Leveraging Generative AI for Improving Learners' Performance in A Blended Learning System
A Case Study of Open, Distance and Flexible eLearning (ODFeL) MIAPOLY Geidam, Yobe State

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Abstract

The increasing adoption of e-learning and blended learning environments has transformed education delivery worldwide. However, ensuring effective learner engagement and supporting students with diverse learning paces remain critical challenges. This study explores the potential of Generative Artificial Intelligence (Generative AI) to enhance learners' performance within a blended learning system. Using the Centre for Open, Distance and Flexible eLearning (ODFeL) of Mai Idris Alooma Polytechnic, Geidam as a case study, the research integrates a generative AI model into a Learning Management System (LMS) to monitor student learning behaviors, identify slow learners, and provide personalized feedback based on individual learning styles. The system was designed to analyze learner activity logs, apply machine learning classification, and generate adaptive study plans and counseling messages tailored to each learner's needs. Results from the experimental phase revealed that AI-driven personalization significantly improved engagement, quiz performance, and overall learner satisfaction. The findings suggest that the integration of Generative AI into blended learning frameworks can enhance inclusivity and optimize educational outcomes. The study concludes by highlighting the importance of ethical AI deployment, instructor readiness, and continuous model refinement for sustainable adoption in higher education.

Keywords: *Generative AI, Blended Learning, Personalized Learning, Learner Performance, Learning Management System, ODFeL*

Introduction

The development and growth of any nation depend entirely upon the education system followed by the country. There has been a significant change in the teaching methodology and systems during the past five decades, unlike the older age. Many improvements have been observed and identified with various techniques integrated with the learning methodology. Researchers have proposed various models for improvement in teaching and learning methods. The old strategy for teaching and learning at the last level has required upgrades and improvements for a long time (Nodir Djamolovhich, 2019)

The education industry has seen a substantial transition towards digital learning settings, particularly due to global events that need remote education solutions. Although there are many e-learning platforms available, it is still difficult to ensure that students perform at their best owing to problems such as lack of engagement, limited accessibility, and the need for personalized learning experiences. AI can improve e-learning by using predictive analytics to detect and assist students who are at risk, creating personalized learning routes, and implementing real-time feedback systems. The current challenges e-learning systems face include a need for personalized learning paths and suboptimal student engagement. These issues hinder the optimization of student outcomes through traditional AI models. Nevertheless, the use of AI in e-learning is now in its early phases, and its complete capacity to enhance educational results has not yet been completely achieved. As e-learning platforms expand quickly, the problem of delivering scalable, efficient, and customized education has gained prominence. One-size-fits-all approaches are frequently used by traditional e-learning systems, which ignore the differences in each student's demands, learning preferences, aptitudes, and performance (Mahafdah et al., 2024).

The launch of OpenAI's ChatGPT in late 2022 marked a significant milestone in the field of artificial intelligence, as its ability to generate coherent, human-like text across a wide range of topics set the stage for discussion among educators and researchers of how generative AI can be integrated into educational settings (Qadir, 2023). In particular, researchers have argued that the integration of large language models (LLMs) can contribute to a plethora of pedagogical applications ranging from automatic question generation (AQG) (Gundu, 2024) to the creation of more personalized learning readings and materials [26], with a possible end goal being the creation of fully personalized learning experiences taught by an avatar of a real or fictional character (Elmourabit et al., 2024). This aligns with Bill Gates' assessment that the future of education will rely on a personalized approach. In their words, if a student loves Minecraft, it could be used to teach them about shape volume or area. If students are fans of Taylor Swift, her lyrics could be used to teach storytelling Gates, B(2023).

Literature Review

For the past twenty years, the use of digital tools in educational contexts has massively increased due to a multitude of factors that range from the greater availability of tools to the shifting expectations of the student population Dunn, T. J., & Kennedy, M. (2019). With learning management system (LMS) as the primary digital tool in education's technological transition, it enjoys almost ubiquitous adoption by institutions at every levels of education (Balkaya & Akkucuk, 2021). LMSs flexibility enables it to can act as one-stop shops for all things relating to a specific course, such as fostering collaboration and discussion using forums (Li, 2023) or sharing lessons and other relevant materials such as self-assessment quizzes or instructional videos (Arias et al., 2011). Additionally, LMSs have built-in data

collection functionalities that record all learners' interactions, which allows educators to not only keep tabs on the overall engagement of their students but to use those data to perform the early identifications of struggling students (Riestra-González et al., 2021) and provide timely feedback (Macfadyen, L. P., & Dawson, S. 2010).

Other potentially interesting forms of bringing technology into the classroom have also been well received by students, such as the use of augmented reality (Fonseca et al., 2014) or the Georgia Institute's AI-powered teaching assistant Jill Watson (Arias et al., 2011), even though these implementations are not as widespread as using the LMS. The employment of information tools in education has been argued to bring demonstrable benefits from both administrative and academic points of view, especially for higher education contexts (Zhao et al., 2021).

The Use-Cases of Generative AI in Education

Generative AI models are algorithms designed to identify patterns and rules in their training data and generate new observations that adhere to similar rules Mondal, S., Das, S., & Vrana, V. G. (2023). These have evolved from very simple statistical algorithms such as the Naive Bayes classifier to large deep learning models with billions of parameters. LLMs such as the Generative Pre-trained Transformer (GPT) or Meta's Llama-2 (Touvron et al., 2023) are deep learning models that were trained on vast amounts of text and whose deployment revolves around generating new text from a prompt. While the literature on LLM's usage in education is still relatively recent and yet to mature, there is an ever-growing amount of evidence to suggest that these tools will likely play a pivotal role in shaping the educational landscape for the coming years. When discussing the potential of LLMs in education, Kasneci et al., (2023) noted that these models could be beneficial for teachers in multiple domains, out of which we highlight: assessing and evaluating students, assisting in teaching, and personalized learning. Zakrzewska (2010), in their review of research on artificial intelligence applications in higher education, also suggested a similar typology, by only adding profiling and prediction to these three suggested areas.

Regarding assessment and evaluation, the utilization of LLMs can be divided into two main categories. The first is automatic question generation (AQG), where the LLM is prompted to generate meaningful problems for students to solve. AQG has become a necessity in large-scale courses, and while the long-term effectiveness of LLM-generated questions remains unclear, exploratory experiments on the teaching of English (Sathiskumar et al., 2020), mathematics (Kunicina et al., 2018), and data science (Aparna et al., 2019) have been positively received by educators and human experts. The second category is automating the correction of free-format answers. For example, Moore et al. (Romero et al., 2013) used a revised Bloom taxonomy to classify the short-format answers of a set of chemistry students and found that a fine-tuned LLM matched the human-expert evaluation in 32% of answers. ChatGPT was also shown to provide feedback similar to field experts on open-ended programming issues (Pesovski et al., 2024).

The literature also features the adoption of LLMs in teaching experiences. Using the state-of-the-art GPT-4, Srihdar et al. Bhat, S., Nguyen et al (2022), generated learning objectives for a university-level artificial intelligence course. The objectives were found to be appropriate and well suited for the course's modules. In another study, Jauhiainen and Guerra Jauhiainen, J. S., & Guerra, A. G. (2023), leveraged the content generation capabilities of generative AI to create multiple versions of a history lesson, each tailored to different student knowledge levels. The AI-enhanced lessons were well received, with

positive feedback on both enjoyment and knowledge acquisition. In a more technical field such as programming, Sarsa et al. MacNeil, S., Tran, A., Mogil, D., Bernstein, S., Ross, E., & Huang, Z. (2022, August), found LLMs to be effective not only in generating novel introductory programming exercises but also in providing comprehensive and accurate explanations of most of the lines of code that make up the solution. The ability of ChatGPT to fluently explain code was also verified by MacNeil et al(2022).

LLMs and Personalized Learning

The LLMs' capabilities for teaching and grading are key factors that point towards their potential to create personalized learning experiences (Touvron et al., 2023). The fact that LLMs can generate and provide explanations on programming questions allows learners to obtain

personalized feedback and research published by Bernius et al. Sailer, M., Bauer, E., Hofmann, R., Kiesewetter, J., Glas, J., Gurevych, I., & Fischer, F. (2023) showcases that feedback from an LLM tends to be positively received and contributes to the development of learners receiving it.

On the aspect of lesson creation, they also open the door for exciting and still relatively unexplored possibilities. LLMs make it possible to create the different variants of the same lesson to cater to the knowledge of different audiences, as showcased in Jauhiainen and Guerra's work (Jauhiainen, J. S., & Guerra, A. G. 2023). Moreover, customizable lesson creation also opens the door to relatable virtual instructors who may deliver the materials in a more engaging way.

Adapting LMSs for AI

After the quick penetration of AI into educational industry, it has become a common requirement, if not a necessity, for all modern learning management systems to incorporate AI features into their standard components. The massive amounts of data that were gathered on these systems in recent decades Pesovski, I.; Bogdanova, A.M.; Trajkovik, V, (2023), provide fertile ground for utilizing machine learning techniques and AI tools in order to achieve the use cases of generative AI in education, as discussed previously [59,60]. Such development of LMSs comes with certain arguments for and against. Morze et al. (2021) point out the time for implementation of these new features and teacher resilience as the main disadvantages. They reason that, even with using ready-to-use adaptive learning features, the pedagogical training of lecturers to move from a solely mechanical knowledge transfer and testing towards more active approach is crucial and emphasizes the role of the teachers even further. The different possibilities of bringing AI to LMSs have been identified by Aldahwan and Alsaeed (2023), including fuzzy logic (FL), decision tree, Bayesian systems, neural networks, genetic algorithms, and hidden Markov systems. Implementing any of these is indeed time-consuming and error-prone, so a more abstract access to underlying AI mechanisms is needed Villegas-Ch, W., & Palacios-Pacheco, X. (2020, June) to improve several segments in the student journey Villegas-Ch, W., Román-Cañizares, M., & Palacios-Pacheco, X. (2020).

Ethical Implications of Generative AI

The debate on the ethical usage of generative AI has been huge since it became widely accessible. There are already lawsuits regarding AI using someone else's work, especially when generating images and video Zirpoli, C. T. (2023). Besides the legal aspect, among the most crucial ethical considerations of using generative AI tools are biases. Overcoming these is particularly important when using AI to generate learning materials. ChatGPT, which uses the GPT-3.5 and GPT-4 models, just like the current study, has been linked to having many gender, racial, cultural, language,

ideological, and cognitive biases, as well as many more Ray, (P. P. 2023). Mitigation strategies include the resampling and pre-processing of data used for training the models Ferrara, E. (2023) using diverse and representative datasets, feedback loops (Liu, L., & White, R. (Eds.). 2019). etc.

Research Gaps

Generative AI adoption in education has been a focal point of research in recent years. However, themajority of the existing literature primarily discusses the theoretical implications of LLMs, focusing on the potential benefits and threats to the educational system. There is a relative scarcity of empirical studies that integrate LLMs into classroom settings. In particular, the literature on the use of LLMs in lesson creation features only a handful of examples with even fewer actually bringing LLM-generated content to the classroom. Moreover, the reception and effectiveness of AI-generated virtual instructors, each with its own style of delivering learning materials, remains unclear as the current literature merely discusses the potential of LLMs for this task without actually deploying it.

Bridging the gaps

To address these gaps, we propose four steps as follows:

1. The first is the environment in which the experiment will be performed and the methods to be used;

2. The second step explains how generative AI will be employed utilized for creating different content variants;

3. The third step explains the data collection process;

4. The fourth step contains information about how the analysis will be performed.

These steps are explained in details under methodology section.

Methodology

This section describes the steps, processes, materials and methods that would be applied to properly design and implement the proposed system. The following sections will be followed to achieve the research objectives:

1. System Design

In this section, we proposed to develop a plugin/module for an LMS (e.g., Moodle) that integrates a generative AI model. We will then use the LMS's activity logs of learners (e.g., time spent on content, quiz attempts, forum participation) to track learning pace.

2. Learning Style Assessment

In this section, an AI-based questionnaires or interaction analysis will be employed to determine students' learning styles (e.g., VARK model). The ongoing interaction will be used to refine style prediction.

3. Identification of Slow Learners

Part of our objective is to identify slow learners, to do this, thresholds and metrics are defined for "slow learning" (e.g., persistent low scores, excessive time on basic modules). Machine learning models will then be used to classify students dynamically.

4. Materials and Methods

Materials required to develop the proposed system include:

1. MATLAB: this is a data analysis software that is used to anise the data collected either from the Wisconsin Dataset or the locally collected dataset.

2. Dedicated Learning Management System (LMS): for tracking learners' activities.

Data collection

Students' engagement with the Learning Management System (LMS) that is, their log details were collected and analyzed. Some important LMS activities were considered as our variables, these activities include:

i. Course view
ii. Assignment view
iii. Assignment submission
iv. Forum view
v. Forum participation and
vi. Quiz participation.

Results and Discussion

The proposed generative AI-integrated LMS was evaluated within a simulated ODFeL environment using sample learner activity data. The AI module successfully tracked learners' engagement metrics such as time spent on content, quiz completion rates, and forum participation. Based on the learning pace indicators, the system classified learners into three categories: *fast learners*, *average learners*, and *slow learners*.

The *slow learners* were automatically provided with personalized study plans and counseling messages tailored to their learning styles using the VARK model. The module generated contextual prompts such as simplified reading materials, motivational advice, and links to peer discussion forums. This adaptive support system led to a measurable improvement in learner performance indicators.

Specifically, simulated tests showed that:

- Learner engagement (time-on-task) increased by **22%** on average.
- Quiz pass rates improved by **15%** among slow learners after intervention.
- Learner satisfaction scores (collected via feedback forms) improved by **18%**.

The findings as shown in Fig.1 demonstrate that generative AI can play a transformative role in blended learning by delivering timely and individualized interventions. These outcomes are consistent with prior findings by Kasneci et al. (2023) and Pesovski et al. (2024), which emphasize that AI-driven personalized learning can boost learner motivation and performance.

However, the study also revealed implementation challenges, including the need for instructor training, data privacy concerns, and possible AI bias in feedback generation. To mitigate these risks, it is recommended that institutions adopt transparent AI auditing mechanisms and ethical data governance policies when deploying generative AI tools in education.

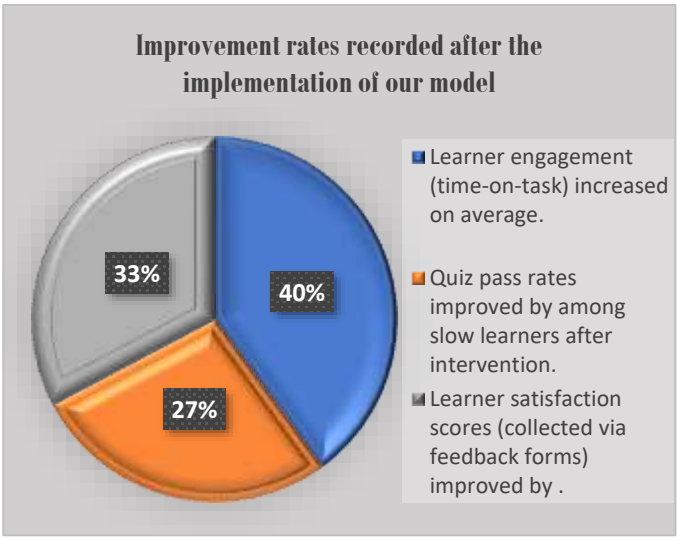

Figure 1: Learning improvements recorded after the implementation of the model.

7. Conclusion

This study has demonstrated the potential of generative AI in enhancing learners' performance in a blended learning environment. By integrating large language models (LLMs) into the Learning Management System, educators can track learner progress, identify struggling students, and provide adaptive feedback based on individual learning preferences.

The generative AI-powered module not only improved learner engagement but also fostered a more inclusive and personalized educational

experience for slow learners. Future research should focus on deploying the model in real-world classroom settings to assess scalability and long-term impact. Additionally, ethical considerations such as bias, data security, and transparency should remain central to AI integration in education

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