ENHANCING STUDENT ENGAGEMENT IN AI EDUCATION THROUGH INTEGRATING VISUALISATION TOOLS IN BLENDED LEARNING

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Deep Neural Networks have found numerous complex applications across various domains, including intelligent robots, autonomous systems, advanced manufacturing, computer vision, natural language processing, and other engineering and scientific fields. These technologies have been increasingly incorporated into higher education curricula and are being taught extensively to learners. However, the inherent "black box" nature of deep neural networks lacks transparency making it difficult to comprehend their inner workings, therefore hindering the learning process and the effective application of these AI techniques in real-world scenarios. To address these challenges, there is a growing demand for explainable AI using visualisation tools and techniques that can enhance educational experience by making deep learning concepts more accessible and understandable. These tools have the potential to demystify the complex processes within neural networks, thereby fostering a deeper understanding and trust in the models' predictive ability and behaviours.

This paper investigates how AI visualisation tools integrated within a blended learning framework can enhance student engagement in teaching AI. We introduced visualisation tools such as TensorFlow Playground, exploRNN, along with explainable AI (XAI) techniques like Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP), to enhance the comprehension of deep learning models such as Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks. The interactive features of the AI visualisation tool, along with explainable AI (XAI) techniques, allow learners to explore the internal patterns of black-box models and help them understand how these models make decisions.

A survey, involving over 30 students, was conducted to gather feedback on the AI lessons, which spanned a duration of 15 hours. The survey included both qualitative and quantitative questions to evaluate the students' experiences across multiple dimensions, such as overall learning experience, lab session interactivity, the effectiveness of pre-class videos, and engagement in classroom discussions. The findings indicate preference among students for the blended learning model, particularly valuing the interactive, hands-on components such as lab sessions that employ AI visualisation tools. These responses highlight the effectiveness of XAI and visualisation tools in enhancing engagement and fostering a deeper understanding of complex AI concepts. The result emphasizes the benefits of integrating interactive visualisation tools within a blended learning environment for AI education. Future research will focus on implementing an integrated AI visualisation toolbox and investigate the long-term impact of the toolbox on student engagement and the retention of deep learning concepts.

Keywords: *Deep Learning, Explainable AI (XAI), Visualisation, Blended Learning*

1. Introduction

Artificial Intelligence (AI), particularly deep neural networks (DNNs) has found widespread application in diverse fields such as computer vision, robotics, autonomous vehicles, and other scientific disciplines. The underlying technologies and applications of DNNs have been integrated into higher education curricula and are now extensively taught to students across various engineering and computer science disciplines. This broad inclusion aims to equip learners with the necessary skills and knowledge to navigate and contribute to the rapidly evolving field of AI. However, the applications of deep learning to solve real-world problems necessitates strong technical skills, including proficiency in a programming language. Learners new to this field, with limited or no technical background in neural networks, tend to be overwhelmed when grappling with the foundational aspects of AI. Furthermore, the "black box" nature of DNNs present a significant hinderance for educators seeking to foster meaningful understanding among learners, preventing the latter from confidently explaining, trusting and applying deep learning techniques to solve real-world problems.

In recent years, the research community has placed increasing emphasis on AI visualisation, recognizing its pivotal role in enhancing the comprehension of complex deep learning concepts. Such tools have become indispensable for demystifying AI model behaviour and facilitating deeper insights into their underlying mechanisms. For example, TensorFlow Playground (Smilkov et al., 2017) provides an interactive interface that enables users to manipulate neural network parameters directly—without requiring programming expertise—thereby accelerating the development of intuition regarding network architectures, loss functions, and learning dynamics. Similarly, GAN Lab offers a specialized environment for non-experts to explore generative adversarial networks (GANs), a sophisticated class of deep learning models. Through a hands-on, intuitive approach, learners can interactively train the models while visualizing real-time training processes, bridging the gap between theoretical principles and practical understanding (Kahng et al., 2019). Nevertheless, while these tools provide powerful visuals, they do not explain the underlying decision-making process of these complex AI systems. For effective real-world application, students must develop not only procedural knowledge of DNN operations but also comprehend and validate system decisions—a critical requirement for establishing trust in AI outputs. XAI techniques, specifically, LIME (Ribeiro et al., 2016) and the SHAP (Lundberg & Lee, 2017) are effective resources for exploring deep learning and presenting the decision process of complex black-box models in a more understandable way to the learners.

In this paper, we propose a blended-learning framework that integrates interactive AI visualisation tools and XAI programming methods to facilitate the learning of foundational AI concepts among AI learners. This integrated framework aims to advance deep learning pedagogy by combining theoretical instruction with experiential learning. Our pedagogical framework integrates a tripartite structure comprising: (1) preparatory video lectures for foundational knowledge acquisition, (2) collaborative in-class discussions to reinforce conceptual understanding, and (3) class activity such as hands-on laboratory (lab) sessions utilizing interactive visualisation tools. The interactive lab components (e.g., TensorFlow Playground, GAN Lab) provide an experimental sandbox environment where learners can directly manipulate core neural network hyperparameters—including learning rates, activation functions, and optimization settings—while visualizing real-time impacts on model behaviour. This hands-on approach is augmented with XAI programming techniques to illuminate the models' decision-making process, thereby demystifying the traditionally "black-box" characteristic of deep learning systems. Our pedagogical framework demonstrates measurable improvements in learner engagement when mastering complex deep learning concepts. The remainder of this paper is organized as follows: Section 2 reviews related work in AI education tools and explainable deep learning pedagogies. Section 3 details our blended learning framework, including its instructional design and technical implementation. Section 4 presents the experimental methodologies, including participant selection, control/intervention group design, and the validated survey questions used to measure student engagement in learning AI. Section 5 provides a comprehensive analysis of the results, comparing quantitative findings with qualitative insights from student feedback. Finally, Section 6 concludes with contributions, limitations, and future research directions in AI education.

2. Related Work

Recent advances in AI education research have established visualisation tools as essential pedagogical instruments for cultivating both conceptual understanding and learner engagement. These studies demonstrate how interactive visual representations significantly enhance cognitive engagement by making abstract algorithmic processes more accessible and intuitively understandable. Naps et. al (2003) explored the role of visualisation and engagement in computer science education, posited that visualisation medium, regardless of its design quality, holds minimal educational value unless it is integrated into an active learning activity. The authors argued that for visualisation to have a significant impact, two key components must work in tandem: the enhancement of learning with visualisation and the successful integration of the visualisation tools in the classroom. Alicioglu and Sun (2022) empirically validated the pedagogical value of visualisation techniques such as XAI for enhancing comprehension of machine learning models. Their research demonstrated that visual explanations significantly improve model interpretability by presenting complex algorithmic behaviours and prediction rationales in more accessible formats. Furthermore, the study conducted a comparative analysis of student engagement patterns, revealing a strong preference for blended learning approaches that incorporate visualisation tools over traditional lecture-based instruction in deep learning curricula. Schultze et al. (2020) established that visualisation-based learning applications reduce the cognitive barriers to deep learning. Their research argued that such tools enable novice learners to develop conceptual understanding of model behaviours and architectural principles prior to attaining programming proficiency, thereby creating a more accessible entry point to the field.

3. Blended Learning Framework

We developed a tripartite blended learning framework comprising:

(1) Asynchronous video lectures establishing theoretical foundations,

(2) Synchronous in-class group discussions to deepen conceptual engagement, and

(3) Class activity such as lab sessions featuring guided experimentation.

This scaffolded approach progresses from knowledge acquisition to applied practice, enabling learners to systematically transition from passive reception to active learners of deep learning systems. A sample learning plan is shown in Table 1 below.

Table 1: Sample Learning Plan for Week 6 and week 7

Week (L/T/P)	Topic	Pre-class	In-class activity and group discussion	Closing/Post-Class	Remarks
6	Deep Learning Methods	30 mins: A. Task: Watch curated videos + guided reading. 1. Gen AI/CNN Video: Google Cloud Tech. (2023, September 12). *What is generative AI?* [Video]. YouTube. https://youtu.be/xA5Hrn2DNbk 2. StatQuest with Josh Starmer. (2021, July 10). *RNN and LSTM explained* [Video]. YouTube. https://youtu.be/hZVblg1h4xM B. Please experiment with 1. TensorFlow Playground. (2023). *Interactive deep learning tool*. https://playground.tensorflow.org 2. exploRNN Team. (2022). *exploRNN: Interactive visualisation tool for recurrent neural networks*. exploRNN. https://explornn.github.io	50 mins: 1. Discuss the advanced features of Deep Neural Networks, such as CNN 2. What are the shortcomings of a RNN? 3. How does LSTM overcome these shortcomings? 10 mins: Break 50 mins: 1. Familiarization with exploRNN at https://papersubmissions42.github.io/exploRNN/ 2. Experiment with sequential input and non-sequential output (many-to-one), such as next element prediction. Tasks with sequential input and sequential output (many-to-many), such as translation. As well as tasks with non-sequential input and sequential output (one-to-many), such as image captioning.	30 mins: 1. Groups discuss and submit answers for ALL questions in the Separate worksheet given. 2. Groups present answers for 3 selected interesting points to the class.	Tutors: Review of deep learning methods, review questions, attendance sheet, spend a few minutes answering questions and clarifying misconceptions. Students: Work on the separate worksheet given Tutors: Interacts with an open Inquiry question in small groups or help clarify concepts.
7	CNN, XAI (LIME, SHAP)	30 mins Task: Watch curated videos + guided reading. Resources: Video 1: "Introduction to LIME for Explainable AI" (StatQuest LIME tutorial) Video 2: "SHAP Values for Model Interpretability" (SHAP library demo)	50 mins: 1.How do LIME and SHAP approximate model behavior differently? 2.What are the limitations of these methods for CNNs? 3.Why is interpretability critical in real-world AI applications? 10 mins: Break 50 mins: Hands-on XAI Visualisation with CNNs Tools: Python notebooks with pre-trained CNN (e.g., ResNet) + LIME or SHAP. Dataset: CIFAR-10 or MNIST for simplicity.	30 mins: 1. Groups discuss and submit answers for ALL questions in the Separate worksheet given. 2. Groups present answers for 3 selected interesting points to the class.	Tutors: Review of last week's lesson, review questions, attendance sheet, spend a few minutes answering questions and clarifying misconceptions. Students: Work on the separate worksheet given Tutors: Interacts with an open Inquiry question in small groups or help clarify concepts.

4. Methodology

This study is a collaborative initiative between Nanyang Polytechnic (NYP) and the University of Glasgow (UofG) to facilitate education research. By integrating pedagogical frameworks and resources from both institutions, this partnership enables the examination of student engagement in AI education leveraging two complementary academic modules. The first module, *Intelligent Services Implementation*, is offered as part of a Specialist Diploma program at NYP, while the second, *Machine Learning*, is an undergraduate subject within the Computing Science degree program jointly administered by UofG and the Singapore Institute of Technology.

Firstly, visualisation tools, like Tensorflow Playground, explorRNN and XAI techniques like LIME and SHAP, were integrated into a blended learning environment. This implementation followed a structured pedagogical framework as operationalized in our sample learning plan (see Table 1) where the tools were strategically deployed to facilitate active learning and promote deeper engagement with AI concepts in different ways (e.g. hands-on, discussion, and presentation). Secondly, a quasi-experimental comparative design was implemented to systematically evaluate differences in learning engagement compared with traditional lecture-based instruction. Finally, following the instructional interventions, a structured survey was administered to assess students' perceived engagement and satisfaction with each pedagogical approach. We adopted a mixed-methods approach, integrating both quantitative and qualitative analyses to triangulate findings and enhance validity. The survey utilized a 5-point Likert scale survey (1 = Strongly Disagree to 5 = Strongly Agree) to assess key dimensions of the learning experience, while parallel qualitative data were collected through open-ended survey responses. We then analysed the performance metrics - including mean satisfaction scores. To assess statistical significance, we used independent samples t-tests compared mean satisfaction scores between the instructional approaches. Survey open-ended responses were thematically coded to identify patterns in student experiences, challenges, and preferences. Finally, we use a repeated-measures design method where the cohort size, N=34, was exposed to both approaches with the schedule as shown in Table 2.

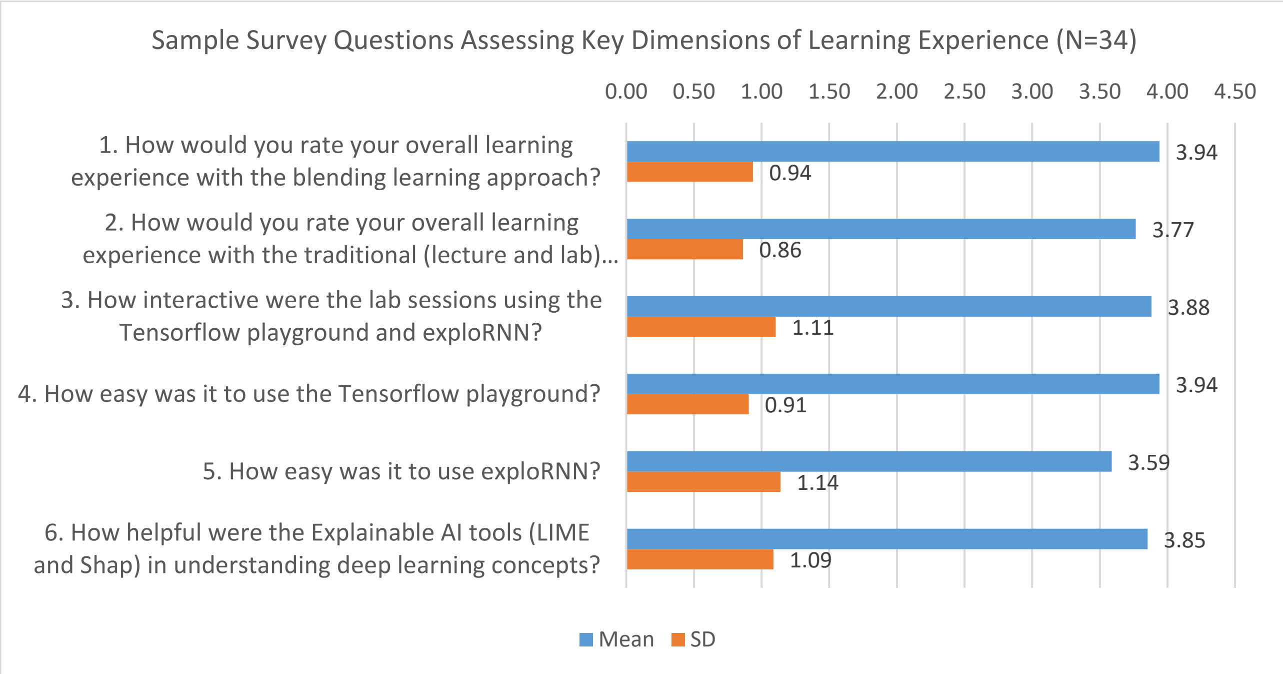
Table 2: Repeated-Measures Design

Group	Instructions	Week
Control Group	Traditional lecture-based instruction and labs (no AI tools or interactive components)	Phase 1 (Week 1-5)
Intervention Group	Blended learning with AI visualisation tools (video lectures, interactive labs, and discussion sessions)	Phase 2 (Week 6 – 10)

5. Survey Results and Discussion

Table 3 presents the aggregated Likert-scale responses (N=34) for each quantitative survey item, comparing student perceptions across several key dimensions of the learning experience.

Table 3: Sample Survey Questions Assessing Key Dimensions of the Student's Learning Experience



A. Overall Learning Engagement with Blended Learning versus Traditional Learning

From the responses to survey item 1, quantitative analysis revealed a preference for the AI-enhanced blended learning approach ($M=3.90$, $SD=0.94$) over traditional instruction ($M=3.79$, $SD=0.84$), as measured on a 5-point Likert scale. The slight preference for AI-enhanced blended learning ($\Delta=0.17$ on a 5-point scale), with $t(33)=2.26$, $p=0.030$ (two-tailed), is statistically significant. The observed effect size, quantified by Cohen's $d = 0.39$ (95% CI [0.04, 0.74]), suggests a small-to-medium practical effect. The findings were also substantiated by three recurring themes in qualitative feedback:

- Flexibility and Accessibility: Students valued asynchronous access to materials (e.g., "Being able to learn at my own pace reduced stress and improved comprehension").

- Reinforcement Through Multimodality: Participants reported enhanced understanding through complementary online/in-person components (e.g., "The combination helped solidify concepts—I could revisit difficult topics after class").

- Improved Workload Management: Many highlighted better study-life balance (e.g., "Online resources allowed me to efficiently integrate coursework with other commitments").

The student critiques of the traditional approach, however, revealed three key thematic concerns:

- Cognitive Overload: "The traditional lectures were informative, but sometimes I felt overwhelmed with the amount of information presented in a single session."

- Structural Rigidity: "I appreciate the structure of traditional classes, but incorporating online elements could make learning more dynamic."

- Pacing Challenges: "While I valued face-to-face interaction, I struggled to keep up with the lecture pace."

These findings substantiate the pedagogical constraints of purely traditional instruction, while highlighting student demand for the multimodal flexibility that our AI-enhanced blended framework provides.

B. Interactivity of AI Visualisation Tools

Survey item 2 on interactivity of AI visualisation tools utilizing TensorFlow Playground and exploRNN demonstrated strong pedagogical efficacy, receiving an average interactivity rating of 3.88 (SD = 1.11) on a 5-point Likert scale. Qualitative analysis revealed three dominant themes in student evaluations:

- Cognitive Accessibility: "TensorFlow Playground demystified the black box of neural networks, making the learning process intuitive and seeing how adjusting learning rates or activation functions affected the model was fascinating."

- Theory-Practice Integration: "The interactive labs allowed me to apply theoretical knowledge in a practical setting, enhancing my learning experience."

- Engagement and Motivation: "The lab sessions were the highlight of the course—engaging and applicable to real-world scenarios. It made learning neural networks fun - I grasped complex concepts without math anxiety."

These findings collectively suggest that interactive AI visualisation tools can effectively bridge the theory-practice gap in deep learning education while maintaining high learner engagement.

Nonetheless, the comparative analysis revealed a statistically significant difference in perceived interactivity between the two visualisation tools. TensorFlow Playground (Survey Item 3) received higher interactivity ratings (M = 3.94, SD = 0.91) compared to exploRNN (Survey Item 4; M = 3.59, SD = 1.14), with this difference being highly significant ($t(33) = 3.78$, $p = .0006$, two-tailed, $d = 0.65$). The lower scores for exploRNN indicate a need for enhanced scaffolding, particularly for recurrent neural network concepts which are inherently more complex than feedforward architectures. Overall, the integration of exploRNN into the blended learning framework proved instrumental in demystifying RNNs, as evidenced by student feedback. Thematic analysis revealed three key pedagogical benefits:

- Visualisation of Sequential Data Processing: "exploRNN provided a clear visualisation of how RNNs process sequences, making hidden states and backpropagation through time more intuitive."

- Comparative Analysis of RNN Architectures: "I could experiment with LSTMs and GRUs, seeing how they performed on different tasks—this hands-on experience was invaluable."

- Reduction of Cognitive Load in Complex Topics: "The tool made sequential data handling less abstract—visualizing information flow was a game-changer."

C. Helpfulness of XAI Tools

The survey results (Survey Item 6) indicate that XAI tools (LIME and SHAP) were perceived as helpful (M = 3.85, SD = 1.09), though slightly lower than TensorFlow Playground (M = 3.94) but higher than exploRNN (M = 3.59). This suggests moderate-to-high utility in aiding conceptual understanding while also highlighting the need for improvement in connecting theoretical concepts to real-world applications. The findings were also substantiated by three recurring themes in qualitative feedback:

- Demystification of AI decision-making processes: "Provides clear visualisations that highlight feature contributions."

- Tools as gateways to deeper engagement: "Will help me further explore to understand AI modelling better."

- Connection between tool outputs and real-world problem-solving: "The tool is simple to use but needs time to relate to real-world challenges I am expected to solve."

6. Conclusions

This study, through rigorous quantitative and qualitative analyses, revealed a statistically significant student preference for the AI within a blended learning approach over traditional instruction, with a small-to-medium practical effect size. It underscored the pedagogical value of integrating AI visualisation tools in the curriculum to enhance student learning experiences.

The key findings from this study are as follows:

1. Enhanced Engagement: Students demonstrated better engagement when using tools and experiences that reduce unnecessary cognitive load and make complex concepts intuitively graspable. This is particularly beneficial for learners new to AI education, as visualisation tools help lower barriers to comprehension and reduce intimidation, which is often caused by the mathematical formalism (e.g., backpropagation equations) prevalent in traditional AI/ML instruction.

2. Bridging Theory and Practice: Interactive labs effectively bridged the gap between abstract theory and applied skills. They demystified the AI decision-making process by providing visuals that highlight feature contributions through hands-on experimentation.

3. Increased Intrinsic Motivation: The dynamic, visual nature of the tools increased intrinsic motivation, transforming challenging topics into engaging and enjoyable learning experiences.

While the study measured engagement and motivation shortly after the intervention, it may not capture long-term retention of knowledge, sustained interest in AI, or the development of deeper conceptual understanding over time. Future research should explore long-term knowledge retention and scalability of these tools across diverse educational contexts.

Nevertheless, this study strongly advocates for the continued integration of interactive AI visualisation tools in AI curricula to foster deeper, more accessible, and engaging learning experiences.

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