilising digital resources in education. Educators increasingly employ digital tools for data analysis, thereby enhancing students' technological competence and improving digital literacy (Teeroovengadum et al., 2017). TAM provides valuable insights into how both educators and students can embrace data analysis as a crucial element of modern education, leading to improved academic outcomes and fostering technological literacy.

Hypothesis

The hypotheses of this research are presented in Table 1.

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Table 1: Research Hypothesis

Hypothesis (H_1)	Null Hypothesis (H_0)
Teaching data interpretation skills will significantly improve student learning outcomes and digital literacy.	Teaching data interpretation skills will have no significant effect on student learning outcomes or digital literacy.
Integrating predictive analytics into teaching strategies will significantly improve student learning outcomes and digital literacy.	Integrating predictive analytics into teaching strategies will have no significant effect on student learning outcomes or digital literacy.
Teaching data-driven decision-making will significantly enhance student learning outcomes and digital literacy.	Teaching data-driven decision-making will have no significant effect on student learning outcomes or digital literacy.

Methodology

Chapter Overview

This chapter outlines the research methods employed to explore the relationship between teaching data interpretation, predictive analytics, and data-driven decision-making, and their impact on student learning outcomes and digital literacy. It covers the research approaches, methodology, data collection instruments, sampling procedures, and data analysis techniques used in the study.

Research Method

The research design is quantitative, as it involves the collection and analysis of numerical data that can be measured and subjected to statistical analysis. This approach facilitates hypothesis testing and helps to determine the correlation between teaching practices and student performance. Given its structured and rigorous nature, quantitative research is well-suited to assess the impact of teaching data skills. According to Hodge (2020), quantitative research involves the collection, analysis, and application of numerical data to make inferences about trends, ratios, or frequencies. It typically utilises tools such as questionnaires, controlled experiments, or secondary data, followed by statistical techniques to minimise bias.

Research Design

This study adopts a primary research method, which involves obtaining first-hand data directly from respondents. The primary data collection method will be a structured questionnaire, administered to both educators and students. The design of the questionnaire aims to generate numerical data that is easy for the researcher to quantify. Schoonenboom and Johnson (2017) suggest that primary research involves gathering data from original sources, which may include surveys, interviews,

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experiments, or observations. This approach ensures that the data collected is directly relevant to the research question and objectives, with the researchers controlling the process to ensure the appropriateness and accuracy of the data gathered for the study.

Data Collection

A questionnaire survey is employed as the primary method of data collection, administered both online and face-to-face to educators and students. The survey consists of closed-ended questions designed to assess the influence of data analysis and the use of data for decision-making on learning outcomes and digital literacy. The questionnaire is organised into various sections, where participants are asked to provide personal details, describe the teaching and learning practices they adopt, indicate their level of digital competency, and report their learning achievements. The survey utilises Likert scale statements, with responses measured based on participants' perceptions and experiences.

Sampling Technique and Size

In this study, stratified random sampling was employed to ensure the selection of representative samples from various sub-groups within the target population. The population was categorised into distinct groups, with teachers and students considered separately. Participants were then randomly selected from each group. The sample consisted of 251 participants, with 100 educators and 151 students. The larger student sample was chosen to better understand the impact of teaching data-driven skills on students' learning outcomes and digital skills. Stratified random sampling enhances the representativeness of the subgroups within the population, thereby increasing the credibility of the results.

Data Analysis

The data were processed using the Statistical Package for the Social Sciences (SPSS), a widely used tool for statistical analysis. The quantitative data analysis employed both descriptive and inferential statistics. Descriptive statistics, including frequency distributions, percentages, and measures of central tendency such as means, medians, and standard deviations, were used to summarise the data. Inferential statistics, including t-tests and ANOVA, were employed to test the research hypotheses and assess whether there were significant differences or correlations between the independent variables—teaching data interpretation, predictive analytics, and data-driven decision-making—and the dependent variables, namely students' learning outcomes and digital literacy. Correlation analysis was used to examine the strength and direction of relationships between variables, while regression analysis was applied to assess how strongly the teaching of data-driven decision-making influences student performance and digital competencies. The use of SPSS ensures that the data analysis is valid and conclusive in addressing the research focus on teaching data

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analysis competence in educational settings.

Ethical Considerations

The study adheres to rigorous ethical standards to ensure the rights of participants are respected. All participants are required to sign consent forms outlining the research objectives, their roles, and affirming that there are no penalties for withdrawing from the study. Participants' identities are kept anonymous by using codes throughout the research process, and no personally identifiable information is collected. All data are securely stored and are accessible only to the research team. Participation is entirely voluntary, and no individual is coerced into taking part in the research.

Findings and Discussion

Overview

This chapter aims to provide a comprehensive analysis of the dataset, focusing on key demographic variables, the reliability of scales, the normality of distributions, and correlations between teaching practices and learning outcomes. Additionally, regression analysis is conducted to identify predictors of student learning outcomes, with a particular emphasis on multicollinearity and model fit.

Descriptive Statistics

The dataset shown in Table 2 comprises 251 participants, with complete data for three variables: age, highest educational achievement, and level of competence with digital tools. There are no missing values for any of these variables (Missing = 0), meaning that each participant's age, educational attainment, and digital proficiency were fully recorded. This completeness allows for a thorough analysis, ensuring that the statistical conclusions drawn are both comprehensive and accurate.

Table 2: Descriptive Statistics

		Age	Highest Level of Education Completed	Level of Digital Proficiency
N	Valid	251	251	251
	Missing	0	0	0

The sample shown in Table 3 includes 251 participants with no missing data. The age group 45-55 years is the most represented, comprising 34.7% of the sample, followed by the 35-44 years group at 28.7% and the 25-34 years group at 25.9%. The 18-24 years group accounts for 6.0%, while those aged 55 and above make up 4.8%. Overall, approximately 63.4% of participants are between 35 and 55 years, indicating a middle-aged skew in the distribution. The total percentage of all age groups adds up to 100%.

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Table 3: Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-24 Years	15	6.0	6.0	6.0
	25-34 Years	65	25.9	25.9	31.9
	35-44 Years	72	28.7	28.7	60.6
	45-55 Years	87	34.7	34.7	95.2
	55 and Above	12	4.8	4.8	100.0
	Total	251	100.0	100.0	

Among the 251 participants, the highest level of education is distributed as follows: 36.3% hold a Master's degree, 27.5% have a Bachelor's degree, and 24.7% have completed some college. High school graduates represent 4.8%, while 6.8% hold a Doctorate. Notably, over 70% of participants have at least a Bachelor's degree, indicating a relatively high level of educational attainment within the sample. The findings are summarized in Table 4.

Table 4: Highest Level of Education Completed

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High School or Equivalent	12	4.8	4.8	4.8
	Some College	62	24.7	24.7	29.5
	Bachelor's Degree	69	27.5	27.5	57.0
	Master's Degree	91	36.3	36.3	93.2
	Doctorate	17	6.8	6.8	100.0
	Total	251	100.0	100.0	

The digital proficiency levels of the 251 participants as shown in Table 5 exhibit a fairly balanced distribution. The largest group falls at the Intermediate level (27.5%), followed by Advanced (26.7%) and Expert (23.5%) levels. Beginners comprise 22.3% of the sample. This suggests that nearly half (50.2%) of the participants self-assess as having Advanced or Expert digital skills, highlighting a strong overall digital skillset, while approximately 22.3% are classified as beginners. The cumulative distribution totals 100%.

Table 5: Level of Digital Proficiency

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	56	22.3	22.3	22.3
	Intermediate	69	27.5	27.5	49.8
	Advanced	67	26.7	26.7	76.5
	Expert	59	23.5	23.5	100.0
	Total	251	100.0	100.0	

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Reliability Analysis

The Student Learning Outcomes scale in Table 6 demonstrates strong internal consistency, with a Cronbach's Alpha of .858 for its 5 items. This suggests that the items are reliable in measuring the concept of student learning outcomes.

Table 6: Scale: Student Learning Outcomes

Reliability Statistics	
Cronbach's Alpha	N of Items
.858	5

Moreover, the Teaching Data Interpretation Skills scale in Table 7 has a Cronbach's Alpha of .848 for its 5 items, indicating reliable data. The high alpha value suggests that the items consistently assess the skill of teaching proficiency in data interpretation.

Table 7: Scale: Teaching Data Interpretation Skills

Reliability Statistics	
Cronbach's Alpha	N of Items
.848	5

Furthermore, the Integrating Predictive Analytics in Teaching scale in Table 8 has a Cronbach's Alpha of .850 for its 5 items, reflecting strong internal consistency. This suggests that the items reliably measure the integration of predictive analytics into teaching practices.

Table 8: Scale: Integrating Predictive Analytics in Teaching

Reliability Statistics	
Cronbach's Alpha	N of Items
.850	5

In addition to this, the Teaching Data-Driven Decision-Making scale in Table 9 demonstrates strong internal consistency, with a Cronbach's Alpha of .855 across its 5 items. This high reliability indicates that the items effectively measure proficiency in data-driven decision-making skills.

Table 9: Scale: Teaching Data-Driven Decision-Making

Reliability Statistics	
Cronbach's Alpha	N of Items
.855	5

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Normality Analysis

An analysis of four scales—Student Learning Outcomes, Teaching Data Interpretation Skills, Integrating Predictive Analytics in Teaching, and Teaching Data-Driven Decision-Making—was conducted using the Kolmogorov-Smirnov and Shapiro-Wilk tests. For all scales, the p-values (Sig.) were .000 in both tests, indicating statistical significance and suggesting that the data significantly deviates from a normal distribution. Given the substantial sample size (df = 251), the Shapiro-Wilk test further confirms the data's non-normality. As a result, the assumptions of normality are violated for all four scales, indicating that non-parametric statistical techniques may be more appropriate for further analysis. The findings are summarized in Table 10.

Table 10: Tests of Normality

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Student Learning Outcomes	.166	251	.000	.907	251	.000
Teaching Data Interpretation Skills	.163	251	.000	.899	251	.000
Integrating Predictive Analytics in Teaching	.171	251	.000	.914	251	.000
Teaching Data-Driven Decision-Making	.168	251	.000	.898	251	.000
a. Lilliefors Significance Correction						

Correction Analysis

The correlation analysis reveals strong positive relationships between Student Learning Outcomes and the three other teaching scales. The Pearson correlation between Student Learning Outcomes and Teaching Data Interpretation Skills is .831, indicating a strong association. The correlation with Integrating Predictive Analytics in Teaching is even higher at .883, suggesting a particularly strong relationship. Finally, the correlation with Teaching Data-Driven Decision-Making is .836, reflecting a robust connection. All correlations are statistically significant at the 0.01 level (2-tailed), with p-values of .000 for each, indicating that improvements in these teaching skills are strongly linked to enhanced student learning outcomes. The strongest relationship is with integrating predictive analytics. The findings are shown in Table 11.

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Table 11: Correlation

Correlations				
		Teaching Data Interpretation Skills	Integrating Predictive Analytics in Teaching	Teaching Data-Driven Decision-Making
Student Learning Outcomes	Pearson Correlation	.831**	.883**	.836**
	Sig. (2-tailed)	.000	.000	.000
	N	251	251	251

**. Correlation is significant at the 0.01 level (2-tailed).

Regression Analysis

The model summary demonstrates a strong relationship between the predictors (Teaching Data-Driven Decision-Making, Teaching Data Interpretation Skills, and Integrating Predictive Analytics in Teaching) and the dependent variable (Student Learning Outcomes). The R value of .905 indicates a very strong correlation, and the R Square of .820 means that 82% of the variance in student learning outcomes is explained by the predictors. The Adjusted R Square is slightly lower at .818, reflecting the model's complexity. The F Change of 374.790 is significant (p = .000), confirming the model's statistical validity. The Durbin-Watson value of 1.876 suggests minimal autocorrelation in the residuals. The outcomes are summarized in Table 12.

Table 12: Model Summary

Model Summary[b]										
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.905[a]	.820	.818	.5127	.820	374.790	3	247	.000	1.876
a. Predictors: (Constant), Teaching Data-Driven Decision-Making, Teaching Data Interpretation Skills, Integrating Predictive Analytics in Teaching										
b. Dependent Variable: Student Learning Outcomes										

The ANOVA in Table 13 indicates that the model is statistically significant. The Regression Sum of Squares is 295.625 with 3 degrees of freedom, and the Residual Sum of Squares is 64.942 with 247 degrees of freedom. The Mean Square for regression is 98.542, and the F-value is 374.790, with a p-value of .000. This demonstrates that the predictors—Teaching Data-Driven Decision-Making, Teaching Data Interpretation Skills, and Integrating Predictive Analytics—significantly explain the variance in Student Learning Outcomes.

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Table 13: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	295.625	3	98.542	374.790	.000[b]
	Residual	64.942	247	.263		
	Total	360.567	250			
a. Dependent Variable: Student Learning Outcomes						
b. Predictors: (Constant), Teaching Data-Driven Decision-Making, Teaching Data Interpretation Skills, Integrating Predictive Analytics in Teaching						

The coefficients in Table 14 shows that all three predictors—Teaching Data Interpretation Skills, Integrating Predictive Analytics in Teaching, and Teaching Data-Driven Decision-Making—significantly contribute to predicting Student Learning Outcomes. The unstandardized coefficients reveal that for each unit increase in Teaching Data Interpretation Skills, Student Learning Outcomes increase by 0.230. For Integrating Predictive Analytics in Teaching, the increase is 0.535, and for Teaching Data-Driven Decision-Making, the increase is 0.213. All predictors have p-values of .000, indicating statistical significance. The VIF values (ranging from 3.973 to 4.425) suggest moderate multicollinearity, but it is not severe. The standardized coefficients indicate that Integrating Predictive Analytics (Beta = .513) is the strongest predictor of student learning outcomes, followed by Teaching Data Interpretation (Beta = .230) and Teaching Data-Driven Decision-Making (Beta = .213). These results suggest that Integrating Predictive Analytics has the most significant influence on student learning outcomes, while the other two predictors also contribute but to a lesser extent.

Table 14: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.022	.102		.217	.828		
	Teaching Data Interpretation Skills	.230	.054	.227	4.216	.000	.252	3.973
	Integrating Predictive Analytics in Teaching	.535	.059	.513	9.037	.000	.226	4.425
	Teaching Data-Driven Decision-Making	.213	.056	.213	3.790	.000	.231	4.321
a. Dependent Variable: Student Learning Outcomes								

The collinearity diagnostics in Table 15 indicate moderate multicollinearity within the

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model. The Condition Index values range from 1.000 to 15.175, with values exceeding 15 potentially signalling multicollinearity issues. The variance proportions show that the third- and fourth-dimensions account for most of the variance in Teaching Data Interpretation Skills, Integrating Predictive Analytics, and Teaching Data-Driven Decision-Making. Notably, Integrating Predictive Analytics has a high variance proportion in the fourth dimension (.90), suggesting that it may be more susceptible to the effects of multicollinearity compared to the other predictors.

Table 15: Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Teaching Data Interpretation Skills	Integrating Predictive Analytics in Teaching	Teaching Data-Driven Decision-Making
1	1	3.886	1.000	.01	.00	.00	.00
	2	.078	7.078	.99	.03	.02	.03
	3	.020	14.012	.00	.92	.07	.41
	4	.017	15.175	.00	.05	.90	.56
a. Dependent Variable: Student Learning Outcomes							

The residuals statistics as shown in Table 16 provide insights into the model's accuracy in predicting Student Learning Outcomes. The predicted values range from 1.1069 to 4.7341, with a mean of 3.2486 and a standard deviation of 1.0874. The residuals, which represent the difference between observed and predicted values, range from -1.8250 to 1.9057, with a mean of 0.0002 and a standard deviation of 0.5096. The standardized residuals range from -3.559 to 3.717, indicating a few potential outliers. Overall, the residuals suggest an acceptable model fit, with some minor exceptions due to outliers.

Table 16: Residual Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.1069	4.7341	3.2486	1.0874	251
Residual	-1.8250	1.9057	.0002	.5096	251
Std. Predicted Value	-1.969	1.366	.000	1.000	251
Std. Residual	-3.559	3.717	.000	.994	251
a. Dependent Variable: Student Learning Outcomes					

Discussion

All four scales demonstrate high internal consistency, with Cronbach's alpha values ranging from 0.848 to 0.858. Hypothesis 1 (H_1) posits that teaching data interpretation skills has a significant positive effect ($r = 0.831$) on student learning outcomes and digital literacy. These results suggest that the scales—Student Learning Outcomes,

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Teaching Data Interpretation Skills, Integrating Predictive Analytics in Teaching, and Teaching Data-Driven Decision-Making—serve as robust, evidence-based measures for evaluating these educational constructs. Lynch et al. (2016) emphasize that explicitly supporting students in data interpretation processes is essential for fostering critical thinking and problem-solving skills, which contribute to a deeper understanding of raw data. Predictive analytics in teaching enables the prediction of student performance based on learning styles, allowing for personalized interventions aimed at maximising student outcomes. Furthermore, Winarto et al. (2022) argue that teaching data-driven decision-making equips students with the ability to analyse trends and make informed decisions based on evidence. Collectively, these tools foster academic success while preparing students for real-world challenges in an increasingly data-centric environment.

The correlation analysis reveals strong positive relationships between all teaching-related variables and Student Learning Outcomes, with particularly high correlation observed for Integrating Predictive Analytics into Teaching ($r = 0.883$). This finding aligns with recent literature, which highlights the growing trend of data analytics in education as a means to enhance educational outcomes. The significant, though slightly less pronounced, correlations observed further support the notion that incorporating data interpretation and analytics into teaching curricula can substantially improve education outcomes. Existing research substantiates this conclusion, arguing that more effective use of data in educational contexts leads to improved decision-making and enhanced performance. In this regard, Wise (2019) observed that analytics in education can be leveraged to improve decision-making by providing real-time insights into student performance, learning behaviours, and interventions. A data-driven approach allows educators to personalise instruction, deliver timely interventions, and customise learning experiences to better meet the needs of each student, thereby boosting engagement and improving outcomes. Moreover, Nguyen et al. (2020) demonstrated that predictive analytics are valuable for identifying trends and forecasting potential challenges, enabling institutions to devise proactive strategies that benefit both students and educators. As the role of data becomes increasingly central in decision-making across various sectors, integrating data skills into education not only improves student performance but also prepares them for careers that demand analytical capabilities and data literacy. Hypothesis 2 (H_2) asserts that integrating predictive analytics into teaching strategies exhibits the strongest correlation ($r = 0.883$) with student outcomes.

The regression analysis results indicate that the primary predictor of Student Learning Outcomes is "Integrating Predictive Analytics in Teaching," with a standardized beta coefficient of 0.513. This finding aligns with existing research that highlights the potential of predictive analytics to transform teaching practices. Although the beta values for Data Interpretation Skills and Data-Driven Decision-Making are smaller in comparison, they still play a crucial role in the model. The collaborative impact of

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these frameworks underscores their importance in enhancing learning experiences, as supported by empirical evidence on the effectiveness of data-driven instruction. Research by Namoun and Alshanqiti (2020) demonstrates that predictive models can reliably predict student achievement, influenced by factors such as attendance, engagement, and prior academic success, thereby helping educators refine their instructional strategies. The use of predictive analytics, therefore, promotes individualized learning and elevates educational quality through data-informed approaches aimed at fostering student success. Similarly, Arcinas (2022) found that applying data to forecast student behaviour, identify at-risk individuals, and customize teaching methods empowers educators to make effective decisions that enhance the overall learning experience. Hypothesis 3 (H_3) posits that teaching data-driven decision-making shows a positive correlation (r = 0.836) with learning outcomes. This finding reinforces the significant impact of data-informed strategies on improving student performance and educational experiences. Based on the findings, the hypothesis of this research are accepted as shown in Table 17.

Table 17: Hypothesis Development

Hypothesis (H_1)	**Null Hypothesis (H_0)**	**Findings**	**Result (Accepted/Rejected)**
Teaching data interpretation skills will significantly improve student learning outcomes and digital literacy.	Teaching data interpretation skills will have no significant effect on student learning outcomes or digital literacy.	Positive correlation found between Teaching Data Interpretation Skills and Student Learning Outcomes.	Accepted
Integrating predictive analytics into teaching strategies will significantly improve student learning outcomes and digital literacy.	Integrating predictive analytics into teaching strategies will have no significant effect on student learning outcomes or digital literacy.	Strong positive correlation (r = .883) between Integrating Predictive Analytics in Teaching and Student Learning Outcomes.	Accepted
Teaching data-driven decision-making will significantly enhance student learning outcomes and digital literacy.	Teaching data-driven decision-making will have no significant effect on student learning outcomes or digital literacy.	Significant positive relationship between Teaching Data-Driven Decision-Making and Student Learning Outcomes.	Accepted

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Conclusion

This study underscores the critical role of data analysis skills in enhancing both student educational outcomes and digital literacy. The integration of data interpretation, predictive analytics, and data-driven decision-making into educational practices offers significant improvements in the personalization and effectiveness of learning environments. The findings indicate that each of these skills has a robust impact on student performance, with predictive analytics emerging as the most influential factor. Educators who utilize data to adapt their teaching strategies and interventions not only achieve better academic outcomes but also foster essential digital literacy skills in students, which are increasingly vital in the technology-driven world. Furthermore, the study demonstrates that a data-informed leadership approach in education is both feasible and effective, as it empowers both teachers and students to make informed decisions, engage in critical thinking, and solve problems more effectively. These findings align with previous research that emphasizes the pivotal role of data interpretation and predictive analytics in academic success. The study also highlights the need for comprehensive training and professional development to equip educators with the necessary data analysis expertise, ensuring that students are prepared for a future characterized by greater technological integration and data-driven decision-making.

Recommendations

The following recommendations stem from this research:

Teacher Training:

Educational institutions should prioritize professional development initiatives to help educators analyse student data and apply it to teaching innovations.

Technology Integration:

Schools should implement digital tools and analytics systems to track student performance in real time, enabling timely interventions and personalized learning.

Policy Development:

Governments and educational authorities must create policies that promote data-driven decision-making in curriculum development, aligning with future digital literacy demands.

Collaboration:

Collaboration between educators, data scientists, and policymakers is essential to develop a cohesive approach to enhancing education through data analysis and

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technology.

Limitations

This research may be subject to bias due to its reliance on self-reported information from teachers and students, which could affect the accuracy of the perceived impact of data-driven teaching methods. Additionally, the study's limited geographical scope restricts the generalizability of the findings. Moreover, the research did not account for subject-specific differences, which could influence the effectiveness of data analysis in various academic disciplines.

Future Directions

Future studies should examine the impact of data analysis skills across different educational areas, such as STEM versus humanities, to understand subject-specific variations. Longitudinal research is also needed to evaluate the long-term effects of data-driven teaching on student outcomes. Additionally, incorporating qualitative methods, such as interviews or classroom observations, could provide deeper insights into the practical application of data analytics in real-world educational settings and its influence on teaching and learning.

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