

Neural Network-Based Adaptive Learning Framework for Personalized Education in Higher Learning Environments

Nidhi Tiwari , Ritu Kadyan

Department of Computer Science and Engineering, GITAM, Kablana, Jhajar

Abstract - The idea and approach behind traditional schooling mainly follows teaching and learning that does not consider the great diversity in students learning rates, prior learning, learning styles, motivation or interest. The recent developments in Artificial Intelligence (AI), Deep Learning and Generative AI have facilitated the implementation of advanced Educational Data Mining (EDM) and student performance prediction systems, although most of these are still in a diagnostic mode of operation. This paper presents an Adaptive Learning Framework that analyse and models the connection in learner specific behavioural and academic patterns hence provides personalized learning interventions in real time. The core behind this framework is strengthened by a Neural Network (NN) model which learns from the behavioural pattern, engagement and academic data of a learner to combine parameters with a neural network architecture to classify different learner types including an adaptive recommendation mechanism and an explainable AI layer to ensure transparency and trust. The model continuously integrates understanding based on each student's parameters and uses its performance evaluation as new information from interactions with them, allowing it to identify significant changes earlier than traditional measurement tools. The model is a continuous real-time learning capability, differs from the existing EDM system which mostly analyse data after the learning outcomes have been decided. This model detects and plots patterns in behaviour and learning for keen analysis as they develop and provide the analytical support for the framework's individual intervention mechanisms. This paper sketches the basic conceptual architecture, proposed methodology and potential contributions, making this framework a move from predictive analytics to proactive.

Keywords - Adaptive learning, neural networks, personalized education, explainable AI, educational data mining, student engagement.

I. INTRODUCTION

The traditional academic system normally adopts a common teaching method and it is implicit that all learners learn and process information in a similar way. Students differs highly in both their learning rate and prior knowledge, as well as factors like their cognitive preferences, motivation, and modes of engagement. All these differences can lead to variation in learning experiences and may lead to a discouragement of other

capable learners who are unable to adjust themselves in the traditional way of teaching. Increased opportunities in the field of Artificial

Intelligence, Deep Learning and Generative AI have allowed to create intelligent educational systems that can understand the behaviour of a learner and offer personalized support. Although significant advances have been made in the field of educational data mining and student performance prediction, most of the current systems are limited to predicting student performance and not directly intervening to enhance the learning process for individual students. This particular gap is notable and inspires the current study that attempts to move beyond prediction to adaptive, personalized intervention.

II. LITERATURE REVIEW

This traditional academic system adopts a uniform approach and expects of students to acquire knowledge at the same rate, in spite of significant differences in prior knowledge, cognitive preferences, motivation and engagement. This is a well-documented difficulty in learning, particularly at the higher education level where diversity among learners is the highest. Over the last 10 years, adaptive learning has become a learning paradigm inspired by the creation and use of adaptive learning technologies that adapt content and pacing to the individual rather than static curricula. Naseer et al. did a controlled study on four courses in the university with 300 students from Pakistan, and developed customized learning path based on deep learning. They found that their AI driven adaptive platform had improved students grade, test scores and engagement by 25% versus traditional instruction ($p = 0.00045$).

Most modern adaptive learning systems are based on neural networks which are computational structures that mimic the biological neural networks in the human brain and can identify complex patterns in data. It introduced a Personalized Learning Planning System (PLPS) which consists of two-levels: Master Learning Path (MLP) providing a long-term planning structure as prompted by the goals and prerequisite structures, and Personalized Learning Planner (PLP) providing a real-time

planning structure based on the performance that evolves. The double-layered structure is designed to address an important drawback of previous systems, that were able to plan, but not adapt. The PLP layer constantly monitors and adapts to the learner's strengths and weaknesses, as well as the difficulty, scheduling and resources, to prevent overloading while keeping the challenge relevant. The combination of Constraint Satisfaction Problem (CSP) methods and Graph Neural Networks (GNNs) further enhances the system's ability to model task dependencies, respecting prerequisites and avoiding overtaxing the cognitive domains.

Neural networks were identified as the key algorithm in digital education, and the most commonly used algorithms were artificial neural networks and support vector machines, according to Munir et al.'s systematic review of AI/ML approaches in digital education, which identified how neural networks are important in the fields of intelligent tutoring, dropout prediction, performance forecasting, and adaptive learning. Researchers determined that deep learning models, especially RNNs and attention-based models, exhibit high predictive power on clickstream data, assessment results and engagement metrics. This validates that neural networks are not just one way of computation but the most influential one used for educational personalization today, as they are capable of processing high dimensional sequential learner data.

In order to effectively personalize, one must not only know what students know but how students' brains process information subject to different cognitive demands. The research and systematic review by Gkintoni et al. (2023) looked at the field-specific convergence of Cognitive Load Theory (CLT), Educational Neuroscience, and AI-based adaptive learning, drawing conclusions from 103 papers. They discovered that deep learning models such as CNN, RNNs and SVMs are able to significantly enhance the efficiency of learning by automatically controlling cognitive load, customizing learning instruction, and dynamically adjusting the learning trajectories based on the real-time neurophysiological information. EEG, functional near-infrared spectroscopy (fNIRS), and other neurophysiological tools were identified as methods to measure cognitive states to facilitate dynamic interventions with AI. The use of multiple modalities, such as EEG and fMRI and ECG and Galvanic skin response (GSR), was determined to enhance robustness of the system by minimizing signal variation and noise. From predicting to "proactive intervention. A recurring theme can be considered as the comparison gap between a prediction system and an intervention theme. Despite the progress made in the field of educational data mining and prediction of student performance, most systems are diagnostic, determining at-risk students but not modifying the educational trajectory, wrote Naseer et al. To fill this gap, Kopylchak et al. developed a system capable of predicting the needs of learners

and adapting the delivery, timing and resources of the content. Similarly, Munir et al. noted that reinforcement learning can be used to implement dynamic content sequencing that promotes learner autonomy, as opposed to static prediction, towards systems that learn from their interactions with the students. This paper proposes a framework which extends this, including an adaptive recommendation mechanism that adapts to current learner information, providing effective and timely interventions at the right time and place.

Explainability, Trust and Ethical issues. The importance of the explainability and trustworthiness of AI's recommendations increases as it becomes more and more involved in instructional decisions. A chief constraint to the effective implementation of AI-based adaptive learning, identified by Gkintoni et al., is data privacy. One of the primary challenges highlighted by Gkintoni et al. for effective implementation of AI-based adaptive learning is data privacy. Kopylchak et al. highlighted that transparency of the way a neural network model is used for recommending a model statement is essential, as sometimes even predictions that are right may still be rejected by teachers and students because they lack understanding of the reasoning. This issue is a central one in the present work, in which an explainable AI (XAI) layer is integrated on top of the model by means of methods that illustrate the factors behind each of the recommendations, such as the SHAP (SHapley Additive exPlanations) and attention-weighted visualization.

While this is the case, there are still some gaps that need to be addressed and the proposed framework is a solution for those gaps. Most of the existing systems pay attention to one of the two only, prediction or adaptation, but do not combine both of them in a unified real-time system. Secondly, although neural networks are found to be an effective model for learner data, few studies integrate behaviour, academic, and engagement data in the same model and architecture that can also classify learner types and provide tailored interventions. Third, in the field of AL in HE, explainability is a topic that is under-explored, yet which has become increasingly recognized as key for adoption. This paper seeks to address these gaps by proposing a Neural Network Based Adaptive Learning Framework (NNBLF) that merges predictive modelling, real-time adaptation and explainable AI into a unified framework to move educational analytics from a diagnostic role to a proactive, interventionist one.

III. RESEARCH OBJECTIVES

1. This study aims to achieve the following five objectives:
2. To find patterns at the learner level: to discover hidden patterns in the learner's academic work, behaviour and engagement that are unique to the individual learner and not usually identified when analysing these.

3. To design a neural network model: to construct a model that is able to really capture individual learning characteristics instead of treating the student as a data point.
4. To build an adaptive recommender system: building a system which creates a customised learning path for each student according to the student's needs.
5. To assess the effectiveness of AI-driven personalization: to compare the effectiveness of AI-driven personalized learning against one-size-fits-all approaches to learning.
6. Investigate explainability and trust: Discuss the effectiveness of AI generated recommendations, as well as their understandability and trustworthiness for educators and students.

IV. RELATED WORK

Over the last decade, the field of educational data mining has come a long way. Researchers have developed a vast body of work on classification and regression models to predict student performance, to predict retention and to identify potential student dropouts. In this context, architectures based on neural networks, particularly recurrent and attention-based, have shown, time and time again, high predictive accuracy on clickstream data, assessment scores and engagement metrics. In addition to these data driven methods, there have been more structured approaches that rely on rule-based systems and Bayesian techniques in the sequencing of learning content based on a student's actual knowledge.

Much of this work shares a common failing, though: the systems are designed to make a diagnosis, but they don't take action. They are good at forecasting what will happen to a student; they don't go so far as to actually change the path as the student's profile evolves over time. But there is an increasing mistrust issue too. With the increasing involvement of AI systems in decision making for teaching and learning, the issue of explainability of the AI's recommendations becomes more critical and begins to be more visible, as the AI may be accurate yet fail to be accepted by teachers and students because its justification is unclear or mysterious [4]. This paper continues both strands adaptive personalisation and explainable AI and draws them together in one, one that does not only predict, but intervenes, and that does not only intervene, but explains itself while doing so.

V. HYPOTHESES

H1: AI-powered learning interventions are more effective than traditional teaching methods by providing personalized learning experiences that lead to better student outcomes.

H2: We can reliably identify learner-specific (behavioural) patterns using neural network models, and these patterns have a strong association with a student's academic achievement and engagement.

H3: With the help of AI systems, adaptive learning pathways foster student motivation and higher persistence in learning.

H4: Recommendations generated by explainable AI mechanisms are seen to be more trustworthy by the learner and the instructor than those that are not generated through explainable AI mechanisms.

H5: Students who receive AI-designed learning support have lower levels of academic disengagement than students who receive traditional learning support.

VI. PROPOSED METHODOLOGY

A. Research Design

The study uses a mixed-methods, quasi-experimental design with quantitative modelling of students' data and a comparative analysis between two groups: the experimental group using AI-based personalized learning and the control group using traditional, non-adaptive teaching methods. In this design, the study can detect both statistical trends (across learner data) and real-world trends (with respect to differences in outcome between the two approaches to learning).

B. Data Collection

Three complementary sources will be used to collect data to provide a comprehensive picture of each learner. The first is academic records grades, assessment scores and historical performance data to provide a baseline understanding of each student's trajectory. The second is behavioural and engagement data directly from the Learning Management System (LMS), which records student interactions with learning materials over time. The third source is self-reported data, which is measured by pre- and post-motivation and engagement surveys, providing the subjective as well as objective data.

C. Proposed Neural Network Architecture

Its architecture is based on a two-tiered neural network. In the first stage, a feature learning network (FLN), which can be a multilayer perceptron or LSTM, depending on whether the data is sequential or not, builds academic and behavioural features into a set of latent learner profiles. The profiles are essentially a reduction of the learner's strengths, patterns and needs. The second phase involves a recommendation layer that matches the suggested learning pathways to the learner's profile, aligning the learning content to the learner's changing profile. An explainability module is placed on top of this recommendation

output, which relies on explainability techniques such as SHAP or attention-weighted visualization, and reveals the rationale behind each recommendation and highlights the specific reasons that led to it, addressing the trust and transparency concerns raised earlier in this literature.

D. Evaluation Plan

Pre and post tests will be used to assess differences between the experimental and control groups in learning outcomes, motivation and disengagement on a set of appropriate statistical tests (paired t-tests or ANCOVA) for the purpose of testing Hypotheses H1, H3, and H5. Standard model performance metrics, namely accuracy and the F1-score, will be used to evaluate the accuracy of the neural network in recognizing true behavioral patterns on a different subset of the learner's data, not used to train the model, to evaluate hypothesis H2. Lastly, in order to test H4, the study will compare the trust ratings that were given by the students and instructors that have been exposed to an explainable recommendation output with the trust ratings that were given by the students and instructors that were exposed to a non-explainable recommendation output, thus enabling direct assessment of whether or not explainability has a positive effect on perceived trustworthiness.

VII. EXPECTED CONTRIBUTION

This research aims at going beyond the traditional diagnostic approach to the prediction of student performance and toward the development of intelligent educational systems that will be able to truly adapt instruction to the individual student. The proposed framework is not just to alert teachers to students who may be having trouble learning and may need support, but to use that information to take action to be able to find out about learning difficulties early, before they become bigger academic problems. It also strives at the same time to provide students with learning support that meets their needs rather than a generic instructional path that is applied equally to a whole class.

An important aspect of this contribution is the explainability layer embedded in the framework. Making the logic behind how AI makes recommendations transparent and explainable helps establish trust between teachers and students, as well as between AI and humans. That's important because, as alluded to above in the literature, even if a recommendation is technically accurate, it is likely to be rejected if the rationale behind it is unclear. The design takes this issue head-on, and could help to improve the uptake of this system in actual higher education environments, where trust is a key factor in making adoption decisions.

VIII. CONCLUSION

The literature review has highlighted the significant gap between predictive educational analytics and the provision of active personalized teaching interventions, so this paper has

proposed a Neural Network Based Adaptive Learning Framework to help bridge that divide. The proposed framework's integration of behavioural and academic data modelling, an adaptive recommendation mechanism, and an explainable AI layer within a unified architecture opens the door to enhancing learning experiences in higher education by promoting equitable access and improving outcomes for learners who are underserved by traditional, one-size-fits-all teaching methods.

Empirical validation is next step for this work in the future. The five hypotheses proposed in this paper will be evaluated by conducting a pilot study in a classroom in a real higher-education setting with real learners, real data, and real outcomes of instruction. This pilot study will provide the groundwork for the further development of the model, the recommendation process and the explainability of the model.

REFERENCES

- [1] R. S. Baker and P. S. Inventado, "Educational data mining and learning analytics," in *Learning Analytics*, Springer, 2014, pp. 61–75.
- [2] X. Chen, H. Xie, and G. J. Hwang, "A multi-perspective study on artificial intelligence in education," *Computers and Education: Artificial Intelligence*, vol. 1, p. 100005, 2020.
- [3] T. Kabudi, I. Pappas, and D. H. Olsen, "AI-enabled adaptive learning systems: A systematic mapping of the literature," *Computers and Education: Artificial Intelligence*, vol. 2, p. 100017, 2021.
- [4] F. Doshi-Velez and B. Kim, "Towards a rigorous science of interpretable machine learning," *arXiv preprint arXiv:1702.08608*, 2017.
- [5] C. Romero and S. Ventura, "Educational data mining and learning analytics: An updated survey," *WIREs Data Mining and Knowledge Discovery*, vol. 10, no. 3, e1355, 2020.
- [6] F. Naseer, M. N. Khan, M. Tahir, A. Addas, and S. M. H. Aejaaz, "Integrating deep learning techniques for personalized learning pathways in higher education," *Heliyon*, vol. 10, no. 11, e32628, 2024.
- [7] H. Munir, B. Vogel, and A. Jacobsson, "Artificial intelligence and machine learning approaches in digital education: A systematic revision," *Information*, vol. 13, no. 4, p. 203, 2022.
- [8] E. Gkintoni, H. Antonopoulou, A. Sortwell, and C. Halkiopoulos, "Challenging cognitive load theory: The role of educational neuroscience and artificial intelligence in redefining learning efficacy," *Brain Sciences*, vol. 15, no. 2, p. 203, 2025.