e-ISSN: 2710-2122, p-ISSN: 2710-2114
2025: Vol 7(s1), pp 1-27. https://doi.org/10.38140/ijer-2025.vol7.s1.09
Interdisciplinary Journal of Education Research

The Intersection of AI and Learning Analytics: Enhancing Institutional Performance

Thabisa Maqoqa[1*]

AFFILIATIONS

[1]Department of Adult and Education Foundations, Walter Sisulu University, Mthatha, South Africa.

CORRESPONDENCE

Email: tmaqoqa@wsu.ac.za*

EDITORIAL DATES

Received: 18 September 2024
Revised: 25 February 2025
Accepted: 02 March 2025
Published: 17 April 2025

DOI: 10.38140/ijer-2025.vol7.s1.09

Abstract: Integrating Artificial Intelligence (AI) and Learning Analytics (LA) in educational settings signifies a significant shift in leveraging data to enhance institutional effectiveness. This paper investigates the merging of these technologies, highlighting their capacity to revolutionise educational practices, improve resource management, and better student outcomes. AI-powered learning analytics provide immediate insights into student performance, facilitating tailored learning experiences and prompt interventions. The paper addresses the challenges faced and suggests strategies to overcome these obstacles to ensure the ethical and fair use of AI and learning analytics in education. Underpinned by computational learning theory, which emphasises understanding the performance and resource needs of machine learning algorithms, this study focuses on a sample from a rural university in the Eastern Cape. Data were gathered from the experiences and views of 65 students through questionnaires. Within the framework of a positivist paradigm, it was found that the introduction of AI has fostered the development of robust evaluation and assessment techniques, leading to increased faculty engagement. The research indicates that factors such as perceived risk, performance expectations, and awareness significantly influence work engagement and the adoption of AI in higher education, mediated by attitudes and behaviours. It is recommended that university administration establish clear ethical guidelines and policies governing AI and learning analytics and provide training and professional development for faculty to enhance their data literacy skills.

Keywords: Artificial intelligence, computational learning, learning analytics, technology, transform.

1. Introduction

In recent years, integrating Artificial Intelligence (AI) with Learning Analytics (LA) has demonstrated great potential for improving institutional performance and transforming educational environments. However, several challenges currently hinder the full realisation of these opportunities. Institutions struggle to collect, analyse, and utilise vast amounts of student data from digital learning platforms. Although AI can enhance data analysis and provide predictive insights, its application in learning analytics is still in its infancy, particularly concerning specific institutional goals. The main challenge lies in creating and implementing adaptive, scalable AI-driven learning analytics systems that provide real-time feedback to students, educators, and administrators. Additionally, concerns surrounding data privacy, ethical usage, and the need to ensure fairness and inclusivity in AI applications further complicate the adoption process. Singh, Meshram, Khandelwal, Tiwari, and Singh (2024) highlighted that adapting to the evolving learning and skill requirements of AI technologies can be challenging for educators and students. Furthermore, the need for skilled personnel to manage and interpret AI-driven analytics remains a significant barrier to widespread adoption (Popoola, Akinsanya, Nzeako, Chukwurah, & Okeke, 2024). Another area needing improvement is the inconsistency in technological resources and expertise across institutions, which creates difficulties in seamlessly integrating AI and learning analytics tools. The central question is how institutions can harness AI and learning analytics to boost performance, enhance student outcomes, and make ethical, data-informed decisions while addressing technological, ethical, and

How to cite this article:
Maqoqa, T. (2025). The intersection of AI and learning analytics: Enhancing institutional performance. *Interdisciplinary Journal of Education Research, 7*(s1), a09. https://doi.org/10.38140/ijer-2025.vol7.s1.09

practical challenges. Answering this question necessitates a multifaceted approach that includes technological advancements and considers educational policy, ethics, and institutional capacity development.

The capacity of AI to analyse extensive data sets can significantly enhance learning analytics by providing proactive insights into students' academic performance and engagement. For instance, Ouyang, Wu Zheng, Zhang, and Jiao (2023) illustrated how AI can improve student learning in online courses by merging performance forecasts with learning analytics and identifying collaborative learning characteristics among student groups. Similarly, Dawat (2023) highlights the significance of data analytics in recognising patterns and trends that can enhance educational decision-making, resulting in better teaching methods and personalised learning experiences. Integrating AI and learning analytics promotes tailored learning and fosters a data-driven culture within schools. Educational institutions should maintain academic integrity while implementing team-based learning strategies. Additionally, Heilala and Kantola (2023) propose that using explainable AI in educational contexts can enhance comprehension of student learning experiences, thus increasing transparency and trust in analytics processes.

In an era where technological advancements are expanding and influencing education, the combination of AI and learning analytics is transforming the operations of educational institutions. This intersection offers distinct opportunities to improve institutional effectiveness by gaining deeper insights into student learning behaviours, enhancing educational outcomes, and encouraging data-informed decision-making. AI-driven learning analytics can assist educational institutions in addressing diverse student needs by customising learning experiences, identifying at-risk students, and improving overall educational efficacy. Integrating AI and learning analytics reshapes how schools approach education in the contemporary educational landscape. This research investigates how the collaboration between AI and learning analytics can revolutionise educational practices and support institutions in a rapidly changing educational environment. The merging of AI with learning analytics alters educational institutions' strategies in their teaching and learning processes today.

This convergence represents more than just a fleeting trend; it constitutes a significant transformation that offers considerable opportunities for enhancing institutional performance and educational outcomes. When AI technologies are incorporated with learning analytics, they yield more comprehensive insights into student learning, enabling educators to customise learning experiences to meet diverse needs. For example, it highlights the role of AI in improving individualised, student-centred learning experiences, which are crucial for maximising educational effects in virtual settings. Furthermore, AI's capacity to interpret complex, multidimensional data enhances traditional learning analytics approaches, leading to a complete understanding of student engagement and success.

1.1 Problem statement

In recent times, educational institutions have increasingly adopted technology to enhance teaching and learning outcomes. Nonetheless, many institutions still face difficulties in effectively leveraging data for informed decision-making and improving institutional performance. The convergence of artificial intelligence (AI) and learning analytics presents a significant opportunity to address this issue. However, there remains a lack of clarity on how to best incorporate AI-driven insights into existing learning analytics frameworks. Additionally, challenges concerning data privacy, resource management, and workforce development can impede the successful integration of these technologies.

One significant obstacle to implementing AI in South African universities is the insufficient training provided to academic staff. Research shows that the effective use of AI tools depends on thorough training programmes that equip educators with the skills needed to utilise these technologies effectively (Nkohla, Munacinga, Marwa & Ncwadi, 2021). For example, the research by Nkohla et al. highlighted the critical role of academic and non-academic personnel in achieving performance outcomes, underscoring the necessity for a collaborative approach to improve institutional efficiency. Moreover, applying experiential learning through virtual and augmented reality tools has been identified as a promising strategy for enhancing educational outcomes. However, this requires a well-trained workforce capable of effectively using these technologies (Jantjies, Moodley and Maart, 2018).

Given the historical inequalities affecting educational access and outcomes, data privacy and ethical considerations in South Africa are paramount. The demand for a "radical linguistic transformation" in higher education aims to promote equity, highlighting the necessity of addressing data governance and ethical standards in AI applications (Xulu-Gama & Hadebe, 2022). Institutions must create robust policies to safeguard student data while ensuring transparency and accountability in deploying AI technologies (Chibuwe & Munoriyarwa, 2023). This is especially relevant after the COVID-19 pandemic, which has expedited the transition to online learning and introduced new ethical dilemmas regarding data use and student privacy (Gumede & Badriparsad, 2022). Resource allocation poses a significant challenge for South African universities aiming to implement AI-driven learning analytics. According to Mkuti and Aucamp (2024), managing resources effectively is essential for improving student success and institutional performance. Additionally, exploring innovative funding models and partnerships can support the integration of AI technologies into educational practices (Musakuro, 2022).

Despite progress in AI-based learning analytics, a considerable gap exists in understanding how to effectively integrate these systems into various educational settings. Previous studies have explored the applications of AI in education; however, there is a need for comprehensive frameworks to assist institutions in adopting these technologies within their existing operations (Knight, Gibson & Shibani, 2020). While some research has highlighted the benefits of AI in personalised learning and intelligent tutoring systems, practical guidance for educators on implementing these technologies is often lacking (Dawat, 2023; Li & Wong, 2023). Furthermore, concerns regarding the acceptance of AI and learning analytics, such as data privacy issues and the need for teacher training, have not been adequately addressed (Salas-Pilco, 2020). Current research reveals a substantial gap between the potential benefits of AI in education and its practical implementation in educational settings. Despite advancements in learning analytics, there is a significant delay in applying these insights to enhance educational practices (Knight et al., 2020). This disparity emphasises the need to thoroughly assess the challenges faced by educational institutions when integrating AI-based learning analytics and to identify strategies to overcome these obstacles.

1.2 Research questions

The following research questions guided the study:

- How can AI-driven learning analytics effectively identify and support students at risk of academic underperformance?
- How can integrating AI and learning analytics improve the personalisation of learning experiences?
- What are the ethical considerations and challenges associated with implementing AI and learning analytics in educational institutions?
- How does AI-driven learning analytics influence decision-making processes in educational institutions?

1.3 Literature Review

This part briefly summarises pertinent literature from different viewpoints - worldwide, countrywide, and community-based.

1.3.1 Utilising AI-driven learning analytics to identify and support students at risk

In the context of higher education, it is essential to recognise the significant role of AI in learning analytics, highlighting its capacity to facilitate personalised, student-centred learning experiences. Ouyang et al. (2023) contend that AI technologies excel at processing complex, nonlinear data and extracting meaningful insights from student information, which is critical for identifying students who may be struggling. Research by Cruz (2024) supports the notion that AI-driven adaptive learning tools can improve students' mathematical skills, indicating that these platforms can lead to better learning outcomes through tailored support.

In Turkey, there will be an examination of AI's influence in schools, primarily on how it can analyse data to enhance the academic growth of students and teachers. Göçen and Aydemir (2020) proposed that AI-enabled data analysis can help reduce absenteeism and support at-risk students more effectively. The use of AI in learning analytics to identify and aid at-risk students has attracted significant attention from various authors in the United States. Wang Lund, Marengo, Pagano, Mannuru, Teel, and Pange (2023) suggested that this approach allows universities to assess the potential benefits and drawbacks of AI, thereby improving support for students, especially those at risk of academic failure. Popenici and Kerr (2017) indicated that AI could facilitate real-time monitoring of student engagement, enabling timely assistance for those in danger of failing. Early identification of at-risk students is vital for delivering personalised support in a nurturing environment.

In Uganda, using AI-based learning analytics to identify and support at-risk students has garnered attention from several authors, each bringing unique insights into the potential benefits and challenges of this approach. According to Darvishi, Khosravi, Sadiq, and Gašević (2022), AI could foster trust in educational systems by providing data-driven insights into student performance and engagement, allowing for prompt interventions for at-risk individuals and promoting the goal of creating personalised learning environments tailored to each student's needs. Furthermore, they discussed the integration of new technologies within the South African education system, highlighting the significant opportunities educational technology provides for improving learning outcomes. However, they noted that many educators are hesitant to embrace these advancements fully. Additionally, Ngqulu's (2018) research analyses the critical factors influencing the adoption of learning analytics in South African higher education, emphasising the importance of fostering a supportive institutional culture and providing adequate training for educators to apply learning analytics, including AI-based methods, effectively.

1.3.2 Integration of AI and LA to improve the personalisation of learning experiences

In recent years, notable attention has been paid to integrating AI and learning analytics in educational environments, particularly in the United States. AI's ability to analyse large datasets enables the tailoring of educational materials and delivery methods to meet the unique needs, preferences, and paces of individual learners, which is a fundamental aspect of personalised learning (Zhao, 2025; Abbas, Maharishi & Mishra, 2023; Hashim, Omar, Jalil & Sharef, 2022). AI techniques can effectively handle complex, non-linear data that traditional learning analytics might struggle with, resulting in a more customised and student-centred educational experience (Ouyang et al., 2023). Furthermore, AI facilitates personalised feedback and assessments, enhancing its significance in educational settings and fostering a more individualised learning approach (Pedy, 2023; Jian, 2023).

In Nigeria, incorporating AI into academic curricula is critical for equipping students for the digital future. Research shows that integrating artificial intelligence in science education programmes can improve learning outcomes and student engagement (Olatunde-Aiyedun, 2024). This underscores AI's capacity to customise experiences and provide immediate feedback, which is vital for effective science education (Okunade, 2024). However, South Africa faces challenges mainly due to negative perceptions, and educators need to better grasp the importance of these technologies. This calls for an urgent shift in mindset (Ohei, 2023).

1.3.3 Ethical considerations and challenges associated with implementing AI and LA

Researchers in China emphasised the need to tackle the ethical issues and challenges linked to the application of AI and learning analytics (LA) in education (Guan, Feng & Islam, 2023). A key ethical concern identified is the necessity for comprehensive guidelines and frameworks addressing the ethical implications of AI and LA. The existing literature highlights the importance of safeguarding student privacy and mitigating potential harms related to data usage within educational contexts (Kitto & Knight, 2019). Developing ethical frameworks is vital for guiding learning analytics and ensuring the responsible management of student data. Furthermore, Osasona, Amoo, Atadoga, Abrahams, Farayola, and Ayinla (2024) explore the ethical impacts of AI in decision-making processes, particularly regarding how algorithms and automation in education can introduce biases and ethical dilemmas. Huang, Lu, and Yang (2023) emphasise the necessity of ethical guidelines in AI systems to mitigate ethical risks while fostering transparency and accountability.

In Ghana, Mohammed (2023) points out the critical need for robust regulatory frameworks to ensure the ethical and equitable use of AI, specifically in early childhood education. This perspective complements the broader discourse on establishing clear ethical standards for AI applications in education, as advocated by Holmes, Porayska-Pomsta, Holstein, Sutherland, Baker, Shum, Santos, Rodrigo, Cukurova, Bittencourt, and Koedinger (2022). They call for a community-wide framework to address the ethical challenges posed by AI in educational environments. Discussions on ethical dilemmas, particularly regarding data privacy and security, are prominent in the literature from Limpopo. Given that AI and LA systems heavily depend on data collection and analysis, there are serious concerns about student data storage, use, and protection. Akgun and Greenhow (2021) highlight these concerns, noting that the ethical implications of AI systems are frequently neglected in K-12 settings, thus underscoring the need for a broader framework to better understand and tackle these issues.

It is crucial to prioritise data privacy and security when integrating AI into educational settings to prevent the mishandling of sensitive information (Mahligawati, Allanas, Butarbutar & Nordin, 2023). Akgün and Greenhow (2021) reiterate that the ethical ramifications of AI in K-12 environments are often overlooked, emphasising the necessity for a comprehensive framework to address these challenges effectively.

1.3.4 The impact of AI-driven Learning Analytics on the decision-making processes

European research has examined how AI-powered learning analytics influence decision-making in educational contexts (Fahimirad & Kotamjani, 2018). These analytics transform decision-making processes by providing educators with insights into student performance and comprehension trends. This information enables teachers to make informed decisions about curriculum adjustments and personalised learning interventions, ultimately enhancing the educational experience (Fahimirad & Kotamjani, 2018). Additionally, integrating AI in decision-making can boost efficiency and effectiveness within educational administration. Ekellem (2023) points out that, similar to its effects on business, AI can innovate educational institutions by simplifying administrative tasks and enhancing strategic planning. Scholars in Zimbabwe, including Opesemowo and Adekomaya (2024), have indicated that the adoption of AI in South Africa's higher education can address issues related to access, affordability, and disparities in educational quality by exploring how AI-driven learning analytics can enhance educational outcomes and institutional effectiveness. This has been a key area of focus in research concerning decision-making processes.

AI-powered learning analytics provide critical insights from data analysis to support decision-making in education. For instance, decision-making has shifted from a reliance on experience to a greater dependence on data and technology, including big data analytics and AI, to guide choices (Han, Xiao, Sheng & Zhang, 2024). Mortaji and Sadeghi (2023) highlighted the advantages of blending business analytics with AI to boost efficiency and stimulate creativity. This strategy could benefit educational organisations seeking to refine their administrative and instructional methods. The research by Opesemowo and Adekomaya (2024) demonstrated AI's substantial influence on enhancing education quality in South Africa. It underscores how AI technologies, particularly within classroom environments, can assist teachers in making informed decisions regarding instructional strategies and student assessments. By integrating information from diverse educational contexts, organisations can better understand key patterns and trends that inform strategic decision-making and resource allocation (Mostert, 2020).

1.4 Theoretical framework

The foundation of this research is rooted in computational learning theory, also referred to as Probably Approximately Correct Learning (PAC-learning), which aims to understand the efficiency and resource needs of machine learning algorithms (Soloveichik, 2008). Computational Learning Theory (CLT) is a branch of artificial intelligence (AI) and machine learning (ML) focused on the computational aspects of learning algorithms. It is part of theoretical computer science and seeks to formalise the learning process by investigating the constraints and potentials of learning models. One significant aspect of CLT is examining the computational difficulty linked to learning tasks, which involves recognising the resources, such as time and memory, needed for learning and the inherent constraints of various learning algorithms (Kearns & Vazirani, 1994). Additionally, CLT has wide-reaching consequences for AI and ML, offering the theoretical basis for creating algorithms that can learn effectively and efficiently from data. Knowledge gained from CLT has impacted fields like natural language processing, computer vision, and cognitive science, where understanding learning mechanisms is crucial for technological progress (Clark & Lappin, 2012).

CLT is highly relevant in AI-powered analytics because the demand for knowledgeable staff (as mentioned in the study) aligns with the learnability argument; complex AI systems require expertise to interpret results. Sample complexity is crucial in training AI models for analytics, ensuring they perform well with limited but relevant data. Computational complexity influences the adoption of AI-driven analytics, as organisations must balance performance with resource constraints. Generalisation is key for AI analytics to make accurate predictions across different scenarios without extensive retraining. Understanding the trade-offs in AI learning can help optimise human-AI collaboration in decision-making. The relevance of these models extends to various applications, including argumentation systems, where understanding the structure and quality of arguments can be enhanced through machine learning techniques (Craandijk & Bex, 2022).

Furthermore, the implications of CLT are evident in the development of argumentation mining techniques, which aim to extract structured arguments from unstructured text. This process involves applying machine learning algorithms to identify and categorise arguments, facilitating a deeper understanding of discourse in various domains, including legal and scientific contexts (Sinha et al., 2021). The ability to automate the extraction and assessment of arguments enhances research efficiency and contributes to the development of intelligent tutoring systems that can support learners in constructing and evaluating arguments (Wambsganß et al., 2021).

2. Research Methodology

The choice to use a quantitative methodology stemmed from the necessity to collect numerical data suitable for statistical analysis. This method facilitates the identification of patterns and connections within the data, establishing a robust basis for drawing conclusions. Considering the research goals, which focused on quantifying the effects of certain variables on outcomes, a quantitative approach was deemed the most suitable. A stratified random sampling method was implemented to ensure adequate representation of different subgroups within the population, thereby enhancing the generalisability of the results. The selection of validated survey tools was crucial for this research. These tools were chosen for their demonstrated reliability and validity in earlier studies, ensuring that the data gathered would accurately represent the evaluated constructs, thus bolstering the credibility of the findings. Additionally, descriptive techniques were a deliberate choice to facilitate comprehensive data analysis. Descriptive statistics were employed to summarise the data and provide an overview of the sample characteristics, while inferential statistics enabled hypothesis testing and the exploration of relationships among variables.

2.1 Research Paradigm

A research paradigm is a foundational framework that guides researchers in their inquiries, shaping their worldview and influencing their methodologies. It encompasses a set of beliefs and assumptions about reality, knowledge, and the researcher's relationship to the subject being studied. Grasping various research paradigms is essential, as they determine the questions posed, the methodologies employed, and how findings are interpreted (Heeks & Wall, 2018).

This study adopted a positivist paradigm to evaluate the convergence of AI and Learning Analytics (LA). According to Kamau (2022), positivism emphasises objectivity, hypothesis testing, and statistical methods, making it particularly appropriate for quantitative research. It underscores the need for quantitative approaches to achieve generalisable results through objective measurements and observable phenomena. Positivism operates on the premise that knowledge should stem from what can be empirically perceived, thus advocating for a structured research approach centred on objectivity, measurability, and causation (Maretha, 2023). The positivist paradigm contributes to the rigour and credibility of research outcomes. By adhering to scientific standards, researchers can mitigate biases and ensure that their findings are based on reliable evidence rather than personal interpretations (Maretha, 2023).

2.2 Research Design

This research employed a correlational design, which helps to explore relationships and patterns, allowing researchers to understand how variations in one variable may correspond with changes in another (Maison, Darmaji, Kurniawan, Astalini, Kuswanto & Ningsi, 2021). A correlational research design is a quantitative methodology that identifies and measures the relationships among two or more variables without manipulation. A key feature of correlational research is its ability to evaluate the strength of associations between variables. For example, Maison et al. (2021) and Jufrida et al. (2019) emphasise that correlational research aims to analyse the relationships between variables by utilising statistical methods to quantify these connections.

2.3 Population and Sampling

The population in research can be defined broadly, encompassing all individuals within a specific demographic or, more narrowly, focusing on characteristics relevant to the specific research question. For example, in clinical trials, the population may consist of all adults with a particular health issue, whereas the target population is a more specific group that meets additional criteria, such as age or severity levels (Willie, 2024; Willie, 2022). This refers to the complete group of individuals or cases sharing common traits that are studied. This research has selected all level 2 and 3 mathematics students across universities in the Eastern Cape to represent the targeted demographic. The study specifically concentrated on university students in levels 2 and 3 of mathematics, utilising questionnaires for data collection. In research, a sample refers to a smaller group selected from a larger population to gain insights into that population's characteristics (Palinkas, Mendon, and Hamilton, 2013). Sampling is vital in research, as it influences how findings can be generalised to a broader audience (Robinson, 2014). This study employed stratified random sampling to gather data from sixty-five participants, specifically Level 2 and 3 mathematics students at a university in the OR Tambo Inland District of the Eastern Cape.

2.3.1 Sampling procedure

The research involved participants who were students in mathematics levels 2 and 3. To ensure a representative sample, the researcher employed stratified random sampling. This technique helped to guarantee that the sample accurately represented the overall population. The purpose of stratified random sampling is to improve the precision of estimates by minimising sampling error, which leads to more reliable results, particularly in heterogeneous populations. In this instance, the researcher selected forty students from levels 2 and 3 of mathematics at a university in the OR Tambo Inland District, making stratified random sampling the most suitable method.

2.4 Data collection

The research data were gathered through questionnaires, which required thoughtful consideration of several key factors. The questionnaire was developed from existing literature and theoretical frameworks related to AI-driven analytics and cognitive load theory (CLT). It featured closed-ended questions (such as Likert scales and multiple choice) and open-ended items to capture quantitative data. This process involved clearly defining the concepts to be evaluated and ensuring the questions aligned with these definitions (Holmes, 2023; Ikart, 2019). Experts in AI, data analytics, and survey methodology reviewed the questionnaire to confirm its content validity. A small cohort of participants completed it to evaluate its clarity, relevance, and response timing. Internal consistency for the Likert-scale questions was measured using Cronbach’s Alpha. Additionally, AI analytics professionals enhanced data collection through engagement at workshops and conferences, contributing to a higher response rate and a broader range of participant perspectives, thus strengthening the study's validity. Gathering individuals' insights, opinions, and personal experiences is essential (Byrne, Brugha, Clarke, Lavelle, & McGarvey, 2015). For instance, the presuppositional interview method aims to reveal and address the researcher's biases and assumptions through dialogue, integrating these elements into the research process (van Veggel, Allison, Goldspink, & Engward, 2024).

2.5 Data analysis

Descriptive analysis was employed for data evaluation, ensuring a thorough assessment through quantitative methods. This quantitative approach focused on structured data obtained from Likert-scale and multiple-choice questions. Descriptive statistics, including mean, standard deviation, and percentages, were utilised to summarise participant demographics and identify general trends regarding challenges in AI adoption. AI heavily relies on machine learning (ML) techniques to create models that predict outcomes, identify patterns, and enhance learning strategies. Putri and Maharani (2023) investigated the application of AI-based decision support systems in education management, illustrating how regression models can assess the impact of AI strategies on educational outcomes. Furthermore, it facilitates data comprehension, making it accessible to stakeholders who may not have a statistical background (Handayani, Utanto & Ghazali, 2023). The dataset included student demographics (such as age and gender), engagement levels, assessment results (including quizzes and assignments), and AI-generated suggestions (such as personalised learning paths). The researcher also removed missing or irrelevant data, addressed outliers, and ensured the data was formatted appropriately for analysis. Ultimately, the data was summarised using measures of central tendency and dispersion.

2.6 Ethical considerations

Turner and Fozdar (2010) emphasised the significance of ethical responsibility in research throughout their study, adhering closely to ethical guidelines to safeguard participants' rights and maintain data integrity. The primary ethical considerations involved ensuring participant rights and data integrity. Before participating, each individual received a comprehensive consent form outlining the study's purpose, their rights, and how their responses would be utilised. They had to accept the terms to continue with the questionnaire. A clear explanation of the study's objectives and the use of their responses was provided, and participants needed to consent before moving on to the questionnaire. No personally identifiable information was gathered unless participants willingly shared it for follow-up communication. The data was securely stored, with access limited to the research team. To ensure anonymity, responses were anonymised during the final analysis to prevent identification. All personal information remained confidential and was solely utilised for research purposes. The questionnaire did not collect identifiable details (such as names or emails) unless participants opted to provide contact information for follow-up. Participants were informed that their participation was voluntary and that they could leave the study without facing any repercussions. No incentives were offered to unduly influence their decision to participate. They were also advised that they could withdraw without any penalty. All gathered information was encrypted and securely stored according to ethical research guidelines, and measures were implemented to prevent unauthorised access or data breaches. The survey was thoughtfully crafted to avoid leading questions and minimise bias. A stratified random sampling method ensured a varied and representative dataset.

3. Presentation of Results

Descriptive statistics were calculated for all interval and ratio variables, while counts and percentages were determined for each nominal variable.

3.1 Frequencies and percentages

The most common response for QUESTION 1 was Yes (n = 45, 100.00%). For question 4, the most frequent answer was Identifying at-risk students (n = 35, 77.78%). The predominant category for QUESTION 7 was Neutral (n = 17, 37.78%). In question 10, the most common response was Important (n = 41, 91.11%). For question 13, the most frequently selected answer was Very comfortable (n = 23, 51.11%). The leading category for QUESTION 2 was No (n = 36, 80.00%). The most noted response for question 5 was Data privacy and security (n = 26, 57.78%). Finally, the most common answer for QUESTION 8 was Strongly agree (n = 25, 55.56%). Frequencies and percentages are summarised in Table 1.

Table 1: *Frequency Table for Nominal Variables*

Variable	*n*	%
QUESTION1		
Yes	45	100.00
Missing	0	0.00
QUESTION4		
Automating administrative tasks	10	22.22
Identifying students at risk	35	77.78
Missing	0	0.00
QUESTION7		
Very comfortable	2	4.44
Somewhat comfortable	15	33.33
Neutral	17	37.78
Somewhat uncomfortable	11	24.44

Missing	0	0.00
QUESTION10		
Very important	4	8.89
Important	41	91.11
Missing	0	0.00
QUESTION13		
Very comfortable	23	51.11
Somewhat comfortable	10	22.22
Neutral	11	24.44
Somewhat uncomfortable	1	2.22
Missing	0	0.00
QUESTION2		
Yes	9	20.00
No	36	80.00
Missing	0	0.00
QUESTION5		
Data privacy and security	26	57.78
Over-reliance on technology	5	11.11
Limited human interaction	14	31.11
Missing	0	0.00
QUESTION8		
Strongly agree	25	55.56
Agree	9	20.00
Neutral	11	24.44
Missing	0	0.00

Note. Due to rounding errors, percentages may not equal 100%.

3.2 Summary statistics

The average value for AGE was 1.27, with a standard deviation of 0.50, a standard error of the mean of 0.07, a minimum of 1.00, and a maximum of 3.00. The skewness for this variable was 1.61, while the kurtosis measured 1.66. For ACADEMIC YEAR, the average was 2.36, with a standard deviation of 0.48 and a standard error of the mean also at 0.07, ranging from a minimum of 2.00 to a maximum of 3.00. This variable had a skewness of 0.60 and a kurtosis of -1.64. A skewness value greater than 2 in absolute terms indicates that the variable is asymmetrical around its mean. Additionally, a kurtosis of 3 or higher suggests that the distribution is significantly different from usual, particularly in its propensity for outliers (Westfall & Henning, 2013). Detailed statistics are summarised in Table 2.

Table 2: *Summary Statistics Table for Interval and Ratio Variables*

Variable	*M*	*SD*	*N*	SE_M	Min	Max	Skewness	Kurtosis
AGE	1.27	0.50	45	0.07	1.00	3.00	1.61	1.66
ACADEMIC YEAR	2.36	0.48	45	0.07	2.00	3.00	0.60	-1.64

Note. '-' indicates the statistic is undefined due to constant data or an insufficient sample size.

Frequencies and percentages were calculated for Question 11 (Field of Study, nominal), as well as for Questions 3, 6, 9, and 12.

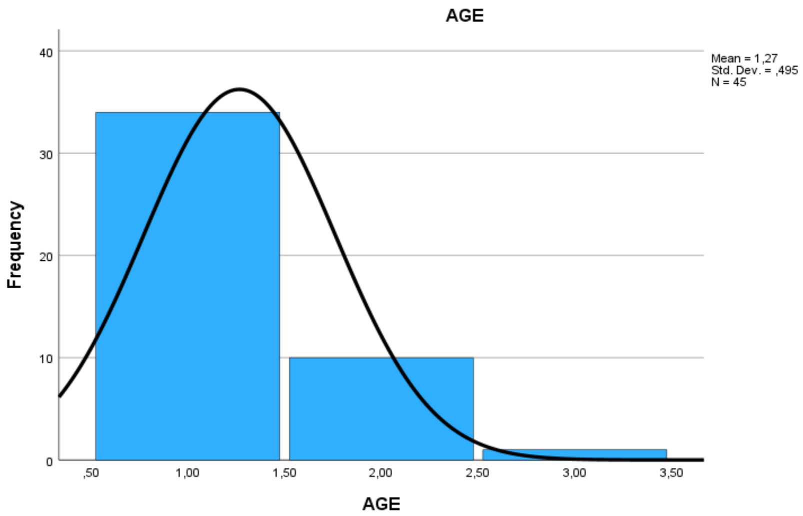
3.3 Frequencies and percentages

The category of QUESTION 11 that was observed most often was Important (n = 26, 57.78%). The nominal category of FIELD OF STUDY that appeared most frequently was 4 (n = 45, 100.00%). The category of QUESTION 3 that was recorded the most was Support (n = 34, 75.56%). The category of Question 6 that was noted most commonly was Yes, significantly (n = 31, 68.89%). The most frequently noted category of QUESTION 9 was Essential (n = 26, 57.78%). The category of Question 12 that was observed most often was Student engagement and participation (n = 26, 57.78%). Frequencies and percentages can be found in Table 3.

Table 3: *Frequency Table for Nominal Variable*

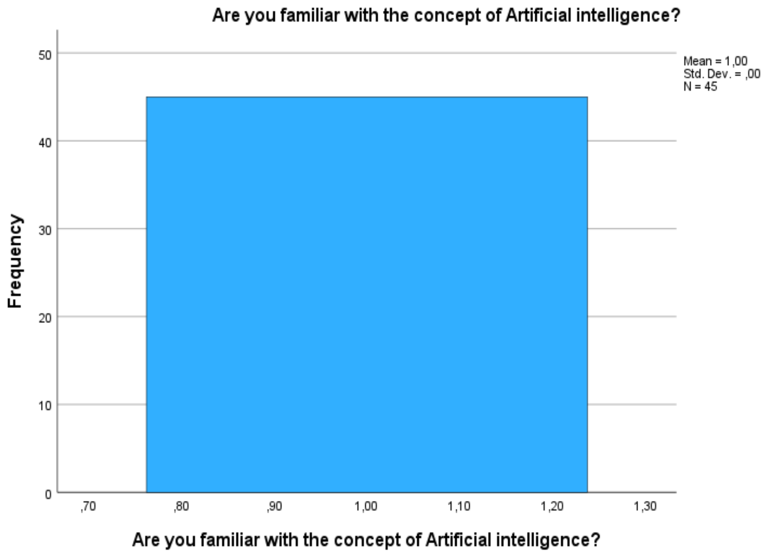
Variable	*n*	%
QUESTION11		
Very important	11	24.44
Important	26	57.78
Neutral	8	17.78
Missing	0	0.00
FIELD OF STUDY Nominal		
4	45	100.00
Missing	0	0.00
QUESTION3		
Strongly support	2	4.44
Support	34	75.56
Neutral	9	20.00
Missing	0	0.00
QUESTION6		
Yes, significantly	31	68.89
Yes, somewhat	14	31.11
Missing	0	0.00
QUESTION9		
Very important	26	57.78
Important	14	31.11
Neutral	5	11.11
Missing	0	0.00
QUESTION12		
Academic achievement	17	37.78
Retention and graduation rates	1	2.22
Student engagement and participation	26	57.78
44	1	2.22
Missing	0	0.00

Note. Due to rounding errors, percentages may not equal 100%.

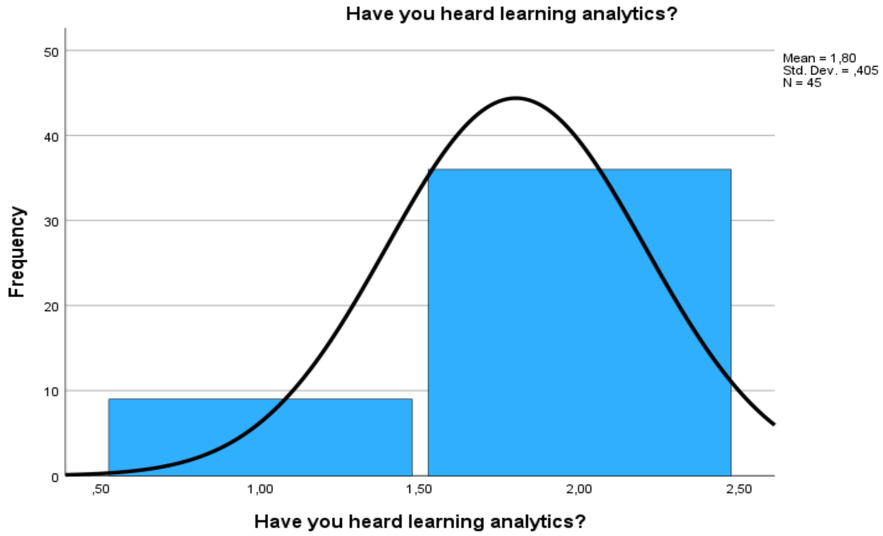


The histogram displaying a bell curve illustrates the age distribution within a sample of 45 people. Here are the main points:

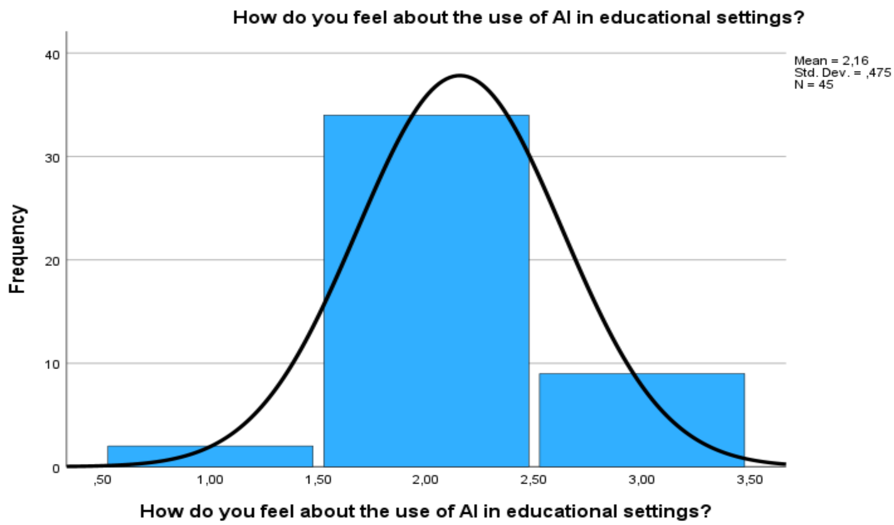
- Average Age: The mean age is approximately 1.27 years.
- Variability: The standard deviation of ages is about 0.495 years.
- Distribution: The bell curve suggests that the ages conform to a normal distribution, with most individuals falling within the age range of 0-0.50 years.



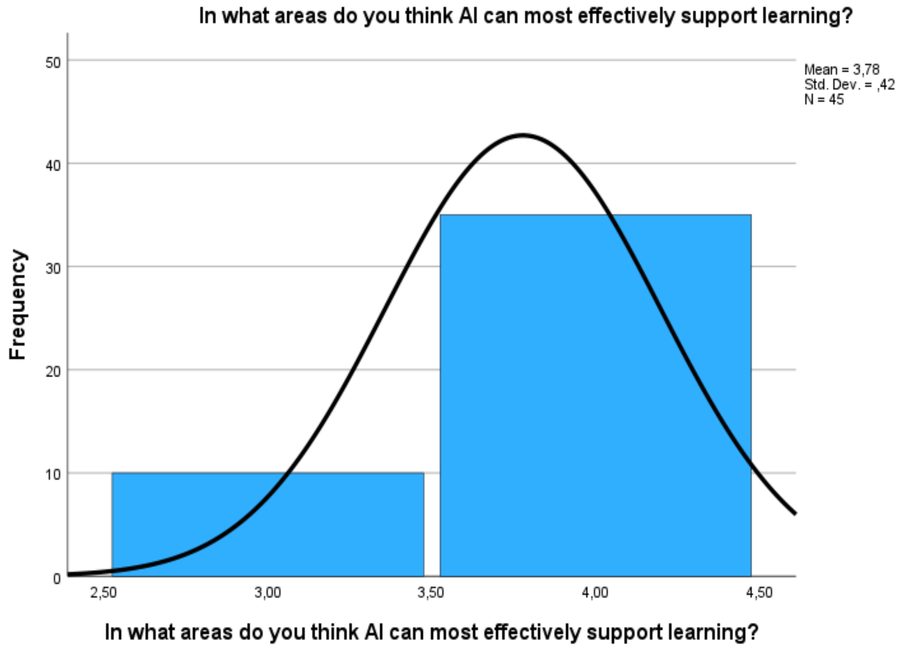
The bar chart illustrates the results of a survey concerning familiarity with Artificial Intelligence (AI). Here are the main points: Uniform Familiarity: Every one of the 45 participants is acquainted with AI, as shown by the mean score of 1.00 and a standard deviation of 0.00. Frequency Distribution: The response frequency is uniform, with no discrepancies, indicating that all participants are unanimously familiar with the topic.



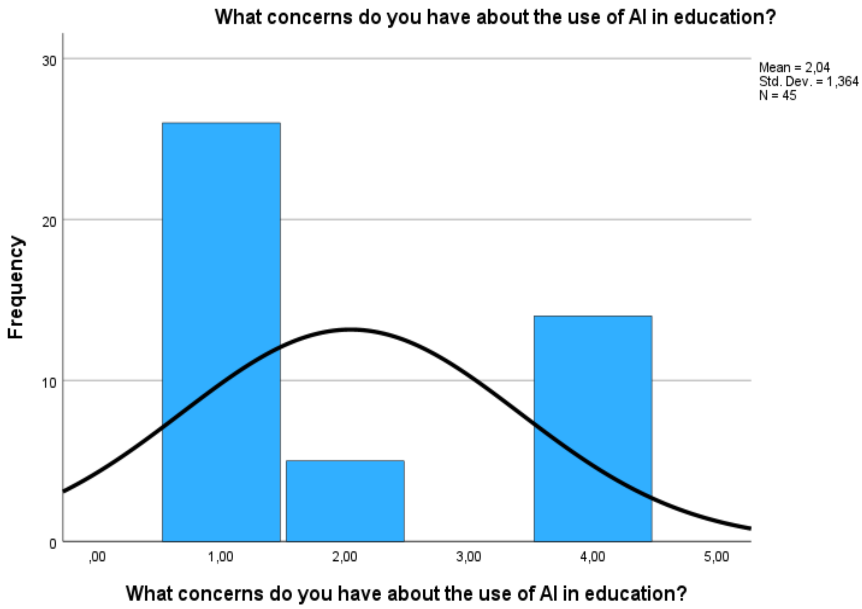
The bar chart titled "Have you heard of learning analytics?" illustrates the distribution of responses concerning learning analytics knowledge. Here are the main points: Average Response: The mean response is 1.80, suggesting that most participants are moderately familiar with learning analytics. Variation: The standard deviation is 0.405, indicating a moderate level of consistency in the degree of familiarity among respondents. Most Common Response: The highest bar at 1.00 reveals this was the most frequently selected response among the 45 participants.



The histogram titled "How do you feel about the use of AI in an educational setting?" offers insights into respondents' attitudes regarding AI in education. The average score is 2.16, reflecting a generally favourable perspective on using AI in educational contexts. The standard deviation stands at 0.475, indicating a degree of consistency in the responses. The highest frequency occurs in the response range of 2.00 to 2.50, illustrating that many participants view AI positively in relation to education.

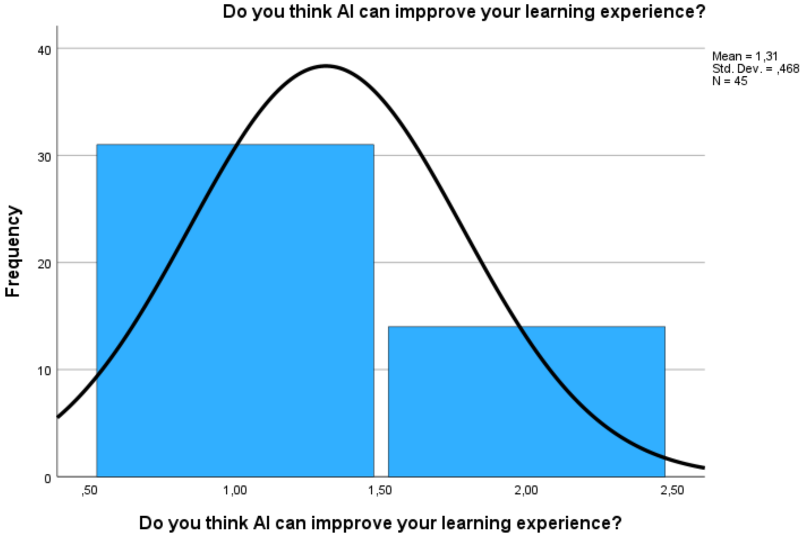


The bar graph labelled "In what areas do you think AI can most effectively support learning?" illustrates the distribution of responses on a Likert scale. Here are the main points: Average Rating: The mean score is 3.78, reflecting a strong conviction in AI's capability to aid learning. Variability: The standard deviation is 0.42, indicating moderate agreement among respondents. Most Common Response: The prevalent response range is between 3.50 and 4.00, demonstrating that many participants consider AI to be quite effective in enhancing learning.



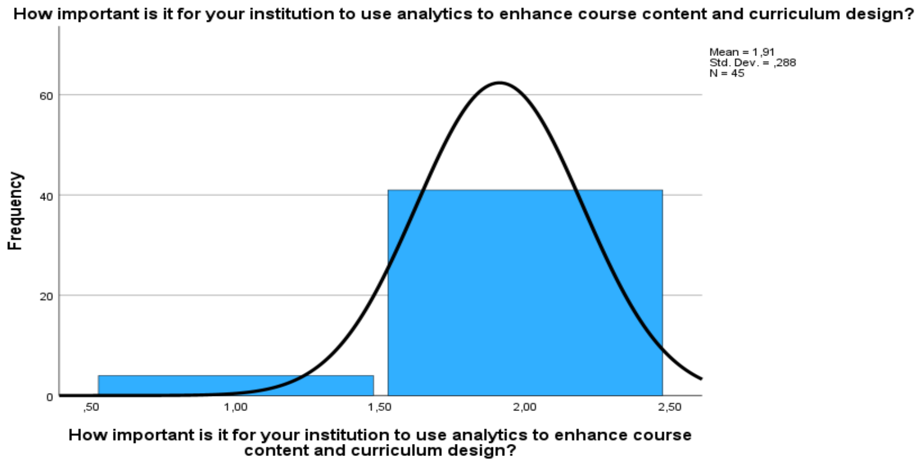
The bar graph titled "What concerns do you have about the use of AI in education?" illustrates the distribution of concerns among respondents. Here are the key points:

- Mean Concern Level: The average concern level is 2.04, indicating moderate concern.
- Standard Deviation: The variability in concerns is 1.364, suggesting diverse opinions.
- Highest Frequency: The most common concern level is 1.00, indicating that many respondents have low concerns about AI in education.



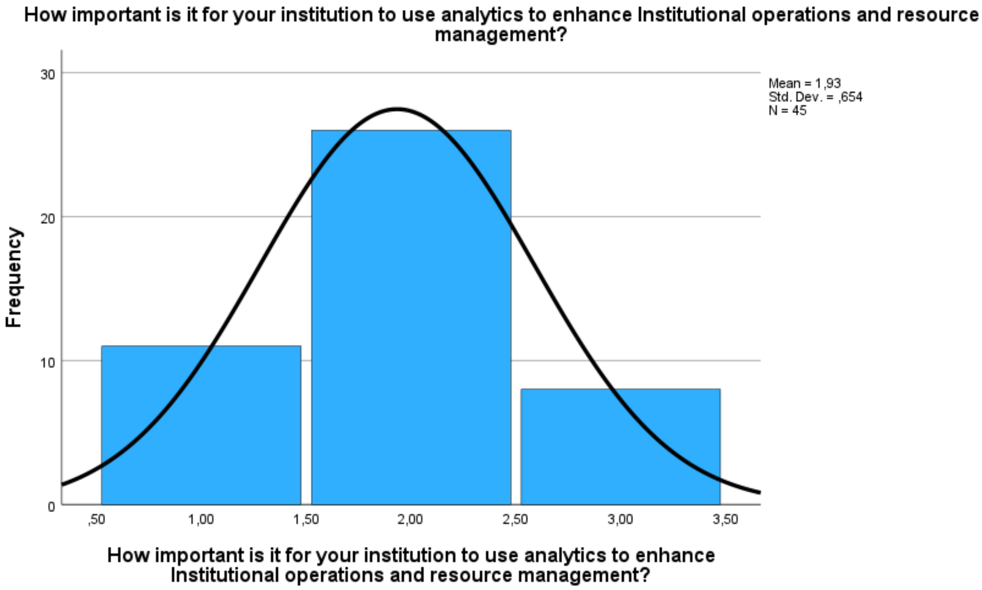
The bar graph "Do you think AI can enhance your learning experience?" illustrates the response distribution from 0 to 2.50 on a scale. Here are the main points:

- Average Response: The mean rating is 1.31, reflecting a generally favourable view that AI can enhance learning experiences.
- Standard Deviation: With a variability of 0.468, there is moderate agreement among the respondents' opinions.
- Most Common Response: The highest frequency of responses is at the lower end of the scale, indicating that many participants believe AI can significantly improve their learning experience.



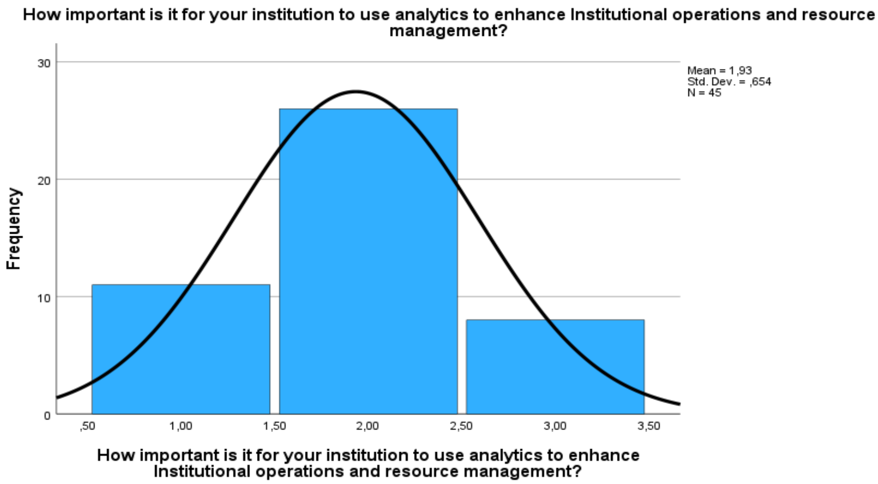
The chart titled "How important is it for your institution to use analytics to enhance course content and curriculum design?" illustrates the spread of responses on a scale from 0 to 3.00.

- Notable Insights: The mean rating is 1.91, indicating that respondents typically perceive the use of analytics as essential for improving course content and curriculum development.
- Variability: The standard deviation is 0.288, demonstrating a strong consensus among the participants.
- Response Distribution: The answers are concentrated around the mean, revealing that most respondents assign similar levels of importance.



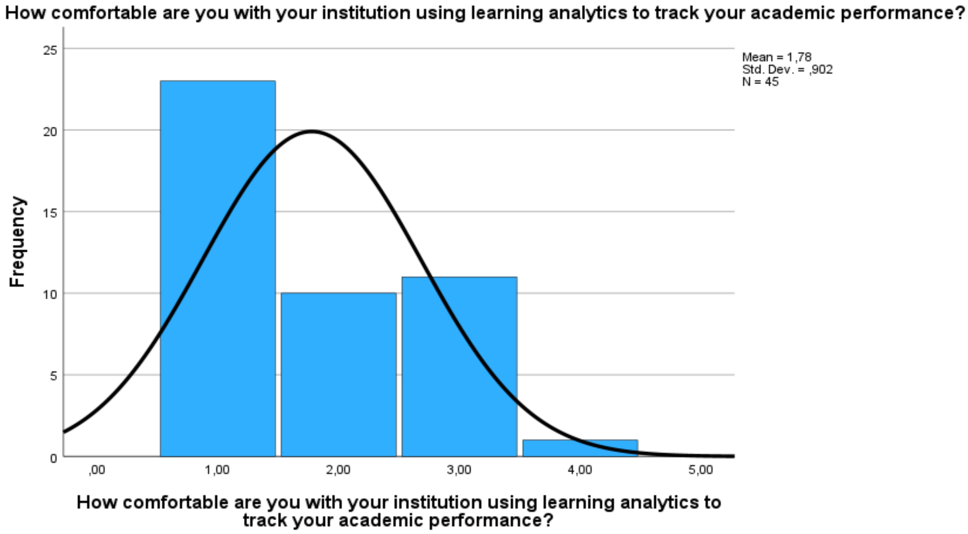
The histogram titled "How important is it for your institution to use analytics to enhance Institutional operations and resource management?" illustrates the distribution of responses on a scale from 0 to 3.50. Here are the main takeaways:

- Average Importance: The mean score is 1.93, indicating that respondents generally perceive analytics as necessary for improving institutional operations and resource management.
- Variability in Responses: The standard deviation is 0.654, which points to a moderate level of consensus among the respondents.
- Response Distribution: Most responses tend to cluster around the mean, highlighting that many participants share similar views on the importance of analytics.



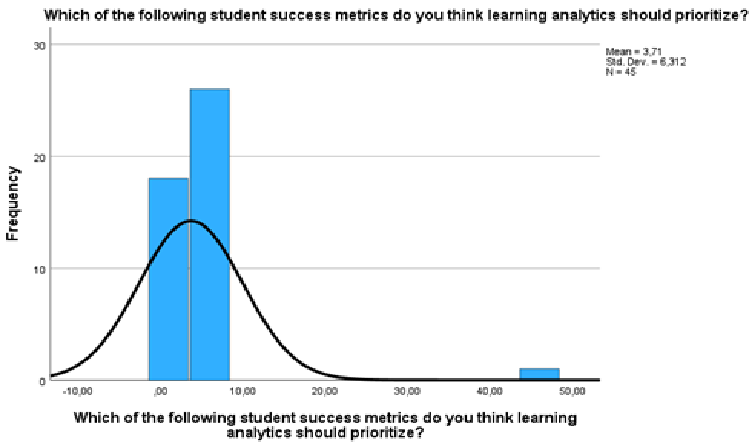
The histogram titled "How important is it for your institution to use analytics to enhance institutional operations and resource management?" illustrates the distribution of responses on a scale from 1.00 to 3.50. Key observations include:

- Average Importance: The mean rating is 1.93, indicating that respondents consider using analytics vital for improving operations and managing resources within institutions.
- Variability of Responses: The standard deviation is 0.654, reflecting a moderate level of consensus among the respondents.
- Concentration of Responses: Many participants rate the importance similarly, as indicated by the clustering of responses around the average.



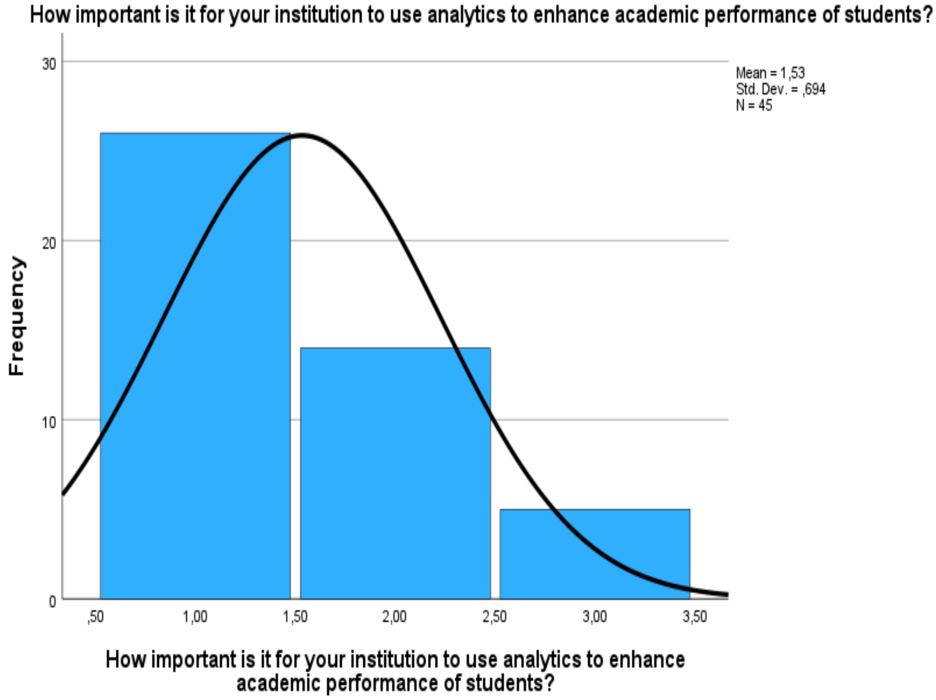
The histogram labelled "How comfortable are you with your institution using learning analytics to track your academic performance?" illustrates the range of comfort levels reported by participants. Key insights include:

- Average Comfort Level: The mean score is 1.78, reflecting a low to moderate degree of comfort regarding learning analytics.
- Variability: The standard deviation is 0.902, indicating a wide range of opinions among respondents.
- Most Common Response: The highest frequency of responses is at 2.00, suggesting that many participants feel moderately comfortable.



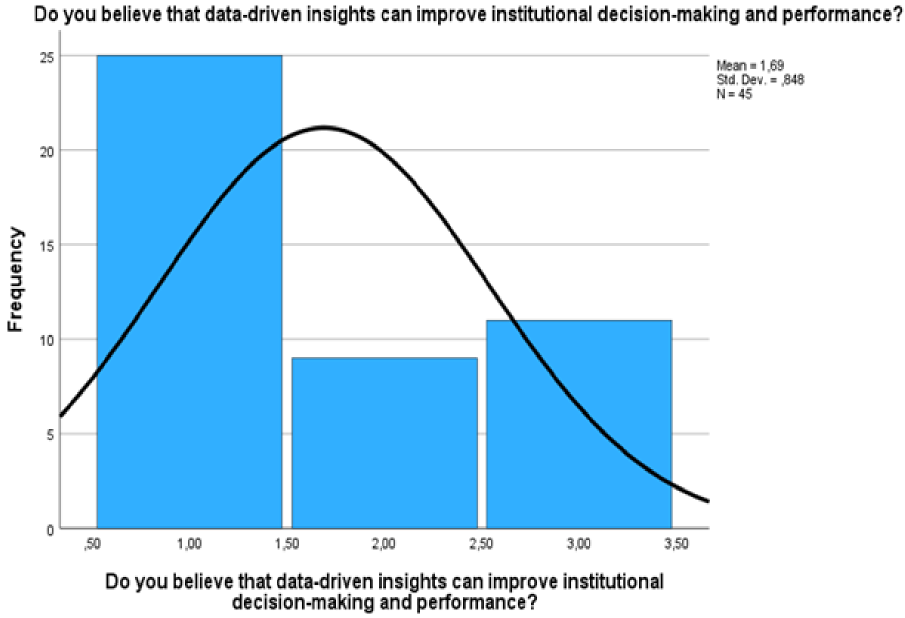
The histogram labelled "Which student success metrics do you believe should be prioritised by learning analytics?" illustrates the distribution of responses ranging from 10 to 50. Here are the main highlights:

- Mean Priority: The average priority score is 37.1, suggesting that most respondents consider specific student success metrics important for learning analytics to focus on.
- Standard Deviation: With a standard deviation of 6.312, there is some variation in the responses, indicating a range of opinions among the participants.
- Highest Frequency: The predominant priority range falls between 10 and 20, indicating that many respondents view specific metrics as having a moderate to high priority. The histogram labelled "Which student success metrics do you believe should be prioritised by learning analytics?" illustrates the distribution of responses ranging from 10 to 50. Here are the main highlights:
- Mean Priority: The average priority score is 37.1, suggesting that most respondents consider specific student success metrics important for learning analytics to focus on.

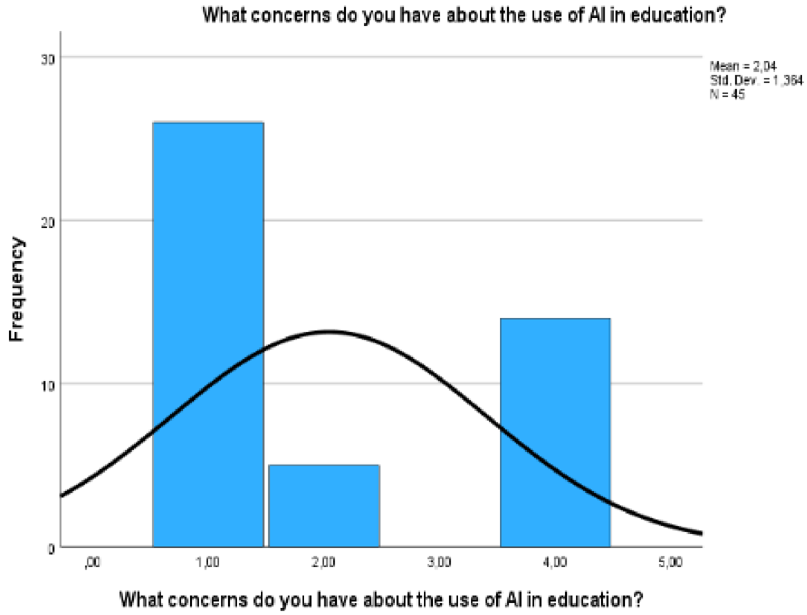


The histogram labelled "How important is it for your institution to use analytics to enhance students' academic performance?" illustrates the spread of responses on a scale ranging from 0 to 3. Key takeaways include:

- Average Importance: The mean score is 1.53, suggesting that respondents generally perceive using analytics to improve academic performance as necessary.
- Response Variation: The standard deviation is 0.894, indicating a range of opinions among those surveyed.
- Most Common Response: The highest frequency of answers is concentrated at the lower end of the scale, reflecting that many respondents consider the importance low.



The bar graph titled "Do you believe that data-driven insights can improve institutional decision-making and performance?" illustrates the range of responses measured between 1.00 and 4.00. Here are the main highlights: Average Rating: The mean response is 1.69, reflecting a generally favourable view that data-driven insights can enhance institutional decision-making and performance. Variability: With a standard deviation of 0.848, there is considerable diversity in the opinions shared by respondents. Most Common Response: The highest frequency is recorded at 1.00, indicating that many respondents strongly support the effectiveness of data-driven insights.



The bar graph named "What concerns do you have about the use of AI in education?" illustrates respondents' varying levels of concern. Here are the main takeaways:

- Average Concern Level: The overall average concern is 2.04, reflecting moderate unease regarding AI in education.
- Standard Deviation: A standard deviation of 1.364 indicates a wide range of opinions among those surveyed.
- Most Common Response: The response level with the highest frequency is 1.00, indicating that many respondents have minimal worries about AI's role in education.

4. Discussion of Findings

The study indicates that participants are generally young, suggesting a focus on early childhood education. Their understanding of AI concepts appears consistent, likely stemming from school curricula, media exposure, or professional background. There is moderate awareness of learning analytics, but many may lack a comprehensive understanding of the topic. A mean response rating of 3.78 reflects strong confidence in AI's role in enhancing learning, with a majority viewing it as an essential educational tool. Previous research has shown that early technology exposure can promote digital literacy and critical thinking skills, which are vital in today's tech-focused environment (Bulfin, Pangrazio & Selwyn, 2014). The discussion includes the incorporation of educational technology into school programmes to better prepare younger generations for future challenges. Interestingly, many participants show little concern about AI in education, suggesting either a belief in its advantages or a lack of awareness regarding potential risks. This range of opinions underscores the need to engage various stakeholders in informed discussions about AI's impact on education, considering diverse viewpoints in decision-making processes (Aithal & Aithal, 2023). This finding aligns with literature emphasising the role of educational institutions in providing students with knowledge about emerging technologies. Arellano underscores the necessity for educational frameworks to evolve to include critical technological perspectives, enhancing students' comprehension of AI (Arellano, 2022). The focus on early technology and AI exposure matches recommendations from educational technology researchers for integrating these subjects into early learning (Bulfin et al., 2014). Furthermore, the overall familiarity with AI concepts suggests that educational curricula have progressively included pertinent technological content, as noted by Arellano (2022). However, the moderate understanding of learning analytics and the identified knowledge gap reveal areas where further research and educational development are necessary, echoing concerns raised by Gašević et al. (2017) and Frey et al. (2017) regarding the intricacies of learning analytics.

A moderate majority of survey participants believe that AI has the potential to enhance their learning experience, although they may not wholly support its capacity to revolutionise education. Most respondents agree on the significance of utilising analytics in curriculum development, indicating a favourable attitude towards its integration. The research underscores the value of data-driven methods in boosting efficiency, supporting decision-making, and optimising resource allocation within educational institutions. The moderate belief that AI can enhance learning aligns with findings from Nawi et al. (2023), which indicate that Malaysian students acknowledge the benefits of learning analytics tools in improving educational outcomes. This reflects a growing awareness of AI's potential among students, consistent with literature emphasising AI's role in personalising learning and delivering targeted feedback, especially in language learning contexts (Nurjanah, 2024). However, the reluctance to fully embrace AI's transformative possibilities may stem from concerns raised by Hilliger et al. (2023), who argue that while there is excitement about AI in education, stakeholders often face challenges regarding its practical application. Despite some variability in opinions, specific stakeholders strongly advocate for incorporating analytics (Chan & Zary, 2019). A segment of respondents expresses a moderate level of comfort with utilising learning analytics for tracking academic progress, believing it can yield valuable insights into student performance, support personalised learning, and improve educational outcomes. The research also emphasises the importance of student success metrics for enhancing academic achievement, advocating for a balanced approach that considers various aspects of student success (Wise, Knight & Shum, 2021). Several studies support the focus on data-driven strategies for enhancing efficiency and decision-making in educational institutions. For instance, Quadri and Shukor (2021) highlight the advantages of learning analytics in pinpointing key courses and improving student learning outcomes. This aligns with the current study's findings concerning the positive effects of analytics on educational practices (Quadri & Shukor, 2021).

Respondents generally perceive analytics as essential for improving academic performance, reflecting a mean importance rating of 1.53. This finding is consistent with existing research on how data-driven decision-making can enhance educational outcomes. However, the variability in responses indicates differences in familiarity with analytics, specific institutional contexts, and varying beliefs about the effectiveness of data-driven methods in education. This discrepancy suggests that respondents may have significantly different comfort levels and experiences with these tools. Research by Wong et al. (2024) reinforces this idea, highlighting that the practical application of learning analytics can differ across educational environments, particularly in medical schools. Educational leaders acknowledge the influence of data-driven insights on institutional performance (Preiksaitis & Rose, 2023). Incorporating artificial intelligence (AI) in education has generated a wide range of opinions, influenced by demographic factors affecting individuals' reliance on AI technologies. Additionally, Broadbent's findings support the notion that views on the effectiveness of analytics in education can vary. Broadbent argues that while learning analytics can yield valuable information, their direct impact on academic performance is unclear (Broadbent, 2016). His meta-analysis suggests that intrinsic motivation and self-efficacy may significantly influence academic achievement more than the mere frequency of using learning management systems, indicating that the perceived significance of analytics does not always result in better outcomes.

5. Conclusion and Recommendations

The research results showed a moderate level of awareness regarding learning analytics, with mixed opinions on the role of AI in education. The study highlighted a young participant demographic, suggesting a focus on early childhood education. Many respondents believed that AI could enhance their learning experiences, although there is some hesitation about its capacity to fundamentally change educational practices. There is a consensus on the value of analytics in developing curricula, indicating an openness to incorporating these tools. Additionally, the study emphasised the benefits of data-driven strategies for improving efficiency, decision-making, and resource management in educational institutions. Participants consistently understood AI concepts, likely due to educational programmes, media consumption, or work experiences. Consequently, institutions are encouraged to take a proactive and comprehensive stance by implementing focused educational initiatives to boost understanding among students, faculty, and staff. This includes weaving learning analytics into relevant curricula, hosting regular workshops, and fostering clear communication about its objectives and advantages. Open discussion forums can help create a collaborative setting where stakeholders can share their views and concerns. AI literacy programmes should also be introduced to teach stakeholders about AI's practical uses, enabling them to engage confidently with these technologies. Furthermore, institutions are urged to invest in AI-driven educational tools and advocate for their integration into teaching practices while monitoring and evaluating their effectiveness in meeting educational objectives. Lastly, a balanced perspective on AI should be promoted, addressing its remarkable benefits and potential risks while cultivating an awareness of ethical issues such as data privacy and algorithmic bias, preparing stakeholders to navigate the various complexities of AI in education.

Educational institutions should introduce focused initiatives to boost comprehension among students, educators, and staff to address the moderate awareness surrounding learning analytics. This could involve incorporating learning analytics into relevant courses, hosting regular workshops to explain its concepts, uses, and potential impacts on education, and ensuring clear communication about its goals and advantages. Given the mixed feelings regarding AI in educational settings, as indicated by a moderate level of concern, institutions should create platforms for continuous dialogue and discussion. These spaces would enable students, teachers, and administrators to openly share their views and worries regarding AI in education. Furthermore, offering AI literacy programs or informative sessions can assist in educating stakeholders about AI's role in education, potentially alleviating concerns and building confidence. With a strong belief in the effectiveness of AI to enhance learning, as shown by an average rating of 3.78, institutions should invest in and expand the use of AI-based learning tools and platforms, such as adaptive learning systems, customised learning experiences, and intelligent tutoring systems. Faculty members should be encouraged to incorporate AI technologies into their teaching methodologies. To maintain a positive outlook on AI, institutions need to implement systems to consistently evaluate the effectiveness of these tools in enhancing educational outcomes. Moreover, a balanced strategy is necessary since many stakeholders either express optimism about the potential benefits of AI or remain unaware of the risks involved. This can be pursued by highlighting AI’s advantages alongside ethical concerns in education. Comprehensive AI literacy programs are crucial for this purpose, focusing on benefits like personalised learning and increased administrative efficiency while raising awareness about potential challenges, including data privacy issues, algorithmic bias, and the constraints of AI decision-making.

6. Declarations

Funding: This research did not receive any external funding.

Acknowledgements: As I conclude my writing journey for this paper, I feel compelled to express my heartfelt gratitude to everyone who has supported and encouraged me, particularly Walter Sisulu University Research and Innovations. First and foremost, I thank God for guiding me in successfully completing this article. I am incredibly grateful to AEF Hod Dr Themba Saziwa, whose insightful advice played a crucial role in enhancing this paper and ensuring its success. His guidance and suggestions were instrumental in my ability to finish the work and helped me to grow my knowledge and skills.

Conflict of Interest: The author declares no conflict of interest.

Data Availability: The data supporting the findings of this study are included within the article. However, due to ethical approval constraints, the raw data cannot be made publicly available but can be accessed upon reasonable request from the corresponding author.

References

Abbas, A., Mahrishi, M., & Mishra, D. (2023). Artificial intelligence (AI) governance in higher education: A meta-analytic systematic review. SSRN. https://doi.org/10.2139/ssrn.4657675

Aithal, P. S., & Aithal, S. (2023). Optimising the use of artificial intelligence powered GPTs as teaching and research assistants by professors in higher education institutions: A study on smart utilisation. *International Journal of Management, Technology, and Social Sciences, 8*(4), 368–401. https://doi.org/10.2139/ssrn.4729191

Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI and Ethics, 2*(3), 431–440. https://doi.org/10.1007/s43681-021-00096-7

Arellano Morales, M. A. (2022). Consecuencias de la COVID-19 en la economía y las finanzas públicas en México: Más allá de la pandemia. *El trimestre económico, 89*(355), 829–864. https://doi.org/10.20430/ete.v89i355.1307

Astalini, A., Darmaji, D., Kurniawan, D. A., Jaya, H., & Husna, S. M. (2022). Analysis of teacher responses to web-based assessment to assess students' attitudes towards science subjects. *Integrated Science Education Journal, 3*(3), 66–71. https://doi.org/10.37251/isej.v3i3.282

Broadbent, J. (2016). Academic success is about self-efficacy rather than the frequency of use of the learning management system. *Australasian Journal of Educational Technology, 32*(4). https://doi.org/10.14742/ajet.2634

Byrne, E., Brugha, R., Clarke, E., Lavelle, A., & McGarvey, A. (2015). Peer interviewing in medical education research: Experiences and perceptions of student interviewers and interviewees. *BMC Research Notes, 8*, 1–11. https://doi.org/10.1186/s13104-015-1484-2

Bulfin, S., Pangrazio, L., & Selwyn, N. (2014). Making 'MOOCs': Constructing a new digital higher education within news media discourse. *International Review of Research in Open and Distributed Learning, 15*(5), 290–305. https://id.erudit.org/iderudit/1065546ar

Chan, K. S., & Zary, N. (2019). Applications and challenges of implementing artificial intelligence in medical education: Integrative review. *JMIR Medical Education, 5*(1), e13930. https://doi.org/10.2196/13930

Chibuwe, A., & Munoriyarwa, A. (2023). Emerging methods and challenges associated with teaching and learning media studies during the COVID-19 pandemic induced lockdowns in Zimbabwe and South Africa. *Sage Open*, *13*(2), 21582440231167113 https://doi.org/10.1177/21582440231167113.

Clark, A., & Lappin, S. (2012). Computational learning theory and language acquisition. *Philosophy of Linguistics*, *14*, 445.

Craandijk, D., & Bex, F. (2022, June). Enforcement heuristics for argumentation with deep reinforcement learning. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 36, No. 5, pp. 5573-5581). https://doi.org/10.1609/aaai.v36i5.20497

Cruz, M. (2024). Exploring the integration of artificial intelligence generative tools in teaching Hispano-American literature: A student-centric approach. In *INTED2024 Proceedings* (pp. 5717–5727). IATED. https://doi.org/10.21125/inted.2024.1489

Darvishi, A., Khosravi, H., Sadiq, S., & Gašević, D. (2022). Incorporating AI and learning analytics to build trustworthy peer assessment systems. *British Journal of Educational Technology*, *53*(4), 844-875. https://doi.org/10.1111/bjet.13233

Dawat, E. R. R. (2023). Advancing education through data analytics and artificial intelligence: A comprehensive literature review. *Advancing Education through Data Analytics and Artificial Intelligence: A Comprehensive Literature Review*, *137*(1), 8.

Ekellem, E. A. F. (2023, October). Conversational AI in academia: A practical exploration with ChatGPT. In *2023 7th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)* (pp. 1-4). IEEE. https://doi.org/10.1109/ISMSIT58785.2023.10304845

Fahimirad, M., & Kotamjani, S. S. (2018). A review of the application of artificial intelligence in teaching and learning in educational contexts. *International Journal of Learning and Development*, *8*(4), 106-118. https://doi.org/10.5296/ijld.v8i4.14057

Frey, R. F., McDaniel, M. A., Bunce, D. M., Cahill, M. J., & Perry, M. D. (2020). Using students' concept-building tendencies to better characterise average-performing student learning and problem-solving approaches in general chemistry. *CBE—Life Sciences Education*, *19*(3), ar42. https://doi.org/10.1187/cbe.19-11-0240

Göçen, A., & Aydemir, F. (2020). Artificial intelligence in education and schools. *Research on Education and Media*, *12*(1), 13–21.

Guan, X., Feng, X., & Islam, A. Y. M. (2023). The dilemma and countermeasures of educational data ethics in the age of intelligence. *Humanities and Social Sciences Communications*, *10*(1), 1–14. https://doi.org/10.1057/s41599-023-01633-x

Gumede, L., & Badriparsad, N. (2022). Online teaching and learning through the students' eyes: Uncertainty through the COVID-19 lockdown: A qualitative case study in Gauteng province, South Africa. *Radiography*, *28*(1), 193–198. https://doi.org/10.1016/j.radi.2021.10.018

Han, X., Xiao, S., Sheng, J., & Zhang, G. (2024). Enhancing efficiency and decision-making in higher education through intelligent commercial integration: Leveraging artificial intelligence. *Journal of the Knowledge Economy*, 1–37. https://doi.org/10.1007/s13132-024-01868-2

Handayani, S. W., Utanto, Y., & Ghazali, M. N. A. B. (2023). The analysis of early childhood learning achievement based on implementing the ABCD5E model in the Merdeka Curriculum. *Educative: Jurnal Ilmiah Pendidikan*, *1*(3), 135–142. https://doi.org/10.37985/educative.v1i3.209

Hashim, S., Omar, M. K., Ab Jalil, H., & Sharef, N. M. (2022). Trends on technologies and artificial intelligence in education for personalised learning: Systematic literature. *Journal of Academic Research in Progressive Education and Development*, *12*(1), 884–903. https://doi.org/10.6007/IJARPED/v11-i1/12230

Heeks, R., & Wall, P. J. (2018). Critical realism and ICT4D research. *The Electronic Journal of Information Systems in Developing Countries, 84*(6), e12051. https://doi.org/10.1002/isd2.12051

Heilala, J., & Kantola, J. (2023, May). Sustainable manufacturer engineering for Industry 6.0. In *International Conference on Axiomatic Design* (pp. 75–87). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-49920-3_5

Hilliger, I., Ceballos, H. G., Maldonado-Mahauad, J., & Ferreira, R. (2024). Applications of learning analytics in Latin America. *Journal of Learning Analytics, 11*(1), 1–5. https://doi.org/10.18608/jla.2024.8409

Holmes, O. (2023). Making the case for Mesearch. *Perspectives on Race in Organizations*, 55-63.

Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Shum, S. B., ... & Koedinger, K. R. (2022). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artificial Intelligence in Education*, 1–23. https://doi.org/10.1007/s40593-021-00239-1

Huang, A. Y., Lu, O. H., & Yang, S. J. (2023). Effects of artificial intelligence–enabled personalised recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom. *Computers & Education, 194*, 104684. https://doi.org/10.1016/j.compedu.2022.104684

Ikart, E. M. (2019). Survey questionnaire pretesting method: An evaluation of survey questionnaire via expert reviews technique. *Asian Journal of Social Science Studies, 4*(2), 1. https://doi.org/10.20849/ajsss.v4i2.565

Jantjies, M., Moodley, T., & Maart, R. (2018, December). Experiential learning through virtual and augmented reality in higher education. In *Proceedings of the 2018 International Conference on Education Technology Management* (pp. 42–45). https://doi.org/10.1145/3300942.3300956

Jian, M. J. K. (2023). Personalised learning through AI. *Advances in Engineering Innovation*, *5*, 16-19.

Kamau, G. N. U. (2022). ICT4D research in developing countries: A call for pragmatism approach. *International Journal of Computer and Information System, 3*(2), 51-55. https://www.ijcis.net/index.php/ijcis/article/view/67

Kearns, M. J., & Vazirani, U. (1994). *An introduction to computational learning theory*. MIT Press.

Kitto, K., & Knight, S. (2019). Practical ethics for building learning analytics. *British Journal of Educational Technology*, *50*(6), 2855–2870. https://doi.org/10.1111/bjet.12868

Knight, S., Gibson, A., & Shibani, A. (2020). Implementing learning analytics for learning impact: Taking tools to task. *The Internet and Higher Education*, *45*, 100729. https://doi.org/10.1016/j.iheduc.2020.100729

Li, K. C., & Wong, B. T. M. (2023). Artificial intelligence in personalised learning: A bibliometric analysis. *Interactive Technology and Smart Education*, *20*(3), 422-445. https://doi.org/10.1108/ITSE-01-2023-0007

Mahligawati, F., Allanas, E., Butarbutar, M. H., & Nordin, N. A. N. (2023, September). Artificial intelligence in physics education: A comprehensive literature review. In *Journal of Physics: Conference Series* (Vol. 2596, No. 1, p. 012080). IOP Publishing. https://doi.org/10.1088/1742-6596/2596/1/012080

Maison, M., Darmaji, D., Kurniawan, D. A., Astalini, A., Kuswanto, K., & Ningsi, A. P. (2021). Correlation of science process skills on critical thinking skills in junior high school in Jambi City. *Jurnal Penelitian Fisika dan Aplikasinya*, *11*(1), 29-38. https://doi.org/10.26740/jpfa.v11n1.p29-38

Maretha, C. (2023). Positivism in philosophical studies. *Journal of Innovation in Teaching and Instructional Media*, *3*(3), 124–138.

Mkuti, S., & Aucamp, E. (2024). Contextualising the South African higher education academic interventions for student success: Challenges and opportunities. In *Proceedings of the International Conference on Education Research*. Academic Conferences and Publishing Limited.

Mohammed, A. S. (2023). Examining the implementation of artificial intelligence in early childhood education settings in Ghana: Educators' attitudes and perceptions towards its long-term viability. *American Journal of Education and Technology,* *2*(4), 36–49. https://doi.org/10.54536/ajet.v2i4.2201

Mortaji, S. T. H., & Sadeghi, M. E. (2024). Assessing the reliability of artificial intelligence systems: Challenges, metrics, and future directions. *International Journal of Innovation in Management, Economics and Social Sciences, 4*(2), 1-13.

Mostert, C. (2020, June). Embarking on the open education resources journey in the 4th Industrial Revolution. In *EdMedia+ Innovate Learning* (pp. 950–959). Association for the Advancement of Computing in Education.

Musakuro, R. N. (2022). A framework development for talent management in the higher education sector. *SA Journal of Human Resource Management, 20*, 1671. https://hdl.handle.net/10520/ejc-sajhrm_v20_i1_a1671

Nawi, N. R. C., Omar, M. K., Sharef, N. M., Murad, M. A. A., Mansor, E. I., Amelina, N., ... & Marhaban, M. H. (2023). Correlation between students' expectations and demographic characteristics toward features of learning analytics system in Malaysia. *International Journal of Academic Research in Progressive Education and Development, 11*(2), 1073-1096. http://dx.doi.org/10.6007/IJARPED/v12-i2/16961

Ngqulu, N. (2018, July). Investigating the adoption and the application of learning analytics in South African higher education institutions (HEIs). In *International Conference on e-Learning* (pp. 545-XVI). Academic Conferences International Limited.

Nkohla, T. V., Munacinga, C. S., Marwa, N., & Ncwadi, R. (2021). A non-parametric assessment of the efficiency of South African public universities. *South African Journal of Higher Education, 35*(2), 158-187. https://hdl.handle.net/10520/ejc-high-v35-n2-a10

Nurmi, S. M. (2018). *Ethically conducted clinical research in hospitals: Views of the stakeholders* (Doctoral dissertation, Itä-Suomen University).

Nurjanah, A. (2024, December). The effect of augmented reality (AR) on the enhancement of vocabulary in elementary school students: A literature review. In *7th Celt International Conference (CIC, 2024)* (pp. 230-249). Atlantis Press. https://doi.org/10.2991/978-2-38476-348-1_17

Ohei, K. N. (2023). Using ICT tools and technological applications in this era of the COVID-19 pandemic to facilitate learning. *HOLISTICA–Journal of Business and Public Administration, 14*(2), 116–136. https://doi.org/10.2478/hjbpa-2023-0019

Okunade, A. I. (2024). Artificial intelligence's role in teaching science education in secondary schools in Nigeria. *European Journal of Computer Science and Information Technology, 12*(1), 57-67. https://doi.org/10.37745/ejcsit.2013/vol12n15767

Olatunde-Aiyedun, T. G. (2024). Artificial intelligence (AI) in education: Integration of AI into science education curriculum in Nigerian universities. *International Journal of Artificial Intelligence for Digital*, *1*(1), 1-14.

Opesemowo, O. A. G., & Adekomaya, V. (2024). Harnessing artificial intelligence for advancing sustainable development goals in South Africa's higher education system: A qualitative study.

International Journal of Learning, Teaching and Educational Research, *23*(3), 67-86. *https://doi.org/10.26803/ijlter.23.3.4*

Osasona, F., Amoo, O. O., Atadoga, A., Abrahams, T. O., Farayola, O. A., & Ayinla, B. S. (2024). Reviewing the ethical implications of AI in decision-making processes. *International Journal of Management & Entrepreneurship Research, 6*(2), 322-335. https://doi.org/10.51594/ijmer.v6i2.773

Ouyang, F., Wu, M., Zheng, L., Zhang, L., & Jiao, P. (2023). Integration of artificial intelligence performance prediction and learning analytics to improve student learning in online engineering courses. *International Journal of Educational Technology in Higher Education, 20(*1), 4. https://doi.org/10.1186/s41239-022-00372-4

Palinkas, L. A., Mendon, S. J., & Hamilton, A. B. (2019). Innovations in mixed methods evaluations. *Annual Review of Public Health*, *40*(1), 423-442. https://doi.org/10.1146/annurev-publhealth-040218-044215

Pendy, B. (2023). Artificial intelligence in the health sector of the USA. *Jurnal Indonesia Sosial Sains*, *4*(3).

Preiksaitis, C., & Rose, C. (2023). Opportunities, challenges, and future directions of generative artificial intelligence in medical education: Scoping review. *JMIR Medical Education*, *9*, e48785. https://doi.org/10.2196/48785

Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*, *12*(1), 22. https://doi.org/10.1186/s41039-017-0062-8

Putri, J. H., & Maharani, I. (2023). Analysis of the effectiveness of AI learning systems in facilitating interactive learning in junior high schools. *EduLine: Journal of Education and Learning Innovation*, *3*(4), 618-628. https://doi.org/10.35877/454RI.eduline2202

Quadri, A., & Shukor, N. (2021). The benefits of learning analytics to higher education institutions: A scoping review. *International Journal of Emerging Technologies in Learning, 16*(23), 4–15. https://doi.org/10.3991/ijet.v16i23.27471

Robinson, O. C. (2014). Sampling in interview-based qualitative research: A theoretical and practical guide. *Qualitative Research in Psychology*, *11*(1), 25–41. https://doi.org/10.1080/14780887.2013.801543

Salas-Pilco, S. Z. (2020). The impact of AI and robotics on physical, social-emotional, and intellectual learning outcomes: An integrated analytical framework. *British Journal of Educational Technology*, *51*(5), 1808–1825. https://doi.org/10.1111/bjet.12984

Singh, A. K., Meshram, S. A., Khandelwal, V., Tiwari, P., & Singh, P. (2024). Implementation of industry-based perspective in technical education: A qualitative and quantitative analysis. *Industrial and Manufacturing Designs: Quantitative and Qualitative Analysis*, 321–346. https://doi.org/10.1002/9781394212668.ch11

Soloveichik, D. (2008). *Molecular computing: Self-assembled nanostructures, molecular automata, and chemical reaction networks*. California Institute of Technology.

Turner, M., & Fozdar, F. (2010). Dependency, partiality, and the generation of research questions in refugee education. *Issues in Educational Research*, *20*(2), 183.

van Veggel, N., Allison, J., Goldspink, S., & Engward, H. (2024). The presuppositional interview is a means of transparent reflexive practice in grounded theory. *Methodological Innovations*, *17*(1), 31–40. https://doi.org/10.1177/20597991231212236

Wang, T., Lund, B. D., Marengo, A., Pagano, A., Mannuru, N. R., Teel, Z. A., & Pange, J. (2023). Exploring the potential impact of artificial intelligence (AI) on international students in higher education: Generative AI, chatbots, analytics, and international student success. *Applied Sciences*, *13*(11), 6716. https://doi.org/10.3390/app13116716

Willie, M. M. (2022). Differentiating between population and target population in research studies. *International Journal of Medical Science and Clinical Research Studies, 2*(6), 521–523. https://doi.org/10.47191/ijmscrs/v2-i6-14

Willie, M. M. (2024). Population and target population in research methodology. *Golden Ratio of Social Science and Education*, *4*(1), 75–79.

Wise, A. F., Knight, S., & Shum, S. B. (2021). Collaborative learning analytics. In U. Cress, C. Rosé, A. F. Wise, & J. Oshima (Eds.), *International handbook of computer-supported collaborative learning* (Vol. 19). Springer. https://doi.org/10.1007/978-3-030-65291-3_23

Wong, R. (2023). Role of generative artificial intelligence in publishing: What is acceptable, and what is not? *The Journal of Extracorporeal Technology*, *55*(3), 103–104. https://doi.org/10.1051/ject/2023033

Wong, B. T. M., Li, K. C., & Liu, M. (2024). An investigation into the application of learning analytics in collaborative learning. In L. K. Lee, P. Poulova, K. T. Chui, M. Černá, F. L. Wang, & S. K. S. Cheung (Eds.), *Technology in education. Digital and intelligent education. ICTE 2024*. Springer. https://doi.org/10.1007/978-981-96-0205-6_16

Xulu-Gama, N., & Hadebe, S. (2022). Language of instruction: A critical aspect of epistemological access to higher education in South Africa. *South African Journal of Higher Education*, *36*(5), 291–307. https://hdl.handle.net/10520/ejc-high_v36_n5_a16

Zhao, Y. (2025). Artificial intelligence and education: End the grammar of schooling. *ECNU Review of Education*, *8*(1), 3-20. https://doi.org/10.1177/20965311241265124