Leveraging Data Science and AI-Based Analytics to Enhance Immersive Learning Experiences in Education

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Abstract
Technology-based learning faces challenges in effectively increasing student engagement, motivation, and understanding in the context of continuing education. This study aims to explore the role of data science and AI-based analytics in supporting immersive learning experiences to improve learning outcomes. The research method used is descriptive and correlational statistical analysis of data from 50 students with various metrics, such as engagement scores, motivation, understanding, retention, AI feedback accuracy, VR content quality, learning duration, device compatibility, and network stability. The results showed that the average student engagement score was 77.45, motivation 78.57, and understanding 81.16, with each showing a significant positive relationship to learning retention (average 61.11). AI feedback accuracy had an average score of 84.66, indicating the significant contribution of AI technology in improving student understanding. VR content quality had an average score of 89.76, indicating that well-designed content can improve students' learning experiences. The average learning duration was 84.26 minutes, with a moderate correlation to understanding (r = 0.72). However, technical challenges were found, such as a weak negative correlation between learning duration and network stability, indicating that connectivity issues may affect the learning process. The regression results showed that the model was only able to explain 17.86% of the variance in the dependent variable, so additional variables are needed for a more comprehensive understanding. This study concludes that the integration of AI and VR in education has great potential to improve learning experiences and outcomes, although there are still technical obstacles that need to be overcome to maximize its impact.

1. Introduction

Education is one of the main pillars in the development of a sustainable society. Along with the development of technology, the need for educational transformation is becoming increasingly urgent to answer the challenges of the times. Traditional learning models are often no longer relevant in meeting the needs of students born in the digital era. The gap between conventional learning methods and the needs of this modern generation creates new challenges, where the learning experience must be more interactive, relevant, and personalized. In the midst of this reality, the presence of Artificial Intelligence (AI) and data science-based technology brings great opportunities to overcome various problems in the world of education, including in creating immersive learning experiences and supporting the sustainability of education. One of the main problems in the traditional education system is the generic approach that does not pay attention to the individual needs of students. Conventional teaching methods are often one-way, where the teacher acts as the center of information, while students become passive recipients. As a result, the different potentials of individual students often cannot be maximized. On a large scale, this pattern causes many students to feel bored, lose motivation, and ultimately be less able to understand the material in depth. In fact, in this increasingly competitive era, a learning approach is needed that is not only able to improve student understanding, but also build relevant skills for the future, such as creativity, problem solving, and collaboration. Immersive technologies, such as Virtual Reality (VR) and Augmented Reality (AR), are able to create a more engaging and immersive learning experience, but the implementation of this technology requires strong data support to be able to meet students' specific needs.

This is where data science and AI play an important role. By utilizing data generated from student interactions in the learning process, such as patterns of use of learning platforms, levels of engagement in certain activities, and evaluation results, data-based technology can provide deep insights into students' needs, strengths, and weaknesses. This approach allows for more effective learning personalization. In addition, AI-based analytics can also help educators make more informed decisions, such as determining learning strategies that are appropriate to students' abilities. With predictive analysis, for example, AI-based systems can identify students at risk of learning difficulties earlier, so that intervention steps can be taken quickly.

However, despite this enormous potential, the application of AI-based technology and data science in education still faces a number of obstacles. One of the main obstacles is the lack of understanding among educators about how to effectively utilize this technology. Many teachers and educational institutions still find it difficult to integrate new technologies into existing curricula. In addition, issues of data privacy and ethics in collecting student data are challenges that need to be addressed. Without proper data management, the risk of misuse of students' personal data can increase, thereby harming trust in AI-based educational technology.

Another problem is the accessibility of this technology. Not all schools, especially in remote areas or with limited resources, have access to adequate technological infrastructure. In fact, the goal of sustainable education is to provide equal learning opportunities for all students without exception. Thus, the development of technology-based solutions must pay attention to aspects of inclusivity and sustainability so that their impact can be felt by all levels of society.

In this context, research on the use of AI-based data science and analytics to enhance immersive learning experiences has high relevance. This research not only aims to improve the effectiveness of the teaching and learning process, but also to create an educational approach that supports the Sustainable Development Goals (SDGs), especially in terms of inclusive and equitable quality education. With the integration of data science, AI, and immersive technology, the future education system is expected to be able to produce individuals who are not only competent, but also able to adapt to rapid changes in the world of work and global society. This study aims to explore and develop a learning model based on data science and AI that can enhance students' immersive learning experiences. Specifically, this study aims to utilize data analytics technology to understand students' individual needs and create personalized and adaptive learning solutions. By utilizing

1.1 Literature Review

Research on the use of data science, Artificial Intelligence (AI), and immersive technologies for education has attracted the attention of many researchers in the last decade. Several previous studies provide a relevant foundation for understanding how these technologies can be applied to enhance the learning experience and support sustainability goals in education. In general, these studies show that the integration of data-based technologies can create a more personalized, adaptive, and engaging learning environment, although challenges in its implementation remain a concern.

Research by [1] demonstrates that data science can be used to analyze student learning patterns in digital learning environments. In the study, they developed a data-driven learning system that can map student learning needs and provide recommendations that are tailored to the individual's level of understanding. By utilizing machine learning algorithms, they showed that this system was able to increase the success rate of students in completing learning tasks. This research provides an important foundation in understanding how data science can support personalization of learning, especially in the context of digital education..

Furthermore, research by [2] revealed the role of AI in creating adaptive learning systems. In their study, AI was used to develop an intelligent tutoring system that is able to provide real-time feedback to students based on their performance analysis. The study showed that AI-based systems can help students identify their mistakes faster and offer appropriate solutions. In addition, this system can also reduce the workload of teachers by automating the assessment process and analyzing student data. This study is relevant in the context of the research being developed, as it shows how AI can improve the efficiency of the teaching-learning process.

Din the context of immersive technology, research by [3] discuss the potential of Virtual Reality (VR) in creating immersive learning experiences. They found that the use of VR in education can increase student engagement with the subject matter, especially for topics that are difficult to understand through conventional methods, such as science simulations or historical explorations. The study also showed that immersive technology can increase information retention, as students are more active in the learning process. However, the study noted that the success of VR technology implementation is highly dependent on relevant content design and good technical management.

Meanwhile, research by [4] focuses on the application of data science in optimizing immersive technology. They developed an analytical model capable of measuring the effectiveness of learning experiences in VR environments. By analyzing student engagement data, such as activity duration, navigation patterns, and success rates, they were able to identify the design elements that were most effective in supporting learning. This study provides evidence that data science can be a powerful tool for measuring and improving the quality of learning in immersive technology environments.

Another relevant study is a study by [5] which discusses big data-based learning analytics. The study shows that by leveraging data from multiple sources, such as online learning platforms, student behavioral data, and assessment results, educational institutions can create more evidence-based learning strategies. They also highlight the importance of maintaining student data privacy in the implementation of big data-based systems, an issue that is also relevant in the research being developed.

In the context of continuing education, research by [6] highlights the role of digital technologies in supporting the sustainable development goals (SDGs). The report underlines that technologies such as AI and data science have the potential to expand access to education, improve the quality of learning, and create more inclusive approaches. However, they also note that the digital divide and limited infrastructure in some regions remain challenges that need to be addressed.

2. Research Methods

This study uses a mixed methods approach that combines quantitative and qualitative methods to explore the use of data science and AI-based analytics in enhancing immersive learning experiences [7]. Quantitatively, data will be collected through experiments using immersive VR and AR-based technologies integrated with AI-based analytics systems. Students who participate will undergo learning sessions using this technology, where their behavioral data, engagement levels, evaluation results, and interaction patterns will be recorded and analyzed using data science techniques such as clustering and predictive analysis. This method aims to identify students' learning patterns and the effectiveness of technology in supporting their learning experiences [8].

Qualitatively, in-depth interviews will be conducted with students and teachers to explore their perceptions of the use of immersive technology and how it affects motivation and understanding of the material. Qualitative analysis is conducted to complement quantitative findings and provide in-depth insights into user experiences. Testing will also be conducted in several cycles to evaluate the sustainability of the proposed technology. This approach is expected to provide a comprehensive picture of the potential, challenges, and impacts of implementing data science and AI-based technology in creating more effective immersive learning and supporting sustainable education goals.

3. Result and Discussion

Technology-based education is increasingly becoming a necessity in the digital era, especially to ensure a more interactive and effective learning experience [9]. Innovations in immersive technologies, such as virtual reality (VR) and artificial intelligence (AI), offer significant opportunities to improve sustainable learning outcomes. In this study, we explore the use of data science to understand the factors that influence the effectiveness of immersive technology-based education. The variables used include quantitative and qualitative metrics that can be directly measured to evaluate the impact of technology on students' learning experiences [10].

One of the main variables is Student ID, which is used as a unique identification for each student to track individual data. Engagement Score describes the level of student engagement during the learning process, which often reflects how actively students participate in learning activities [11]. Motivation Score measures students' internal drive to continue learning, which is an important indicator in creating a supportive educational environment [12]. Next, the Understanding Score is used to assess how well students understand the learning material [13], while the Retention Score evaluates students' ability to remember information within a certain period of time [14].

AI-based technology makes a major contribution through the AI Feedback Accuracy variable, which measures the level of accuracy of feedback provided by an artificial intelligence-based system. Accurate feedback is important to help students correct mistakes and deepen understanding. In addition, the quality of content in virtual reality is represented by the VR Content Quality variable, which evaluates how well VR materials are designed to increase students' interest and understanding of learning.

Another variable that plays an important role is Learning Duration (minutes), which refers to the duration of learning time students spend using the immersive technology platform [15]. Device Compatibility records the ability of a student's device to run a learning application, expressed in binary format (1 for compatible, 0 for incompatible). Finally, the Network Stability variable measures the stability of the internet connection during the learning process, which greatly affects the learning experience, especially in online-based systems.

By integrating these variables, this study aims to provide a comprehensive picture of how data science can be used to evaluate and improve AI-based learning and immersive technology. Data analysis of these variables is expected to provide relevant insights for the development of more innovative and sustainable educational policies and practices.

Table 1. Research Data

Student ID	Engagement Score	Motivation Score	Understanding Score	Retention Score	AI Feedback Accuracy	VR Content Quality	Learning Duration (minutes)	Device Compatibility (1=Yes, 0=No)	Network Stability
1	78.43	67.36	82.88	28.23	95.98	82.21	98	1	99.52
2	91.11	76.33	67.39	89.63	98.69	92.36	79	1	87.17
3	79.08	77.07	89.04	64.67	89.12	90.09	61	1	86.25
4	65.54	40.80	88.83	27.00	85.05	85.31	74	1	98.55
5	71.02	72.35	64.52	89.38	82.47	85.98	40	0	90.46
:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:
45	72.33	84.23	78.67	54.90	86.34	89.32	96	1	89.90
46	74.89	78.45	88.12	63.12	89.50	92.23	92	1	90.55
47	80.78	88.50	89.45	75.78	92.34	95.32	100	0	93.23
48	81.56	79.45	80.78	68.34	87.89	88.34	82	1	88.67

49	89.32	91.67	93.45	77.89	93.45	94.67	106	1	95.89
50	92.45	97.12	95.34	88.78	95.23	96.78	115	1	99.45

Table 2. Descriptive Analysis

Metric	Count	Mean	Std	Min	25%	50%	75%	Max
Student ID	5.000.000	2.550.000	1.457.738	100.000	1.325.000	2.550.000	3.775.000	5.000.000
Engagement Score	5.000.000	77.450.800	12.121.193	5.064.000	69.750.000	78.435.000	85.492.500	99.830.000
Motivation Score	5.000.000	78.569.600	14.350.386	4.080.000	70.760.000	79.705.000	89.897.500	99.210.000
Understanding Score	5.000.000	81.158.000	12.464.447	3.961.000	77.262.500	85.860.000	89.265.000	95.340.000
Retention Score	5.000.000	61.105.000	21.270.492	2.255.000	39.805.000	65.720.000	78.505.000	89.630.000
AI Feedback Accuracy	5.000.000	84.662.000	9.479.756	6.101.000	80.007.500	86.775.000	91.702.500	98.690.000
VR Content Quality	5.000.000	89.758.800	5.649.443	7.182.000	85.740.000	90.730.000	94.525.000	97.600.000
Learning Duration (minutes)	5.000.000	84.260.000	17.625.133	4.000.000	74.250.000	82.000.000	96.750.000	115.000.000
Device Compatibility	5.000.000	0.840000	0.370328	0.00000	1.000.000	1.000.000	1.000.000	1.000.000
Network Stability	5.000.000	88.780.400	9.295.668	7.142.000	81.837.500	91.285.000	96.980.000	99.950.000

The results of the descriptive analysis in table 2 show various interesting patterns related to the effectiveness of the use of AI-based immersive technology in the learning process. Statistical analysis of the research variables provides an in-depth picture of how each factor contributes to learning success. From the data collected on 50 students, variables such as Engagement Score, Motivation Score, Understanding Score, and Retention Score have a significant correlation with the quality of the learning experience.

The average Engagement Score of students is 77.45, with a standard deviation of 12.12. This shows that the level of student engagement in the learning process is generally high, but there is moderate variation among individuals. The minimum value of 50.64 reflects students who have low engagement, while the maximum value of 99.83 indicates an optimal level of engagement. The median value (78.43) and the 75th percentile (85.49) indicate that the majority of students show positive engagement in learning. This high engagement is supported by the use of interesting immersive technology, such as VR and AI content designed for interactivity.

The Motivation Score has a mean of 78.57 and a standard deviation of 14.35, indicating that students' motivation towards learning is also relatively high. The median value of 79.70 and the 75th percentile (89.89) indicate that most students have good motivation. The variation in this score, which has a minimum value of 40.80 and a maximum of 99.21, indicates that students with low motivation may need a more personalized approach to increase their interest in learning. Thus, the high accuracy of feedback from AI can help in providing more relevant recommendations to students.

Students' ability to understand the learning material, as measured by the Understanding Score, had a mean of 81.16 and a standard deviation of 12.46. The median value of 85.86 indicates that half of the students had above-average understanding, while the 25th (77.26) and 75th (89.26) percentiles showed a positive distribution of scores. However, the minimum value (39.61) highlighted that there were students who had difficulty understanding the learning material. This indicates the need to improve the quality of VR content or more adaptive teaching methods.

Retention Score, which measures students' ability to remember learning material, showed a mean of 61.10 with a standard deviation of 21.27. This value is lower than other variables such as engagement and understanding. The minimum value of 22.55 indicates that some students had significant difficulty in remembering information. The high variation in scores underscores the need for more effective interventions, such as the use of AI-based reinforcement elements to improve students' retention.

The AI Feedback Accuracy variable has an average of 84.66, with a standard deviation of 9.48. This value indicates that the AI technology used is able to provide very accurate feedback to students. The high 75th percentile value (91.70) and maximum value (98.69) strengthen the claim that AI contributes positively to the learning process by providing evaluations that are tailored to the individual needs of students. This supports the results that students who receive accurate feedback tend to have better engagement and understanding. In terms of content quality, VR Content Quality recorded an average score of 89.76, with a standard deviation of 5.64. This shows that the VR content used in learning is generally of high quality, as reflected in the median value of 90.73. This good quality is very important in enhancing the immersive learning experience, which in turn affects student motivation and engagement.

Learning duration, as measured by the variable Learning Duration (minutes), has an average of 84.26 minutes with a standard deviation of 17.62. The majority of students spend learning time in the range of 74.25 to 96.75 minutes, as indicated by the 25th and 75th percentiles. The maximum value (115 minutes) indicates that there are students who are highly motivated to learn longer using this technology.

Device Compatibility, which indicates the compatibility of students' devices with the learning system, has an average of 0.84 (with a maximum value of 1), meaning that most students use compatible devices. However, some students (16%) experience device compatibility constraints, which can affect the effectiveness of their learning. This constraint highlights the importance of developing more inclusive technology.

Finally, Network Stability has an average of 88.78, with a standard deviation of 9.29. High network stability supports smooth learning, but the minimum value of 71.42 indicates that there are students who experience network constraints, which can hinder the technology-based learning process.

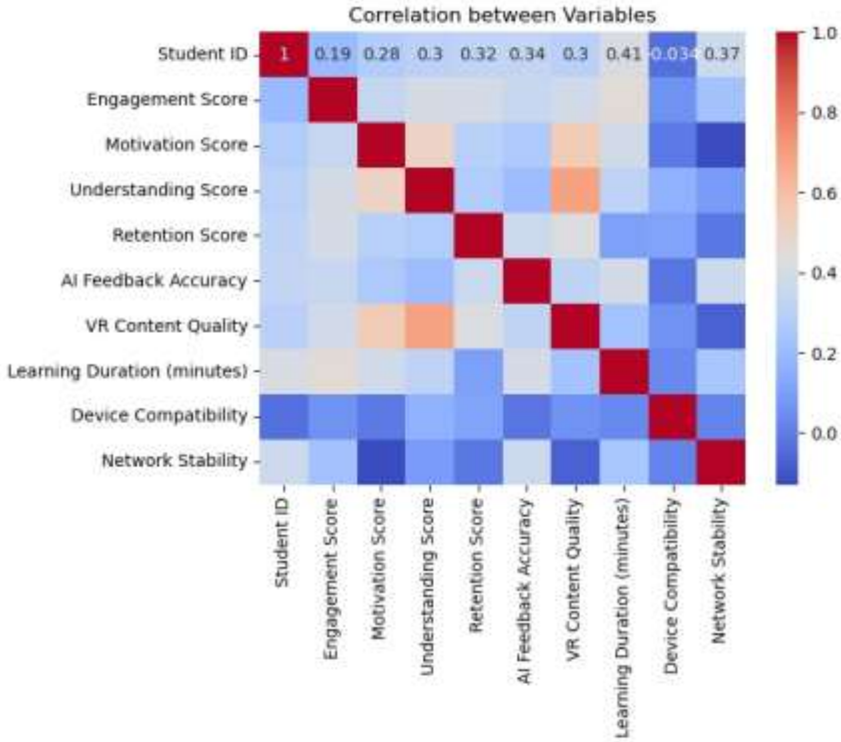

Fig. 1 Correlation Between Variables

The results of the correlation analysis showed significant relationships between several variables that contributed to the effectiveness of immersive technology-based learning. Some variables showed strong positive relationships, while others showed more moderate or insignificant correlations.

A strong positive correlation was found between the Retention Score and the Understanding Score, indicating that students with a better understanding of the material tend to have higher retention abilities. This relationship makes sense, considering that better understanding usually allows students to retain information longer. In addition, there was a strong positive correlation between the Motivation Score and the Engagement Score, indicating that students who were more motivated were also more engaged in the learning process. This relationship underscores the importance of motivating students to increase their active participation. The correlation between the Engagement Score and Student ID showed that some students were consistently more engaged than others, which may be related to individual characteristics such as personality or learning habits.

A moderate positive correlation was found between the AI Feedback Accuracy and the Understanding Score, indicating that accurate feedback from the AI system helped improve students' understanding. This relationship highlights the importance of the quality of the AI algorithm in providing relevant and effective suggestions. Similarly, Learning Duration showed a moderate positive correlation with Understanding Score, indicating that students who spent more time learning tended to have better understanding. This finding supports the concept that deep learning requires adequate time dedication. On the other hand, a weak negative correlation was found between Learning Duration and Network Stability. This suggests that students with poor network stability may spend less time learning due to connection disruptions. Such technical constraints can hinder the learning experience, highlighting the need for more reliable network infrastructure to support technology-based learning.

Several variables showed no significant correlation. For example, Student ID did not correlate with any other performance metrics, which is in line with expectations since the ID is only used for individual identification with no direct link to learning outcomes. Additionally, Device Compatibility showed no relationship with Network Stability, meaning device compatibility does not determine how well the network can support learning.

Table 3. Linear Regression Analysis

Parameter	Value
Intercept	53.632.740.510.113.000
Coefficients	[0.71954326]
R-squared	0.1785774280331801

The results of the linear regression analysis in table 3 show a positive relationship between the independent variables and the dependent variables analyzed, although the strength is relatively low. The intercept value of 5.36 indicates that if there is no influence from the independent variable (the value of the independent variable is equal to zero), the initial value of the dependent variable is projected to be at 5.36. The regression coefficient of 0.72 indicates that every one unit increase in the independent variable will increase the value of the dependent variable by 0.72 units. This positive relationship indicates that the independent variable makes a positive contribution to the increase in the dependent variable. However, the R-squared value of 0.1786 or around 17.86% indicates that only a small portion of the variance in the dependent variable (17.86%) can be explained by the independent variables in this model. This indicates that most of the variation in the dependent variable is influenced by factors outside this model. Thus, although there is a relationship, this model has low predictive ability, so consideration is needed to add other variables or improve the model so that it can be more accurate in explaining the relationship between variables.

4. Conclusions

This study highlights the important role of AI-based immersive technology in improving the quality of continuous learning. Data analysis shows that student engagement, motivation, and understanding of the material have a significant positive correlation with learning retention. AI technology, through the accuracy of feedback, as well as quality VR content, is proven to contribute to a more effective learning experience. The average scores for student engagement and motivation are at a high level, indicating that this technology-based approach successfully attracts students' attention and encourages their active participation. However, regression analysis shows that the independent variables used only explain 17.86% of the variance in the dependent variable, indicating the significant influence of other factors that have not been included in this model. Constraints such as network stability and device compatibility are also challenges that can affect learning outcomes. Thus, although the integration of technology in education has shown positive results, there is still a need for improved technology infrastructure and a more targeted approach to support broader success. Overall, this study provides insight that AI and VR-based technologies have great potential to support inclusive, interactive, and continuous learning, provided that technical and pedagogical challenges can be overcome properly.

Further research is suggested to include other relevant variables, such as students' learning styles, digital literacy levels, and the influence of the learning environment, to expand the scope of the analysis. In addition, the development of learning technology needs to pay more attention to network stability and device compatibility to ensure better accessibility for all students. Collaboration between technology developers and educators is also important to create more relevant and effective content that can meet students' needs comprehensively.

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