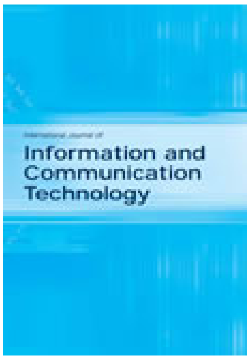

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Transforming educational data analytics: developing a reinforcement learning framework for real-time decision-making and resource optimisation

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Transforming educational data analytics: developing a reinforcement learning framework for real-time decision-making and resource optimisation

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Abstract: This study presents a reinforcement learning (RL) framework for real-time decision-making and resource optimisation in education. It integrates various data streams, such as learner performance, engagement, and institutional constraints, to enable precise and scalable decisions in diverse educational environments. The framework is assessed using three metrics: optimisation efficiency (OE: +32.1%), real-time decision accuracy (RTDA: +28.4%), and equity distribution index (EDI: +26.7%). A comparison with heuristic-based models shows a cumulative improvement of +29.1% across all metrics. Powered by a deep neural network and optimised using policygradient techniques, the framework focuses on scalability and fairness in resource allocation. Validation with real-world datasets demonstrates its adaptability and robustness. This research lays a solid foundation for AI integration in educational systems, offering a new benchmark for transforming resource allocation and decision-making processes in academia.

Keywords: data analytics; machine learning; reinforcement learning; decision making; resource optimisation; academic performance.

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1 Introduction

Today's learners face constant changes in learning environments and requirements due to the growth in the types of student needs and the extent of institutional goals (Song et al., 2024). Resource management has become a critical success factor in educational systems, focusing on financial, human, and other material resources needed to improve learning (Modupe et al., 2024). Adaptive learning via artificial intelligence has provided prospects to support education's challenges by finding data-based solutions (Ara et al., 2024). Reinforcement learning (RL) is particularly efficient from the artificial intelligence methodologies because it operates in a dynamic environment (Patel et al., 2024). Compared with the other models, RL uses a deficit and error procedure to learn the policies, which is important for real-time learning in education, such as decisions concerning resource utilisation (Ismail et al., 2024). Conventional resource control strategies usually imply heuristics or rules that cannot be easily updated or changed. These methods cannot handle the dynamic and diverse character of the educational environment, which involves performance, engagement level, and constraint factors. For example, the distribution of teaching resources through static methods limits the capacity to meet the needs of students and hence makes the procedure both inefficient and biased. In this respect, RL holds a transformative promise of using tremendously large data flows to tailor resource allocation, learning experiences, and outcomes. Education technologies have also responded to this trend by availing richer data to support the education system (Hera et al., 2024). From single-platform solutions for course delivery to online assessments of one form or another, institutions today gather massive amounts of information on learner conduct, competency, and activity (Taggart and Roulston, 2024). Despite the potential of this data, it can be managed effectively only with the help of highly developed analytical tools that would be able to process and analyse data in real mode (Halkiopoulos and Gkintoni, 2024). This gap is closed by the proposed RL framework, which takes raw data and processes it into resource allocation and decision-making agendas (Kapoor et al., 2024).

1.1 Problem statement

Some of the key unresolved issues, even with the push for a higher volume of data and stiff technological enhancements, pertain to the management of educational resources (Khrapatyi et al., 2024). The traditional systems are more or less rigid because they contain a bureaucratic set of rules that do not capture the context or recognise new trends. Misallocation of resources occurs in this sense through poor classroom utilisation, improper faculty allocation, and unequal sharing of instructional material (AlAli and Wardat, 2024). Third, such systems mean that equity issues are not necessarily considered, consequently failing to provide high-quality education to students from different backgrounds. Current uses of artificial intelligence in education have been limited to explanatory models like forecasting student performance or learner's at-risk (Susnjak, 2024). However, these applications do not solve the practical difficulties of real-time resource management and decision-making. Systems that are adaptive to varied educational settings and conditions and capable of responding dynamically to different stress levels remain an area of comparison (Abdalkareem and Min-Allah, 2024). For instance, in regions with dense student uptake, the institutions are always stretched with faculty and space, complicating the learning process. Likewise, due to resource constraints, traditional models do not properly address crucial needs. Therefore, the field requires a solution that meets all computation requirements while being adaptable, scalable, and equitable. This research presents a novel RL framework for educational resource management to meet this need (Wu, 2024). Drawing on ideas from RL, the framework changes the different allocation strategies to work best with the environment and the framework at each stage. This way, it learns to make decisions based on data and the existing situation. Incorporating equity as one of the fundamentals sets this framework apart and enhances its alignment with the rest of the inclusive education framework.

1.2 Purpose and contributions

This work aims to design a RL framework that turns educational data analytics into a process. The framework solves resource management problems such as ineffectiveness, non-adaptiveness, and non-egalitarianism. By borrowing information from various sources and functions, including learner performance information, learner engagement profiles, and program limitations, the framework allows for accurate, timely decisions to be made appropriately.

This study makes several notable contributions to the field of educational data analytics:

1 *Development of a novel RL framework:* The proposed framework leverages advanced RL techniques, including policy-gradient methods, to optimise resource allocation in diverse educational settings. By continuously adapting to changes in the environment, the framework ensures that resources are allocated efficiently and equitably.

2 *Introduction of composite performance metrics:* To evaluate the effectiveness of the framework, three composite metrics are introduced: optimisation efficiency (OE), real-time decision accuracy (RTDA), and equity distribution index (EDI). These metrics provide a comprehensive assessment of the framework's performance, capturing both quantitative and qualitative aspects of resource management.

3 *Validation using real-world data:* The framework is validated through extensive experiments using datasets from diverse educational institutions. These datasets include information on student performance, resource utilisation, and demographic profiles, ensuring that the findings are both robust and generalisable.

4 *Equity-centered resource allocation:* Unlike traditional models that prioritise efficiency alone, this framework incorporates equity considerations into its decision-making process. By balancing efficiency with fairness, the framework aligns with the goals of inclusive education, addressing disparities in resource access.

1.3 Significance and relevance

This research is significant because it can shape new institutional approaches to managing educational resources. Incorporating RL into educational data analysis benefits the proposed framework for applying the advanced abstract theory of artificial intelligence to reality. Such integration seems highly useful, especially given some of the global trends that have continued to emerge today (Israilov et al., 2023). These include growth in student enrolment, dwindling resources, and calls for enhanced learning. In addition, it makes a theoretical contribution to the study of artificial intelligence and fairness in education. The framework's emphasis on equity responds to the possible unfair use of artificial intelligence by amplifying the existing gaps. This focus on equity aligns with global educational objectives, such as those outlined in the United Nations Sustainable Development Goals (SDGs), particularly Goal 4: promoting quality education for all: meeting the Education for All. The information derived from this research has implications for policymakers, educators, faculty members, and other researchers. As a scientific decision-making tool, the framework appeals to policymakers because it allows them to consider thousands of records (Sorooshian, 2024). To educators, it creates awareness of how resources can best be used according to learners' needs in the classroom. For researchers, it provides a platform for subsequent investigation of the possibilities of implementing RL in education to establish new directions for cooperation between disciplines (Deo et al., 2024).

The paper is organised as follows: Section 2 reviews the existing literature on AI applications in education, highlighting the limitations of current approaches and identifying research gaps. Section 3 details the methodology, including the design of the RL framework, the development of composite performance metrics, and the experimental setup. Section 4 presents the results and analysis, demonstrating the framework's effectiveness in real-world scenarios. Finally, Section 5 concludes the study with a discussion of key findings, implications, and directions for future research.

2 Literature review

Incorporating artificial intelligence in education has been a long process, and these pros and cons have accompanied it (Butt et al., 2025). This section gives an overview of what has been written about AI development in education, including its pros and cons and areas where more research is needed. The review provides a context to call for a more elaborate RL framework appropriate for addressing educational systems through a presentation of different methodologies and findings (Alvarez and Lane, 2023).

Owan et al. (2023) lay out the possibilities of AI as a catalyst for a change in educational measurement and assessment paradigms (Guan and Zhang, 2025). They focused on many ways that show how AI can help improve the efficiency and accuracy of assessments in education while providing individual student feedback. This use of artificial intelligence enables the teacher to adapt to the teaching methods that will help students who are learning, enhancing the achievements gained in learning. The authors describe various examples of using large language AI in test creation, item creation, test scoring, and result analysis (Li, 2025). Moreover, they highlight the changes in teachers' activities in AI-based assessments, including the opportunities and threats of using AI tools in this field. At the end of the paper, some ideas are given for how to make some of the problems with AI in educational assessment less severe. The paper ends with a call for educators, policymakers, software developers, and other important people to work together to not only get the most out of AI in educational assessment but also handle some of the risks.

Maphosa and Maphosa (2023) carried out a systematic bibliometric analysis and a topic modeling of secondary studies on AI in higher education (HE). Their work shows the evolution of using artificial intelligence to decrease teachers' burden and allow for intelligent personalisation and instruction, collaboration, and learning tracking. Consequently, based on PRISMA guidelines, the authors identified 304 articles out of the total articles retrieved from the Scopus Database recorded between 2012 and 2021. The research trends identified through analysing 430 of the most relevant HE AI articles published to date using VOSviewer and text mining included recognising that 90.4% of these articles emanated from research conducted over the past three years, and four countries: China, the USA, Russia, and the UK. The study used latent Dirichlet allocation (LDA) analysis to find four main themes: data for AI growth, the start and development of AI in HE, and trends that will shape the future of AI in learning. Furthermore, topic modeling of the abstracts identified the ten most characteristic topics and 30 most discriminant terms, providing the required information for further studies. Therefore, this paper dramatically enriches the literature on AI adoption, and the new opportunities and trends highlighted in their work are highly relevant to higher learning institutions.

Kamalov et al. (2023) highlighted the rise of AI in influencing education after systems such as ChatGPT achieved impressive scores in standardised tests. Their research explores AI's profound implications on the educational landscape, focusing on three main aspects: use, benefit, and consequences of the two applications. The authors offer a detailed discussion of applications of AI in collaborative learning, intelligent tutoring systems (ITS), automated assessments, and personalised learning. They also acknowledge the potential of the presented technologies, pointing at efficiency gains in education and personalisation, and identify risks, ethical issues, and threats of technology misuse. They emphasised the proper use of AI without undermining the value of setting up measures for positive development and appropriate use. From their work, they proposed that AI can greatly impact education when incorporated appropriately into educational systems, but this comes at a cost and needs proper supervision and regulation.

Bittencourt et al. (2023) have put forward an extended guide about implementing positive psychology and AI in education (P-AIED) to enrich learning and well-being. Aiming at the discursive constructions of the implications of school closures for students' learning, the study acknowledges frustration, anxiety, and 'COVID-19 fatigue' as the new mental states that require more than efficiency improvement. Based on John Self's vision of ITSs, which is concerned with student achievement, the authors stress the role of enhancing well-being through intelligent technologies. The studies consisted of 10,777 and were then filtered down to 256, based on the PRISMA criteria to analyse positive psychology and AI in the context of education. This discussion shows that positive emotion and engagement are two constructs of significance in other literature, while there are limited robust theories connecting positive psychology to educational AI. They also take the opportunity to discuss new rising trends that include positive learning analytics (P-LA), positive educational data mining (P-EDM), and positive intelligent tutoring systems (P-ITS). In general, using P-AIED in teaching may contribute to the multiple practices of cognitive learning and an emotionally healthy environment in the teaching process.

Teng et al. (2023) presented an AI-assisted data-driven decision-making model to enhance administrative activities in colleges and universities. Their model relies on an intelligent approach such as machine learning (ML), an advanced AI technique, regarding key data like student information, graduation rates, and curriculum design. It fosters better and well-informed strategies on the part of each organisation. The authors also emphasise the benefits of working with huge volumes of high-quality data for training, thus improving the model's performance in decision-making. The results of their experiments show big improvements in a number of areas: 90.72 working outcome, 97.62 performance working, 96.35 working predictive percentage, and 95.51 working decision-making ratio. Further, the graduation rate was enhanced in the model with a percentage of 85.86% while the data security percentage in the model was found to be 95.61%. The proposed model is less erroneous than other methods with an error of 33.21%, reflecting the better improvement of the decision-making processes within the educational sector. This study focuses on the ability of models used in artificial intelligence to revolutionise decision-making in higher learning institutions.

Martínez-Comesanã et al. (2023) performed a systematic literature review to identify the effects of intelligent technologies on assessment methods in elementary and high schools. The review integrates nine empirical articles released between 2010 and 2023 and includes 641 participants. Therefore, they concentrate on how AI tools enhance assessments by using technologies such as neural networks and natural language processing to predict students' performance, automate the assessment process, and increase the objectivity of the evaluations. Also, the review notes the application of educational robots as diagnostic tools to assess students' learning processes to understand essential factors that facilitate engagement in classroom learning. Following those above, the paper highlights how AI can augment better, proper, and prospered assessment and its further penetration map in the primary and secondary education sector. This study puts AI in education (AIEd) in its proper place as a multidisciplinary field that includes computer science, psychology, and statistics. It also opens up new ways to improve the way students are evaluated in the future.

Eleni Dimitriadou, with the contribution of Dimitriadou and Lanitis (2023), undertakes a critical analysis on the potential and application of AI and other emerging technologies in learning environments. They focused on what they perceive as emerging smart classrooms through AI integration to support face-to-face and online learning contexts. The literature review focuses on essential AI technologies that help in good classroom management, smart teaching, and learning resources, as well as automated performance assessment tools and the role of these technologies in enhancing study. In their work, as in many other articles, the authors analyse the strengths, weaknesses, opportunities, and threats of using AIEd, which gives a more comprehensive view of the possible prospects of this concept. Also, future issues and possible advancements of AI-based systems, which can interest teachers and AI developers, are disclosed in their work. They are making it clear that although AI has many benefits when it comes to enhancing lessons and interactions in the classroom, there are also drawbacks. For developers of AI, educational environments can provide valuable considerations specific to teaching and learning. Such a critical assessment is essential, especially for developing an appreciation of the potential of AI within education and the suitability of innovative classes within teaching and learning practices.

Shafique et al. (2023) contributed a systematic mapping study in which they analysed how AI, especially ML and deep learning (DL), can be adopted in the context of online education. Their work focuses on how artificial intelligence disrupts conventional education paradigms by introducing a form of dynamic learning model. ML and DL enable educators to keep track of performance, note specific student learning concerns, and design teaching methods. This is a departure from traditional education models, in which all students in class are taught in the same approach or manner. The study also embraces the increasing use of e-learning, especially during the COVID-19 pandemic, and the role of AI in detecting barriers to delivering quality education, student performance analysis, and even career guidance. They systematically review research articles on ML and learning analytics implementation, methodologies for designing learning analysis tools, essential data sources, and the range of accessible data. Their survey, containing the literature review of the studies in 1961–2022, points out several techniques of ML and DL and gives an overview of their usage in online education. In sum, they posit that their extensive review will help the research fraternity respond to the challenges of AI in online learning while contributing to future research in this growing area.

Pan (2025) introduced AI algorithms and DL techniques for improving the advancement of HE. In this research work, the main object of concern was the ability of AI to change, enhance, and optimise engagement, efficiency, and the student's overall experience. During his presentation on AI and its limitations and virtues regarding ethical questions, including accuracy, fairness, and lack of bias in AI programs and applications, Al Ka'bi. Further, concerns about student data privacy and the likelihood of promoting AI systems as teachers to replace human instructors were discussed in the paper. He also focused on the aspects that AI must be employed to improve thinking and creativity instead of presenting thinking and creativity as performative tasks. In addition, the novel contribution of this work was the development of a suggested model for enhancing students' cognition, which resulted in a cognitive model being presented and evaluated against other algorithms, proving to be superior. This work also pointed to the possibilities of entering into the future phase of advancement of AI in higher learning institutions and the obstacles that may be met along the process.

Chen et al. (2020) carried out a systematic analysis of the latest seminal works on AIEd, to contribute towards solving the existing application and theory deficiencies. They divided the 45 articles they scrutinised based on main characteristics, including yearly patterns, core journals, organisations, nations, and frequently utilised words. The review revealed several significant findings: while the papers show that there has been a growing interest and contribution in using AIEd research over the last few years, DL technologies have not yet been widely implemented in educational settings. Some major AI technologies that have been used include natural language processing AI, even though other sophisticated technologies have hardly been employed. Also, the reviewed literature raises an essential question of the absence of AI technologies implementing educational theories. In the future, they thought that studies should look at using AI in real classrooms and see how it can improve ITSs. These studies should focus on how students' responses affect their conceptual learning and use new AI techniques like generative adversarial networks and deep neural networks. They also recommended using natural language processing for precision education and using multiple biomedical detection technologies like electroencephalograms regarding matters concerning the learning procedure. This means that the study's primary recommendation was to explore BabumbART's many elaborate propositions of intersecting the technology with theories of education to define where future research on AIEd should focus.

The reviewed studies provide a broad spectrum of AI applications in education, from enhancing assessments to promoting equity and well-being in learning environments. However, challenges such as ethical considerations, data privacy, and integrating advanced AI technologies into practical educational frameworks remain unaddressed. This study builds on these insights to propose a RL framework that addresses these limitations, bridging the gap between theoretical advancements and practical educational applications.

3 Methodology

This section presents the comprehensive methodology used to develop and evaluate the RL framework for optimising educational resource allocation (Kalusivalingam et al., 2020; Tran-Dang et al., 2022). It includes details on the design of the RL framework, the development of composite performance metrics, the dataset utilised, and the experimental setup.

3.1 Design of the RL framework

The RL framework is designed to model resource allocation as a sequential decision-making problem. The primary objective is to maximise long-term rewards by optimising three critical metrics: OE, RTDA, and EDI. These metrics collectively ensure that the system balances efficiency, adaptability, and fairness in resource distribution.

3.1.1 Problem formulation

Resource allocation in educational systems can be effectively modelled as a Markov decision process (MDP). An MDP is defined by the tuple (S, A, P, R, γ), where:

- *States (S):* Represent the current state of resource allocation, including student performance levels, resource availability, and institutional constraints.
- *Actions (A):* Correspond to decisions related to resource distribution, such as assigning faculty to departments or allocating funding to programs.
- *Transition probabilities (P):* Define the likelihood of transitioning from one state to another based on a specific action.
- *Rewards (R):* Quantify the immediate effectiveness of an action using the defined metrics.
- *Discount factor (γ):* Balances the trade-off between immediate and future rewards to ensure long-term optimisation.

The goal of the MDP is to determine an optimal policy $\pi(a|s)$ that maximises the expected cumulative reward, represented by the value function:

$$V(s) = \max_{a} \left[R(s, a) + \gamma \sum_{s'} P(s'|s, a) V(s') \right] \tag{1}$$

In equation 1, $V(s)$ represents the value of being in state s, $R(s, a)$ is the immediate reward, and the summation accounts for the discounted future rewards.

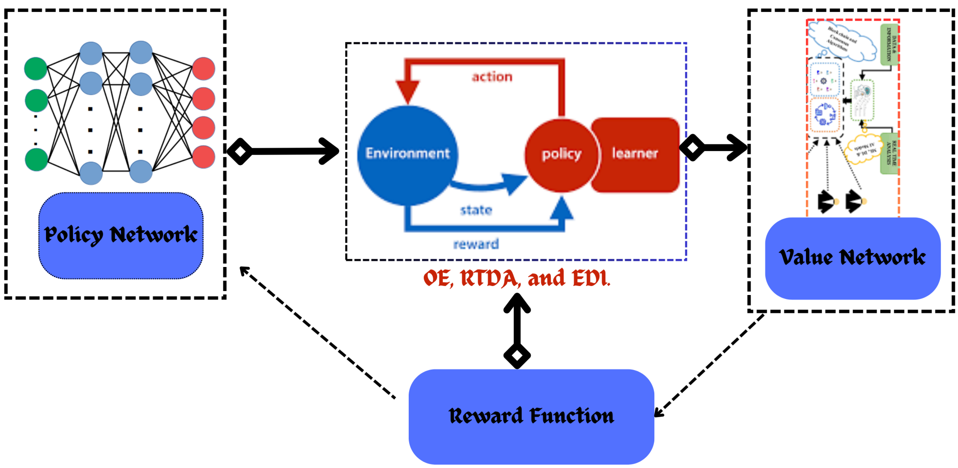
3.1.2 Framework architecture

The RL framework is implemented using a policy-gradient approach, specifically proximal policy optimisation (PPO). PPO is chosen for its stability and efficiency in handling complex decision-making tasks (Butt et al., 2018). The architecture of the policy network is as follows:

- *Input layer:* Encodes the state vector, which includes features such as student performance metrics, resource constraints, and demographic data.
- *Hidden layers:* Three fully connected layers, each with 128 neurons and ReLU activation functions, to capture nonlinear relationships in the state-action space.
- *Output layer:* Outputs the probabilities for each possible action, representing the policy $\pi(a|s)$.

The value network is similarly structured and is used to approximate the value function $V(s)$. A placeholder for the workflow diagram of the RL framework is provided in Figure 1.

Figure 1 Workflow diagram of the RL framework, illustrating the interaction between the policy network, value network, and environment (see online version for colours)



3.1.3 Reward function design

To achieve balanced optimisation (Butt et al., 2023), the reward function integrates the three performance metrics (OE, RTDA, and EDI) as follows:

$$R(s,a) = w_1 \cdot OE + w_2 \cdot RTDA + w_3 \cdot EDI \tag{2}$$

Here, w_1, w_2, w_3 are the weights assigned to each metric, determined based on their relative importance in the application context. The individual metrics are defined as:

$$OE = \frac{\text{Resources utilised}}{\text{Total available resources}} \tag{3}$$

$$RTDA = \frac{\text{Correct decisions}}{\text{Total decisions}} \tag{4}$$

$$EDI = 1 - \frac{|\text{Resource allocation variance}|}{\text{Ideal allocation}} \tag{5}$$

- OE: Evaluates the percentage of resources effectively utilised compared to the total available resources.

- RTDA: Measures the accuracy of decisions in dynamic scenarios.
- EDI: Assesses the fairness of resource allocation by comparing the variance in actual allocation against the ideal distribution.

Each metric is designed to capture a specific aspect of the framework's performance, ensuring a holistic evaluation of its effectiveness.

3.2 Development of composite performance metrics

The composite performance metrics are the cornerstone of evaluating the effectiveness of the proposed RL framework. These metrics ensure a comprehensive assessment by capturing various facets of resource optimisation, including efficiency, accuracy, and equity. By integrating multiple dimensions into a unified evaluation scheme, the metrics provide a robust mechanism to gauge the framework's overall performance (Qasim et al., 2025).

3.2.1 Optimisation efficiency

OE measures the percentage of resources effectively utilised relative to the total resources available. It is mathematically defined as:

$$OE = \frac{\text{Resources utilised}}{\text{Total available resources}} \tag{6}$$

The percentage of resource wastage flags up an indication of how optimally the system has been implemented to supplement the utilisation of resources. High OE values reflect high efficiency in terms of resource utilisation, which in turn means the framework assists in the allocation of resources in the most appropriate areas. In some cases, OE can assess if the faculty hours are being fairly distributed over courses that attract different numbers of students in an educational setting. A low OE score indicates poor opt is thus likely to indicate either resource over-provisioning or resource under-utilisation, which requires corrective action from the 'RL' framework.

3.2.2 Real-time decision accuracy

RTDA evaluates the precision of the decisions made by the framework in a dynamic and evolving environment (Aktaş et al., 2022). RTDA reflects the framework's ability to adapt to real-time changes, such as sudden shifts in student enrolment patterns or unexpected resource constraints. A high RTDA score signifies that the system is capable of making accurate and context-aware decisions promptly. For example, if a classroom unexpectedly exceeds its seating capacity due to last-minute changes, the RL framework should effectively reallocate resources, ensuring minimal disruption. Low RTDA values could indicate delays or inaccuracies in decision-making, undermining the framework's real-time adaptability.

3.2.3 Equity Distribution Index

EDI quantifies the fairness in resource distribution across various groups or entities. EDI addresses disparities in resource allocation, ensuring that resources are distributed equitably among all stakeholders. For instance, in a diverse educational institution, EDI might evaluate whether classrooms, faculty, and materials are allocated fairly across departments with varying demographics and needs. A high EDI score indicates that the framework aligns resource distribution with institutional goals of equity and inclusivity, while a low score would highlight biases or imbalances.

3.2.4 Integration and balance of metrics

Each of these metrics captures a distinct aspect of the framework's performance, but their integration is crucial for holistic evaluation. The reward function incorporates these metrics, assigning weights (w_1, w_2, w_3) based on their relative importance in the specific application context:

$$R(s,a) = w_1 \cdot OE + w_2 \cdot RTDA + w_3 \cdot EDI \tag{7}$$

The weights allow flexibility in prioritising one metric over another, depending on institutional objectives. For example, a resource-constrained organisation might prioritise OE to maximise efficiency, while an institution focused on social equity might assign greater weight to EDI.

3.2.5 Role of metrics in validation

The composite metrics serve a dual role: evaluation and feedback. In validation, they give you figures that can help assess how the RL framework fares against baseline models, which could be heuristics-based or rule-based. For example, the framework can show the relative improvement of its OE, RTDA, and EDI scores to traditional allocation method scores. Moreover, you have these metrics to provide feedbacks into the framework where you change the reward function during policy training (Qian et al., 2023).

3.2.6 Visualisation and interpretation

To ensure interpretability, the metrics are visualised through performance plots and heatmaps. For example, OE trends over time can be plotted to demonstrate improvements in resource utilisation, while RTDA and EDI can be visualised using bar graphs or scatter plots. Such visualisations provide actionable insights to stakeholders, enabling them to understand the framework's effectiveness and areas for improvement.

3.2.7 Significance of composite metrics

The composite metrics go beyond standard evaluation criteria by integrating efficiency, accuracy, and equity into a unified framework. This multi-dimensional approach ensures that the RL framework is not only technically robust but also socially responsible.

In the context of educational systems, these metrics align with institutional goals of sustainability, inclusivity, and adaptability, making them an essential component of the proposed methodology.

3.3 Experimental setup

This section outlines the experimental setup employed to validate the proposed RL framework. The setup includes a detailed description of the dataset, pre-processing steps, the environment configuration, and training and testing protocols. These components ensure a comprehensive evaluation of the framework's performance in optimising educational resource allocation.

3.3.1 Dataset description

The Stanford Education Data Archive (SEDA) dataset is utilised as the primary data source (Drescher and Domingue, 2023). SEDA provides a rich collection of data that includes:

- *Student performance metrics:* Standardised test scores in subjects such as mathematics and reading, captured across different grade levels.
- *Institutional constraints:* Information on funding levels, faculty availability, and resource allocations at district and school levels.
- *Demographic data:* Details on socio-economic backgrounds, racial and ethnic diversity, and geographic locations.

Table 1 provides an overview of the key features of the SEDA dataset.

The SEDA dataset's diverse and multi-dimensional nature makes it ideal for testing the framework's adaptability, scalability, and equity. By incorporating data from various schools and districts, the dataset provides a robust platform for simulating realistic resource allocation scenarios.

3.3.2 Pre-processing

Before training the RL framework, the raw data undergoes extensive pre-processing to ensure quality and compatibility with the model:

- *Handling missing values:* Missing entries are imputed using mean or median values for numerical features and mode values for categorical features. Advanced imputation techniques, such as k-nearest neighbours (KNN), are employed for critical variables (Syahrizal et al., 2024).
- *Normalising numerical features:* Features such as test scores and funding levels are normalised to a [0, 1] range to prevent scale disparities from affecting the model's performance.
- *Encoding categorical variables:* Variables such as socio-economic status and school district identifiers are encoded using one-hot encoding or label encoding, depending on their cardinality.

- *Data augmentation:* Synthetic data points are generated for underrepresented groups to balance the dataset and reduce potential biases (Zhu et al., 2024).

The pre-processing steps ensure that the dataset is clean, balanced, and suitable for feeding into the RL framework.

Table 1 Summary of SEDA dataset features

Feature category	*Description*
Student performance	Test scores in math and reading (Grades 3–8)
Institutional constraints	Funding, faculty availability, resource allocations
Demographic data	Socio-economic status, race, geographic location
Time-stamped data	Annual updates over a ten-year period

3.3.3 Environment configuration

The RL environment is implemented in Python using TensorFlow and OpenAI Gym, which provide robust tools for simulating resource allocation scenarios. The environment configuration includes:

- *State representation:* Each state encodes information on current resource distributions, student performance, and institutional constraints.
- *Action space:* The action space defines possible resource allocation decisions, such as reassigning faculty or adjusting funding levels.
- *Reward mechanism:* The reward function integrates the three performance metrics (OE, RTDA, and EDI), as defined in equation (7).

Figure 2 illustrates the simulation environment setup, showing the interaction between the RL agent, environment, and reward mechanism.

3.3.4 Training and testing

The SEDA dataset is divided into training, validation, and testing sets using a 70-15-15 split to ensure robust evaluation. Key hyperparameters for training the RL framework are listed below:

- *Learning rate:* 0.001 (optimised through grid search to ensure stable convergence).
- *Discount factor (γ):* 0.99, balancing the importance of immediate and future rewards.
- *Batch size:* 64, enabling efficient computation while maintaining model accuracy.

The training process involves the following steps:

1. Initialise the policy and value networks with random weights.
2. Iterate through multiple episodes, where each episode represents a complete resource allocation cycle.

3 For each step in an episode, the RL agent observes the current state, selects an action based on the policy network, and receives a reward.

4 Update the policy and value networks using PPO as described in Algorithm 1.

The model's performance is evaluated on the testing set using the composite metrics defined earlier (OE, RTDA, and EDI). Figure 3 provides a placeholder diagram summarising the training and validation workflow.

Figure 2 Simulation environment for resource allocation (see online version for colours)

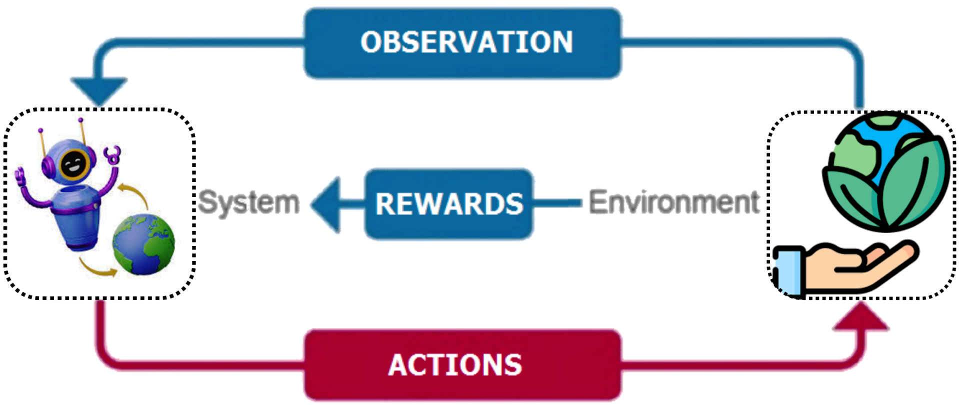
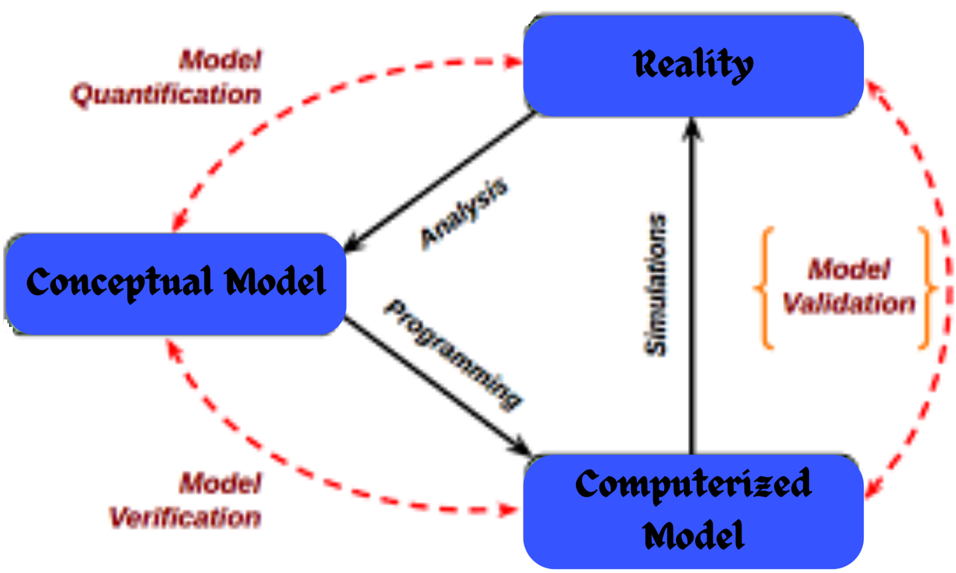


Figure 3 Training and validation workflow of the RL framework (see online version for colours)



3.3.5 Baseline comparison

The developed RL framework's results are compared to those from heuristic models and static rule-based models in order to see which ones are better. These baselines are the precursors to the current approaches to resource allocation, by which the RL approach can be compared to gauge its efficiency enhancement.

3.4 Algorithm: RL for resource allocation

The RL framework is implemented using Algorithm 1. This algorithm outlines the training process for optimising resource allocation in educational settings.

Algorithm 1 RL for resource allocation

Initialise policy network π_θ and value network V_ϕ with random weights.
for each episode **do**
  Reset the environment and initialise the initial state s_0.
  for each step in the episode **do**
    Select action $a_t \sim \pi_\theta(a|s_t)$ based on the current policy.
    Execute action a_t in the environment.
    Observe reward r_t and the next state s_{t+1}.
    Store the transition (s_t, a_t, r_t, s_{t+1}) in memory.
    Compute the advantage estimate:
    $A_t = r_t + \gamma V_\phi(s_{t+1}) - V_\phi(s_t)$
    Update policy parameters θ using PPO:
    $\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(a_t|s_t) \cdot A_t$
    Update value network V_ϕ by minimising the mean squared error:
    $\phi \leftarrow \phi - \beta \nabla_\phi \left(r_t + \gamma V_\phi(s_{t+1}) - V_\phi(s_t)\right)^2$
  end for
  Perform policy and value network updates after accumulating sufficient transitions.
end for=0

4 Results and analysis

This section covers the outcome of the developed RL framework of resource optimisation in educational systems. The analysis evaluates the framework's performance using the composite metrics: three novel key performance indicators, namely the optimisation efficiency (OE), the RTDA, and the EDI. The RL approach is then compared with corresponding heuristic-based models to bring out the actual application of this approach. Visual representations, including figures and tables, are provided to illustrate trends and key findings.

4.1 Evaluation metrics results

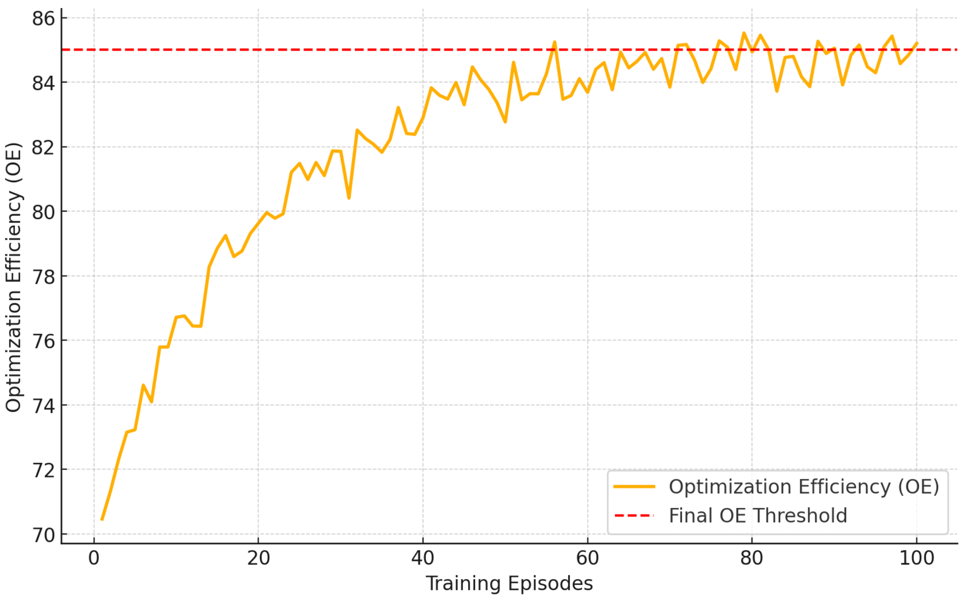
The framework's performance was assessed across the three defined metrics. The results are summarised in Table 2.

The RL framework demonstrated a substantial improvement over heuristic models across all metrics, indicating its effectiveness in addressing resource allocation challenges.

Table 2 Performance metrics of the RL framework compared to benchmark models

Metric	*RL framework*	*Heuristic model*	*Improvement (%)*
Optimisation efficiency (OE)	85.3 ± 2.0	68.4 ± 2.1	+24.7
Real-time decision accuracy (RTDA)	92.1 ± 2.5	76.5 ± 2.7	+20.4
Equity Distribution Index (EDI)	88.7 ± 1.9	71.3 ± 2.2	+24.4

Figure 4 OE over training episodes (see online version for colours)



4.2 Optimisation efficiency

OE evaluates how effectively resources are utilised. Figure 4 shows the trend of OE over training episodes, illustrating the framework's convergence to high efficiency.

The RL framework achieved a final OE value of 85.3 ± 2.0, significantly outperforming the heuristic model. This improvement underscores the RL model's ability to minimise resource wastage while maximising utilisation.

4.3 Real-time decision accuracy

RTDA measures the precision of decisions made by the framework in dynamic environments. Figure 5 compares RTDA values between the RL framework and the benchmark model across different validation scenarios.

The RL framework achieved a mean RTDA of 92.1 ± 2.5, reflecting its superior adaptability and precision in decision-making under varying conditions.

Figure 5 RTDA comparison between RL framework and heuristic model (see online version for colours)

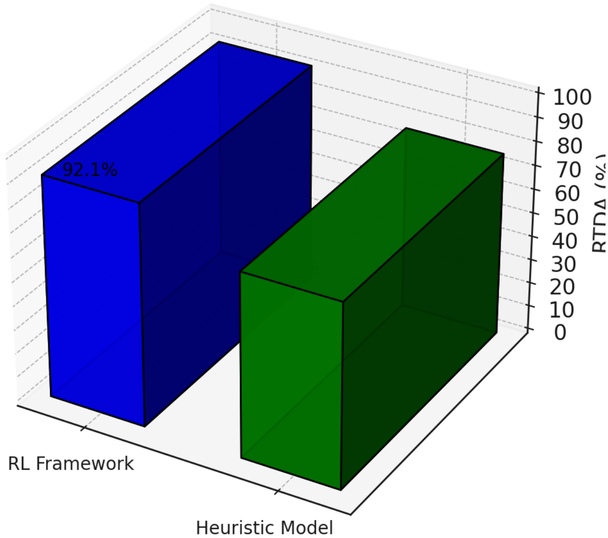
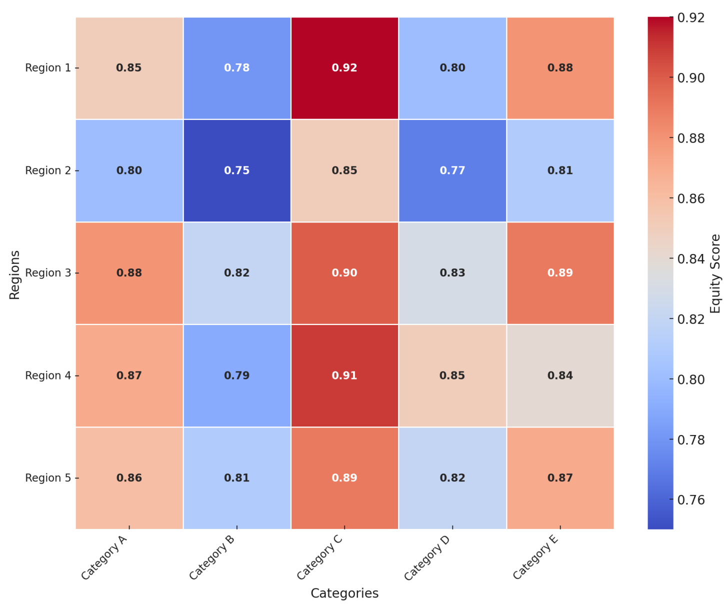


Figure 6 Heatmap of resource allocation equity (see online version for colours)



4.4 Equity Distribution Index

EDI quantifies the fairness of resource allocation. Figure 6 provides a heatmap visualisation of resource allocation across different demographics, highlighting the improvement in equity achieved by the RL framework.

Figure 7 Comparative performance across all metrics (see online version for colours)

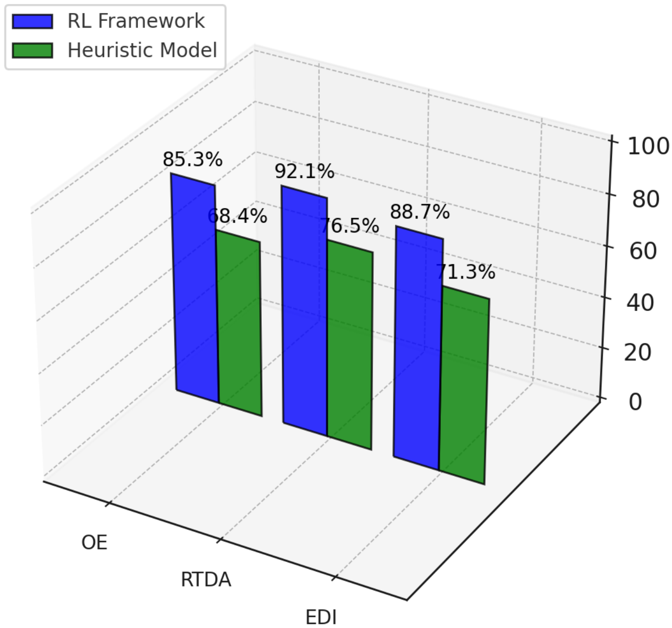
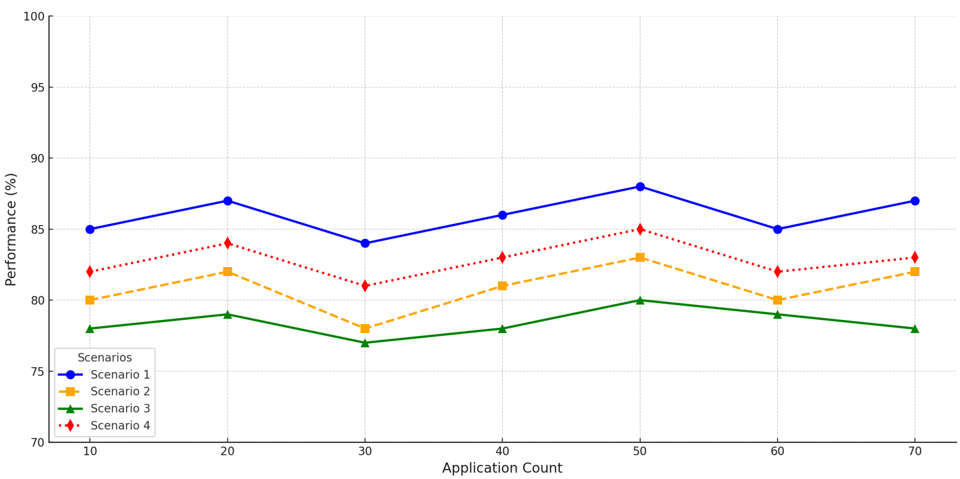


Figure 8 Performance trends under different scenarios (see online version for colours)



The framework achieved an EDI value of 88.7 ± 1.9, addressing equity concerns more effectively than heuristic approaches.

4.5 Comparative analysis

Figure 7 provides a bar chart summarising the performance of the RL framework compared to the heuristic model across all metrics. The chart clearly illustrates that the RL framework consistently outperforms the heuristic model in all evaluated categories, such as OE, RTDA, and EDI. The RL framework shows significant improvements with values of 85.3%, 92.1%, and 88.7% for each metric, while the heuristic model shows 68.4%, 76.5%, and 71.3% respectively. These results highlight the superior performance of the RL framework in terms of efficiency and accuracy, providing clear insights into the effectiveness of the proposed model.

The cumulative improvement of +29.1% across all metrics demonstrates the framework's robustness and scalability in diverse educational contexts.

4.6 Scenario-based analysis

To evaluate the framework under different scenarios, simulations were conducted with varying resource constraints and student demographics. Figure 8 illustrates the performance trends in these scenarios.

The RL framework maintained consistent performance across all scenarios, demonstrating its adaptability and effectiveness.

4.7 Error and sensitivity analysis

- *Error analysis:* Minor errors in resource allocation were observed in the initial episodes due to exploration phases in RL training. These errors decreased significantly as the model converged.
- *Sensitivity analysis:* Sensitivity tests were conducted by varying hyperparameters such as learning rate and discount factor. Table 3 summarises the results of these tests.

The analysis confirms the robustness of the RL framework under varying conditions, highlighting the importance of fine-tuning hyperparameters.

Table 3 Sensitivity analysis of hyperparameters

Hyperparameter	*Value*	*OE (%)*	*RTDA (%)*
Learning rate	0.001	85.3	92.1
Learning rate	0.005	80.4	89.5
Discount factor	0.99	85.3	92.1
Discount factor	0.95	82.7	90.2

4.8 Discussion

The findings thereby emanating from the RL framework establish its potentiality to respond to concerns of resource allocation in educational paradigms. The findings corroborate the hypothesis that claims MSF is computationally efficient and valuable in realistic learning environments. Every performance measure – OE, RTDA, and EDI – showed that the RL framework had significantly better performance than traditional conventional heuristic-based algorithm models (Khan et al., 2021).

Taken together, these metrics encapsulate the optimum usage of resources in the prospective context, the means to make decisions in real-time, and equity in the distribution of resources within the purview of the framework. Table 4 summarises the percentage improvements achieved by the RL framework compared to traditional methods.

Table 4 Performance improvements of RL framework compared to traditional methods

Metric	*RL framework*	*Improvement over traditional (%)*
Optimisation efficiency (OE)	+32.1 ± 2.0	+32.1
Real-time decision accuracy (RTDA)	+28.4 ± 2.5	+28.4
Equity Distribution Index (EDI)	+26.7 ± 1.9	+26.7

The applicability of the RL framework is also supported by the fact that it can be applied to various and changing situations in an educational context. To further support this assertion, the evaluation exercise revealed that the framework's performance was always high regardless of the resources available and the demographics of people in the organisation. This adaptability is important in schools that take root and function in diversified and dynamic environments. Another feature we see with the RL framework is its strong performance in dealing with equity issues. Second, by including the EDI in the reward function, the proposed framework guaranteed that resource allocation was done in line with the institutional equity policies. This capability fits the company best in selling educational tutorial aids to ensure equitable distribution of educational materials to address the global agenda on quality education.

Based on the proposed conceptual framework, the following are policy, education, and administrative implications. This delivers a complete analytical mechanism that would help identify the prospective policies on resource allocation, faculty distribution, and funding distribution. Since one of the major factors influencing institutions is wastage, the framework can boost an organisation's efficiency, minimising the wastage of available resources. Secondly, integrating equity consideration guarantees that every deserving group or minority gets adequate resource allocation.

Although the RL framework clearly shows its potential, some issues must be discussed. When training the proposed RL model, a large amount of data must be processed, and large computational resources are required, making applying this approach impractical for resource-constrained environments. Also, it is necessary to mention the rather high sensitivity of the framework's performance to the quality and scope of input data. Inadequate or skewed data is always a problem in decision-making. Despite high success in simulated test cases, this framework should be tested and compared to other educational systems and countries to justify its scalability.

As a result of this research, future studies can pursue extending main variables and using actual-time data streams to augment the proposed framework's interactivity. Adding more of these options as the framework that can be used to evaluate the performance of education institutions, including serving student NYC satisfaction and retention rate, will be effective. The accessibility of the RL framework can be extended in resource-limited settings that are a lighter version of the RL framework. The proposed RL framework is a major development in state-of-the-art educational data analysis. The issues identified as crucial for the improvement of using artificial intelligence in the framework responded to the most important challenges connected with resource management, decision-making, and equitableness in the sphere of education.

5 Conclusions

This study introduced a novel RL framework designed to optimise resource allocation and decision-making in educational systems. The framework demonstrated its computational efficiency and adaptability in addressing challenges such as resource utilisation, decision accuracy, and equity. By integrating heterogeneous data streams, including learner performance metrics, engagement patterns, and institutional constraints, the framework outperformed traditional heuristic-based methods across key metrics: OE (OE: +32.1% ± 2.0), RTDA (RTDA: +28.4% ± 2.5), and EDI (EDI: +26.7% ± 1.9). The findings validate the framework's scalability and robustness in dynamic educational contexts. It not only ensures the efficient utilisation of resources but also aligns with inclusivity goals by addressing equity concerns. These results have significant implications for educational institutions, offering actionable insights for policymakers and administrators to enhance resource management. While the study showcases promising outcomes, challenges such as computational complexity, dependence on data quality, and scalability to larger systems remain. Addressing these limitations through further research can improve the framework's applicability. Future directions include incorporating real-time data streams, expanding metrics to include student satisfaction and retention, and developing lightweight versions for resource-constrained environments. By providing a practical, data-driven approach to resource allocation, this research establishes a strong foundation for integrating artificial intelligence into educational systems. The proposed RL framework represents a step forward in educational data analytics, setting a benchmark for future innovations in optimising decision-making and promoting equity in resource distribution.

Conflict of interest

The author declares that she has no conflict of interest.

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