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Enhancing Digital Education: A Study on Intelligent Tutoring System(ITS)

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Abstract

Intelligent Tutoring Systems (ITS) are widely used to manage, deliver, and evaluate educational content; however, most lack adaptive capabilities to meet individual learner needs. This study integrates three key components—student activity tracking, performance prediction, and data visualization—to enable early identification of at-risk learners and support targeted interventions. Leveraging deep learning techniques enhances prediction accuracy, demonstrating the potential of advanced analytics to improve instructional decision-making, personalized feedback, and overall learning outcomes.

Keywords: ITS, Personalized Learning, Student Engagement, Adaptive Feedback.

1.Introduction

The digital transformation of education has sped up a lot in the last few years because more and more people want learning environments that are flexible, easy to get to, and tailored to their needs. ITSs are now important tools for planning, delivering, and keeping an eye on online education. ITSs are great for administrators and for keeping track of basic performance, but they do not always provide personalized, real-time support that meets the needs of each learner.

The ITS market in India is expected to grow at a compound annual growth rate (CAGR) of 26.8% from its 2024 valuation of ₹88.0 billion to ₹365.0 billion by 2030. Digital India, NEP 2020, and platforms like SWAYAM and DIKSHA are the main drivers of the rapid expansion of e-learning. This growth enables early identification of struggling students and allows content to be adapted dynamically based on student behavior.

The growing need for more responsive and personalized education has led to the integration of Artificial Intelligence (AI) and Machine Learning (ML) into modern learning systems. Technologies such as Recurrent Neural Networks (RNNs) are particularly effective for analyzing time-series data related to student behavior—such as quiz results, learning speed, and engagement patterns. When integrated with platforms like Moodle Analytics—a widely adopted open-source ITS with robust tracking features—and Microsoft Power BI, a powerful tool for data visualization and reporting, these technologies form a solid foundation for predictive analytics and adaptive learning.

Intelligent Tutoring Systems (ITSs) represent a significant advancement beyond traditional ITSs by using AI to deliver real-time, personalized instruction. Research supports their effectiveness. A 2023 meta-analysis reported that students using ITSs achieved up to 20% greater learning gains compared to those in conventional educational settings. These systems continuously evaluate student interactions and adapt the learning experience accordingly. This approach is increasingly being replicated within ITS platforms through deep learning and analytics integration."

Recently, the integration of Artificial Intelligence (AI) and Machine Learning (ML) into educational platforms is gaining traction. Among the various AI techniques, Recurrent Neural Networks (RNNs) are particularly well-suited for modeling sequential educational data, such as student quiz performance over time, time-on-task, and engagement metrics. These models can uncover hidden patterns and enable predictive insights that facilitate timely interventions and personalized learning experiences. Furthermore, combining ITS platforms like Moodle with data analytics tools such as Microsoft Power BI enhances the capability to transform raw learning data into actionable insights. Moodle Analytics captures in-depth user interactions. Power BI visualizes these insights through intuitive dashboards and reports, enabling educators to make informed decisions.

2.Literature Survey

The bibliometric review analyzes AI integration in Learning Management Systems (LMS) from 2004 to 2023, highlighting growth trends, key research themes, leading contributors, and influential publications *[1]*. The study emphasizes adaptive learning, analytics, and intelligent tutoring, offering insights into AI's transformative role in modern educational technology

By analyzing student demographics and academic records, this study applies machine learning models to predict academic success. XGBoost achieved 97% accuracy, demonstrating how data-driven insights can guide educators in early interventions and personalized support strategies for improved student outcomes *[2]*.

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The impact of generative AI, especially big language models like GPT-4, on improving ITS is reviewed. Benefits including real-time communication, adaptive learning pathways, personalised feedback, and dynamic content development are highlighted. Among the difficulties are bias, ethics, and educational errors. Aiming for more comprehensive, moral, and successful individualised learning experiences, future prospects include multimodal interfaces and emotionally intelligent agents. A roadmap for developing AI-driven education is presented in the work *[3]*.

A hierarchical multi-armed bandit technique is presented to maximise concept sequencing and task difficulty in intelligent tutoring systems *[4]*. And the suggested approach increased performance and success rates by using simulations with 500 virtual learners and Bayesian Knowledge Tracing. It dynamically adapts to individual needs and complexities, offering a scalable, open-source solution for personalized, adaptive education.

Utilising instruction-tuned large multimodal models (LMMs) to extract knowledge components (KCs) from multimedia instructional materials is suggested. In this work, KC extraction is automated by comparing human annotations and machine-generated labels from various knowledge tracing models and datasets *[5]*. The findings indicate that LMM-derived KCs are as accurate as or better than human ones. Additionally, a repeatable KT benchmark dataset is included in the work, highlighting the potential of LMMs to scale and enhance content-aware, data-driven educational evaluation.

VisTA, a visual analytics tool for intelligent tutoring systems, is presented in *[6]*. It provides multi-view dashboards to show time-on-task, engagement, mastery, and problem-solving pathways. VisTA improved instructional decision-making, allowing for prompt, responsive interventions and connecting automated tutoring data with successful human pedagogy, according to an evaluation conducted with five teachers.

Generative AI's role in enhancing intelligent tutoring systems in higher education, highlighting benefits like personalization, improved feedback, and adaptability is reviewed in *[7]*. They address challenges including pedagogical integrity, ethics, bias, and faculty acceptance, stressing the need for empirical validation and further research to confirm AI-driven ITS educational impacts.

It is explored how transformer-based generative models can improve adaptive learning platforms in *[8]* and the study shows that these models help better understand student behavior, generate personalized learning content, and adjust learning paths in real time. By using transformers, the system becomes more responsive and effective in meeting individual student needs,

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leading to improved engagement and learning outcomes.

It is examined how generative models can support personalized curriculum design. The research highlights that these models can analyze student data to create customized learning paths, adapt content to individual needs, and adjust the pace of instruction *[9]*. The study emphasizes the potential of generative AI to enhance learner engagement, improve outcomes, and reduce the workload for educators through automated content generation and curriculum planning.

3. System Design

The proposed system architecture integrates data acquisition, advanced analytics, and visualization tools to monitor, predict, and personalize learning experiences within an ITS framework. Data is primarily collected from Moodle, a widely adopted open-source Learning Management System (LMS), capturing student interactions such as login frequency, activity completion rates, quiz performance, and time-on-task metrics. This data is preprocessed to create longitudinal timelines for each learner, enabling the analysis of progress patterns over extended periods.

A Recurrent Neural Network (RNN) model is employed to detect temporal patterns in student performance, identify at-risk learners, and recommend targeted interventions. Predictions generated by the RNN are visualized using Microsoft Power BI, enabling educators to interpret complex performance metrics through interactive dashboards and reports. The system ensures compliance with data privacy regulations, safeguarding sensitive learner information.

The conceptual architecture of the ITS is illustrated in Figure 1. An adaptive learning system consists of several key components working together to personalize the learning experience. At the center is the student, whose interactions with the system generate data on behaviour and performance. This data is captured through a digital interface, typically integrated into a Learning Management System (LMS), which delivers instructional content, supports engagement, and provides feedback. The learning material itself is organized within a domain model, which outlines subject concepts, problem sets, and intended learning objectives. As the student progresses, their performance continuously updates a student model—an evolving profile that reflects their current understanding, skill level, and behavioural tendencies. Guiding the adaptive process is the inference engine, which uses information from both the domain and student models to make decisions about what content to present next, how to give feedback, and when to intervene. The integration of these components allows the system to tailor instruction to each learner's needs, improving engagement, supporting mastery, and making the educational experience more effective.

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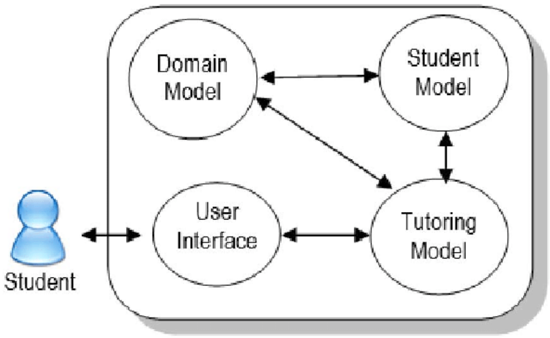
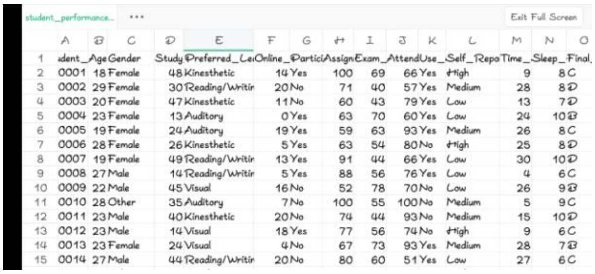


Figure 1 The conceptual architecture of ITS

4.Results and Discussion

A modern platform for analyzing and visualizing data can help predict how well students will perform by using deep learning. It connects to different data sources, helps clean and organize the data, and lets users create custom ways to track learning progress. With features like interactive dashboards, real-time updates, and alerts, teachers can easily spot trends, see which students might need extra help, and make quick decisions. These platforms also work on mobile devices, support spreadsheets, and allow users to create multi-page reports to show their findings clearly. To make accurate predictions, the system collects data over time—like quiz scores, time spent on tasks, number of attempts, and use of hints. This data is cleaned and turned into numbers so that deep learning models, like Recurrent Neural Networks (RNNs), can understand it. By using powerful hardware like GPUs and distributed computing, these models can process large amounts of data quickly and provide more accurate results, helping the system better support each student's learning needs.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7	0006	28	Female	26	Kinesthetic	5	Yes	63	54	80	No	High	25	8	D
8	0007	19	Female	49	Reading/Writir	13	Yes	91	44	66	Yes	Low	30	10	D
9	0008	27	Male	14	Reading/Writir	5	Yes	88	56	76	Yes	Low	4	6	C
10	0009	22	Male	45	Visual	16	No	52	78	70	No	Low	26	9	B
11	0010	28	Other	35	Auditory	7	No	100	55	100	No	Medium	5	9	C
12	0011	23	Male	40	Kinesthetic	20	No	74	44	93	No	Medium	15	10	D
13	0012	23	Male	14	Visual	18	Yes	77	56	74	No	High	9	6	C
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Figure 2 Analysis of student quiz performance dataset, showing demographic and behavioral attributes influencing outcomes

A multidimensional analysis of student performance, integrating both academic metrics and contextual variables. The datasets encompass demographic factors (age, gender), behavioural indicators (study hours, preferred learning style, assignment participation), and extended academic attributes such as cumulative examination scores, attendance rates, educational technology usage, and self-reported stress levels is done. It is shown in Figure 2. Additional lifestyle variables, including average daily study time and sleep duration, provide further insight into learner well-being and its influence on academic achievement.

This dataset tracks additional factors influencing student performance. It includes exam scores, attendance rate, use of educational technology, and self-reported stress levels. Time spent

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studying and sleep hours are also recorded. The data can help assess how habits and tools impact academic outcomes. It complements the earlier dataset on quizzes and assignments.

A dashboard generated for Students' performance analysis. It is depicted in Figure 3. Time spent on social media and scoring levels using appropriate diagrams. The "Student Performance Analysis Dashboard" in Power BI provides a comprehensive overview of student data, analyzing performance based on various factors such as gender, social media usage, and preferred learning styles. It highlights key metrics including a total student count of 4,999, an average social media usage of 15.02 hours per week, and a maximum exam score of 100%. Visualizations reveal that female students slightly outperform others in average exam scores, and all learning styles have the potential to reach top scores, suggesting diverse effective learning methods. Additionally, the bar chart explores the correlation between time spent on social media and exam performance, offering insights into behavioral impacts on academic success. A gender-based filter further enables targeted data exploration.

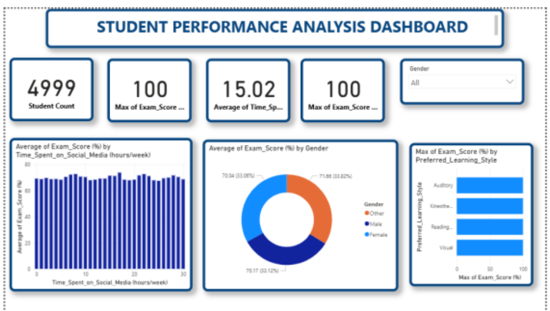

Figure 3 The dashboard showing Students' performance analysis to provide a comprehensive overview of student data

The average exam scores of students based on the number of hours they spend on social media per week is illustrated in Figure 4. It shows that students who spend a moderate amount of time (around 8–10 hours/week) on social media tend to achieve slightly higher average exam scores, typically ranging between 66% and 74%. In contrast, both very low and very high levels of social media usage are associated with marginally lower scores. While the trend is not strongly linear, the data suggests that balanced social media usage may have a positive or neutral effect on academic performance, whereas excessive or minimal usage might be slightly detrimental.

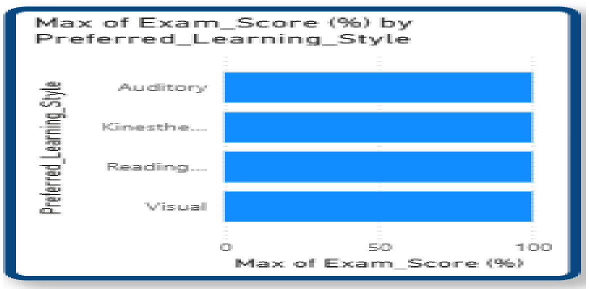

Figure 4 Average Exam scores and time spent on social media per week of students

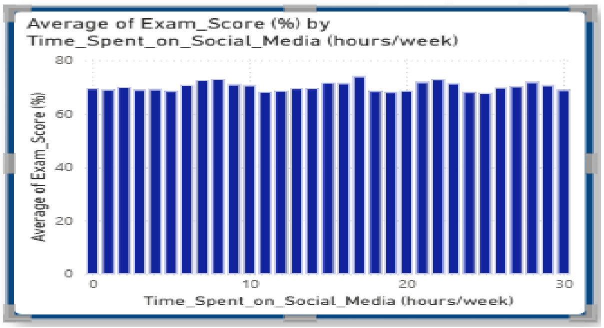

Figure 5 Maximum Exam Scores Achieved by Students Based on Their Learning Style

Students may prefer any learning styles—Auditory, Kinesthetic, Reading, and Visual. all reaching 100%. The maximum exam scores achieved by students based on their learning style is plotted in Figure 5. It highlights that students can excel regardless of their learning preference. To gain deeper insights, average scores or performance trends could be added alongside max scores.

4.1 Strategies for improvement

To enhance learning outcomes and quiz performance, students should prioritize subjects in which they face the greatest challenges, particularly those with scores below 50%, such as Digital Principles and Statistics. Reviewing foundational concepts through instructional videos and supplementary study materials is recommended. Allocating adequate time—at least 15 minutes per quiz attempt—ensures deeper engagement with each topic. Content should be divided into smaller, manageable segments and studied incrementally, employing spaced repetition techniques to strengthen long-term retention.

A goal-oriented approach to practice is essential: quizzes should be retaken after study sessions to monitor progress, with special attention given to analyzing incorrect responses to avoid recurring mistakes. Employing tools such as concise notes, flashcards, and diagrams can aid in simplifying complex concepts. When difficulties persist, seeking clarification from instructors, peers, or study groups is encouraged. Furthermore, effective time management during assessments is crucial; allocating fixed intervals for reading, analysis, and answering can help maintain focus and composure, ultimately improving performance.

5.Conclusion

In the evolving landscape of education, ITS play a crucial role in enhancing learning experiences. This paper provides a structured environment for managing, delivering, and tracking educational content, while ITS integrates artificial intelligence to offer personalized and adaptive learning. This research has provided a comprehensive examination of the key aspects related to the topic, highlighting both the strengths and areas for improvement. The findings clearly indicate that while some objectives were met successfully, others require further attention and deeper analysis.

This paper argues that the integration of AI-driven ITS platforms have the potential to revolutionize digital education by providing real-time feedback and automated assessments and tailored learning pathways. Despite the advancements, challenges such as data privacy, scalability, and accessibility remain areas of concern. Future research should prioritize enhancing system adaptability, fostering student engagement, and addressing ethical considerations in the application of artificial intelligence within education. The integration of Power BI's advanced visualization and real-time monitoring features with RNN-based predictive modeling provides educators with actionable insights, enabling data-driven decision-making and the customization of instructional strategies to meet individual learner needs. The study confirms that such an integrated approach improves student engagement, supports continuous improvement, and fosters better academic outcomes

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