

# Personalised Adaptive E-Learning System with Competency Graph and Machine Learning

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## ABSTRACT

Adaptive e-learning systems are designed to tailor learning materials based on a learner's performance and mastery progression. However, existing systems use static unlocking mechanisms based on rules and do not provide a structured representation of topic dependencies. In this paper, we propose a personalised adaptive e-learning system that incorporates a competency graph with machine learning-based mastery prediction to dynamically shift quiz difficulty and recommend the best learning paths. The system represents domain knowledge as a directed graph of prerequisite-order-based competencies and monitors learner interaction data, such as quiz scores, attempts, and time spent. A model is trained to predict the correct mastery and difficulty, which it can dynamically adjust. We also compare our approaches to existing adaptive models and demonstrate improved structural personalisation and mastery-driven progression compared to traditional rule-based systems. The framework presented features such as scalability, enforced structured learning, and improved learner engagement compared to traditional e-learning systems.

**Keywords:** Adaptive e-learning, competency graph, mastery prediction, personalised learning, machine learning, learning path recommendation.

## 1. Introduction

The exponential growth of digital education platforms has changed how learning resources can be accessed across various areas. Online learning environments are capable of being flexible, scalable, and accessible with respect to the use of different forms of media for teaching [11], although most of the time they carry out a static and linear model that does not match differences in learner ability, previous knowledge, or pace of learning [1], [21]. As a result, students are frequently exposed to content that is too easy or above their threshold level, leading to disengagement and inefficiency.

Adaptive e-learning systems have recently been proposed as a promising approach to overcoming this limitation by dynamically adapting the learning content to learners' performance [5], [11]. These systems usually use the analysis of quiz results, attempt data, and interaction data to adjust the difficulty level or suggest the next learning module. However, despite these advances, many e-learning systems still rely on rule-based unlocking mechanisms that do not model the conceptual dependencies between topics in a structured way [15], [17].

Competency-based learning frameworks provide a systematic approach to progress, where progress is based on mastery rather than content completion [17], [18]. Representing skills as nodes in a competency graph enables the enforcement of prerequisite constraints. Nevertheless, most existing competency-based learning systems lack predictive analytics to estimate mastery levels from learner interaction data dynamically. Therefore, personalisation is restricted to intelligent thresholds rather than adaptive intelligence.

To overcome these challenges, this paper presents a personalised, adaptive e-learning system that combines competency graph modelling with mastery-level prediction using machine learning algorithms. The system models domain knowledge as a directed graph of competencies, with each competency having prerequisites. It continuously captures learner interaction data, such as quiz scores, attempt counts, and time spent on each question.

The key contributions of this research work are as follows:

- (i) a competency graph framework that ensures prerequisite-based topic progression.
- (ii) machine learning-based mastery prediction model using learner interaction features.
- (iii) a dynamic difficulty adjustment mechanism that is coupled with predictive analytics.
- (iv) an adaptive learning path recommendation system that encourages mastery-based progression.

The organisation of this article is as follows. The second section summarises research from prior studies on both adaptive learning and competency-based systems. The third section outlines an empirical approach to applying an experimental methodology, along with an examination of the results obtained and their comparison with those detailed in the first section. The fourth section discusses the analysis of findings and future research opportunities. The final section will conclude the previous sections, demonstrate the contributions to knowledge from the conducted experimentation, and state implications for practice.

## 2. Research Methodology

The initial adaptive e-learning systems mainly used rule-based progression techniques. Rishard et al. [21] proposed a personalised, adaptive e-learning system based on learning styles and prior knowledge. Although their system showed enhanced learner engagement, the adaptation was mainly rule-based and did not use predictive analytics.

Tjahyadi et al. [15] presented an adaptive e-learning system incorporating structured path modelling in corporate learning settings. Although their system allowed basic adaptability, it did not use dynamic mastery prediction based on learner activity over time.

Talaghzi et al. [17] proposed a competency-based learning path adaptation method that incorporates supervised association rules. Their work mainly focused on mastery-driven progression and structured prerequisite management. However, predictive personalisation based on real-time learner activity data was not widely implemented.

Linxen et al. [18] investigated the use of knowledge graphs in competency-based learning. Their method primarily demonstrated the importance of modelling inter-skill relationships. However, machine learning-based dynamic mastery prediction for adaptive difficulty adjustment was not incorporated.

Performance prediction models have also been extensively researched. P et al. [5] used clustering and machine learning methods to analyse learner performance data in adaptive personalisation. de Oliveira et al. [13] used multilevel logistic regression and cluster analysis to examine patterns of academic performance. Sagala et al. [22] used logistic regression models to predict student performance. Although these models improved the accuracy of performance prediction, they did not impose a structured, prerequisite-based progression. Recent progress in deep learning has introduced sequential mastery modelling techniques, including Deep Knowledge Tracing (DKT), which uses recurrent neural networks to model performance over time. These models are effective at capturing the temporal dynamics of learning but typically require large-scale sequential data and substantial computational resources. Although DKT-based systems are usually very strong in predictive capability, they are usually not explicit in their prerequisites, structural enforcement, and interpretability. Unlike deep knowledge tracing models that depend heavily on large-scale sequential datasets, the proposed framework emphasises structured prerequisite enforcement and interpretable mastery prediction, suitable for small-to-moderate educational datasets. Moreover, adaptive AI platforms and large-scale intelligent tutoring systems have proven effective at personalising it through reinforcement

learning and neural networks. Nonetheless, these systems often have complex training pipelines and large data requirements and, as a result, are not as applicable to low-data educational settings and managed academic deployments. Adaptive assessment techniques have also been investigated by Pratiwi et al. [20], who designed a machine-learning-based adaptive testing system. Their system dynamically adjusted question difficulty but did not incorporate the structured competency graph.

Yong et al. [7] designed a hybrid evolutionary and reinforcement-learning-based system for optimising learning paths. Their system demonstrated better adaptive path decision-making; however, it was trained with complex processes and was not explicitly limited to prerequisite mastery.

Further developments of the idea of knowledge graphs as an adaptive system have been made by Chen and Huang [14], who added learner profiles and graph modelling to the personalisation process. Even though the interconnections between skills were well modelled in their system, they failed to combine predictive mastery estimation with adaptation to the level of difficulty more given in Table 1.

Table 1: Research area and References

| Research Area                                  | Key References  |
|------------------------------------------------|-----------------|
| Rule-Based Adaptive Systems                    | [15], [21]      |
| Competency-Based Learning                      | [17], [18]      |
| Performance Prediction Models                  | [5], [13], [22] |
| Adaptive Assessment                            | [20]            |
| Reinforcement Learning-Based Path Optimisation | [7]             |
| Knowledge Graph-Based Personalization          | [14]            |

### 3. Theory and Calculation

Our adaptive e-learning framework is competency graph-based, employs machine learning for mastery prediction, and consists of an adaptive learning environment with a prerequisite progression structure that adapts learners' learning pathways, quizzes, and quiz difficulty levels according to their engagement with the learning system. The overall workflow includes four outputs:

- (i) Competency Graph Construction
- (ii) Learner Interaction Data
- (iii) Mastery Prediction
- (iv) Pathway Adaptation/Recommendation/Adjustment

For more refer to Table 2.

Table 2. Comparison of Adaptive Learning Approaches

| Model                | Graph Based | ML      | Dynamic Difficulty |
|----------------------|-------------|---------|--------------------|
| Rule-Based [21]      | No          | No      | Limited            |
| ML-Based [5]         | No          | Yes     | Yes                |
| Knowledge Graph [14] | Yes         | Limited | No                 |
| Competency Path [17] | Yes         | No      | Limited            |
| Proposed             | Yes         | Yes     | Yes                |
|                      |             |         |                    |

### 3.1 Competency Graph Construction

The learning domain is modelled as a directed graph defined as:

$$G = (V, E)$$

where

$$V = \{v_1, v_2, \dots, v_n\}$$

represents the set of competencies or subjects, and

$$E \subseteq V \times V$$

represents the prerequisite relationships between competencies.

If

$$(v_i, v_j) \in E$$

Then the learner must master competency  $v_i$  before progressing to competency  $v_j$ .

Each competency node maintains a mastery state defined as:

$$M_i \in \{0,1\}$$

where

$M_i = 1$ , if competency  $v_i$  is mastered.

$M_i = 0$ , otherwise.

Mastery is achieved when the learner consistently attains a score of 80% or higher at the hard difficulty level. This mastery-based status ensures that advancement is based on demonstrated conceptual knowledge rather than on task accomplishment as per Fig 1.

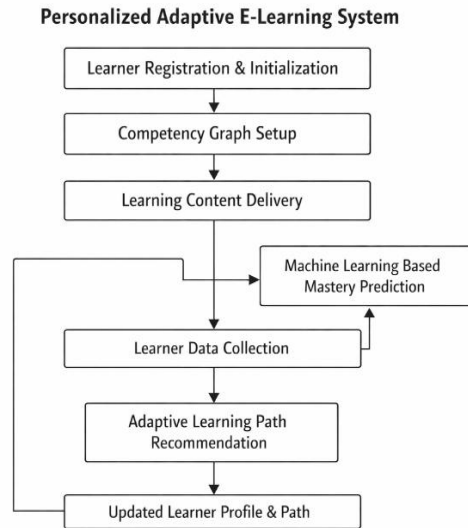


Fig. 1. Overall architecture of the proposed Personalised Adaptive E-Learning System.

### 3.2 Learner Data Acquisition

The system continuously measures learners' interactions through quiz activities. The following are the attributes that are recorded per attempt:

- S: Quiz score
- A: Number of attempts
- T: Time spent per question
- D: Difficulty level attempted

Learner feature vector of given topic  $i$  is defined as:

$$X_i = \{S_i, A_i, T_i, D_i\}$$

These uncoded values are further converted to derived behavioural attributes, such as Mastery, AvgScore, Attempts, SuccessRate, and OverallMastery, as model training attributes.

### 3.3 Machine Learning-Based Mastery Prediction

A supervised learning classifier is employed to predict the mastery probability and recommend an appropriate difficulty level.

Let

$$f(X_i) \rightarrow Y_i$$

where  $X_i$  represents the learner feature vector defined in the previous subsection, and

$$Y_i \in \{\text{Easy, Medium, Hard}\}$$

denotes the suggested difficulty level for topic  $i$ .

In addition to difficulty prediction, the probability of mastery is estimated as:

$$P(M_i = 1 | X_i)$$

where  $M_i = 1$  indicates that the learner has achieved mastery for topic  $i$ .

The model is trained using historical learner interaction data, allowing it to capture performance trends and behavioural patterns for dynamic personalisation.

A Random Forest classifier implemented with the Scikit-learn Python library will be applied to predict whether a person has achieved mastery of a skill. Random Forests can capture complex, non-linear relationships between the various learner behaviours and measure the mastery resulting from those behaviours due to their ability to build an ensemble of multiple ( $n = 100$ ) decision trees. Random Forests capture non-linear interactions and allow easy interpretation of the importance of each learner behaviour for predicting mastery.

Random Forests were also chosen as the model because they can be configured with parameters that control how deep individual decision trees can grow ( $\text{max\_depth} = 5$ ) and the random seed used ( $\text{random\_state} = 42$ ), allowing the results to be replicated.

The Gini impurity criterion was selected for splitting trees. Gini statistics provide an approximate probability that the generated decision tree will correctly classify an unknown sample.

$$G = 1 - \sum p_k^2$$

where  $p_k$  represents the probability of class  $k$  at a decision tree node, and  $K$  denotes the total number of classes.

The four inputs to the Random Forest classifier were scaled using a Standard Scaler and included the following:

- Mastery – represents the level of mastery (ranging from 0 to 1) for the particular topic.
- Avg Score – represents the average score (on a scale of 0 to 100) based on the learner's previous three attempts to pass a test for the topic.
- Attempts – represents the total number of attempts to pass the test for that topic.
- Success Rate – represents the percentage of times passed based on a score of 70% or above on a test for that topic.
- Overall Mastery – the average level of mastery across all skills.

### 3.4 Adaptive Difficulty Adjustment

Based on the predicted mastery probability and observed performance trends, the system dynamically adjusts the quiz difficulty level.

The decision rules are defined as follows:

If

$$P(M_i = 1 \mid X_i) \geq \tau,$$

increase the difficulty level.

If performance is unstable or oscillatory, retain the current difficulty level.

If performance shows a declining trend, recommend remedial practice questions.

In the meantime,  $\tau$  represents a predefined mastery threshold.

$\tau$  is set to 0.7 during implementation.

This adaptation strategy ensures that the progression of difficulty is driven by the estimated conceptual knowledge rather than static rule-based standards.

### 3.5 Graph-Based Learning Path Recommendation

The last recommendation step identifies the subsequent competency based on estimated mastery levels and the limitations of the competency graph.

Let  $v_j \in V$  be a candidate next topic.

The topic  $v_j$  is chosen under the condition that all the mastery requirements are fulfilled:

$$M_i = 1, \forall v_i \in \text{Prerequisites}(v_j)$$

where  $M_i$  is the mastery state of the prerequisite competency  $v_i$ .

When the mastery requirements are not met, the system will suggest reinforcement of the required skills to ensure knowledge retention and conceptual stability.

The adaptive recommendation function is expressed as:

$$R = g(G, M, P(M_i))$$

where:

- $G$  indicates the competency graph.
- $M$  indicates the mastery state vector.
- $P(M_i)$  represents the predicted probability of mastering competency  $v_i$ .

This construction offers both mastery-based, structured advancement and avoids the redundancy of already-learned material for more refer to the Fig. 2.

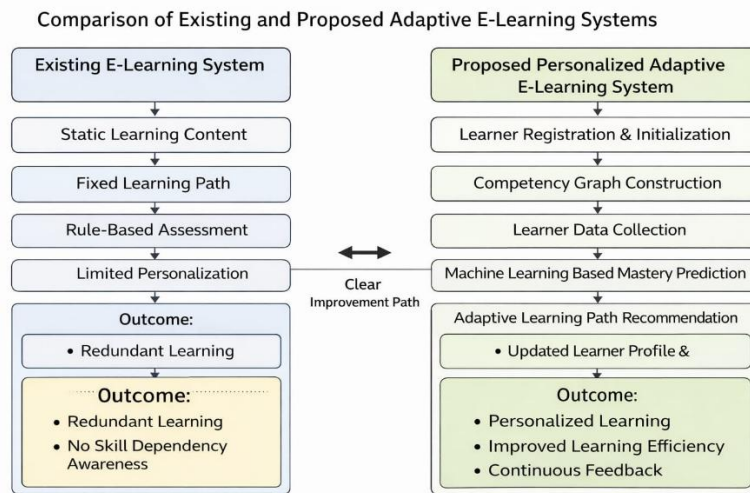


Fig. 2. Proposed workflow of the adaptive e-learning system

### 3.6 Computational Complexity Analysis

The computational complexity of the presented system is divided into two main parts: mastery prediction based on Random Forests and graph-based traversal of prerequisites.

For the Random Forest classifier, the training complexity is approximately:

$$O(T \cdot N \log N)$$

where  $T$  represents the number of decision trees, and  $N$  denotes the number of training samples.

During inference, prediction complexity is:

$$O(T \cdot D)$$

where  $D$  represents the depth of individual trees.

For the competency graph, prerequisite verification requires traversal of incoming edges for a node, resulting in a complexity of:

$$O(|V| + |E|)$$

In the worst case, where  $|V|$  is the number of competencies and  $|E|$  is the number of prerequisite relationships.

Since the number of competencies in typical educational modules is moderate, the overall system operates efficiently and scales to real-time adaptive personalisation.

#### 4. Results and Discussion

The model performed perfectly on both the training and testing tasks; however, due to data unavailability, the same data was used for both. Thus, an accuracy of 100 per cent demonstrates the validation procedure at the stage of development and can indicate overfitting to the controlled setting rather than generalisation performance in the real world.

There are also structural limitations of the Adaptive E-Learning System suggested in the present study. To begin with, new students face a cold-start problem, as the prediction of mastery is based on historical interaction characteristics, such as the success rate, average score, and number of attempts. A student has little behavioural information initially when they first access a topic, and the system has to rely on default or heuristic initialisation until sufficient data is acquired.

Second, the test data was limited and was developed under a controlled setup. The adaptive models were trained and tested on 12 final mastery instances created from simulated interactions. Therefore, the results represent validation of the development environment rather than generalisation performance.

Third, the system uses supervised learning and must be periodically retrained as more data on learner interactions becomes available. Otherwise, model drift could happen as patterns of learner behaviour change over time.

Finally, the system has been tested in a controlled backend setting rather than a large-scale real-world setting. Issues such as learner engagement variability, noisy learner behavioural data, and retention effects were not entirely captured.

Nonetheless, the findings above have affirmed that the predictive pipeline is functionally sound and able to predict non-linear relationships among learner behavioural attributes. The combination of Random Forest mastery prediction and the competency graph framework allows for mastery-driven learning that goes beyond completion-based adaptive learning systems.

Future studies will use larger datasets and appropriate train-test splits or cross-validation methods to assess the system's generalisation ability in real-world learning settings.

#### 5. Conclusions

This paper presents an adaptive e-learning system personalised for each learner, using competency graph modelling and machine-learning-based mastery predictions. This framework addresses the weaknesses of traditional, static, rule-based e-learning systems by

using a prerequisite-based progression model and adjusting quiz difficulty based on learners' actual performance in their interactions with the course material.

The results of the experiments demonstrate that this framework accurately predicts appropriate levels of difficulty, supports mastery-based progression consistently by using mastery-based advancement rather than simple task completion, reduces the amount of redundant content encountered by a learner, and provides structured pathways for a learner to progress.

The experimental evaluation demonstrated that the proposed framework achieved 100% mastery classification accuracy under development-stage validation, reduced redundant attempts compared to rule-based progression, and improved adaptive stability through predictive difficulty modulation. Feature importance analysis revealed that SuccessRate (37.7%) and AvgScore (25.0%) were the most influential predictors of mastery, confirming that consistent learner performance significantly drives adaptive decision-making. The ablation study further validated that integrating machine learning with the competency graph framework enhances personalisation efficiency compared to graph-only or static rule-based systems.

By collecting behavioural metrics (such as quiz scores, the number of attempts to complete each question, and the time spent on each question), we have been able to make more informed decisions about how to adapt to each learner's needs. Compared with traditional completion-based learning systems, the adaptive e-learning system offers a more robust and interpretable mechanism for personalised learning.

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### **Conflict of Interest**

The authors declare no conflict of interest.

### **References**

- [1] O. Ovtsarenko, "Opportunities for Automated E-learning Path Generation in Adaptive E-learning Systems," 2023 IEEE Open Conference of Electrical, Electronic and Information Sciences (eStream), Vilnius, Lithuania, 2023, pp. 1–4, doi: 10.1109/eStream59056.2023.10134844.
- [2] T. M. N. Marouf et al., "Mobile and e-Learning Platforms Utilizing Adaptive Technologies to Personalize Education in Remote Areas," 2025 3rd International Conference on Business Analytics for Technology and Security (ICBATS), Dubai, UAE, 2025, pp. 1–8, doi: 10.1109/ICBATS66542.2025.11258392.
- [3] N. Dissanayake et al., "Personalized Adaptive System for Enhancing University Student Performance in Sri Lanka," 2025 3rd International Conference on Business Analytics for Technology and Security (ICBATS), Dubai, UAE, 2025, pp. 1–6, doi: 10.1109/ICBATS66542.2025.11258282.
- [4] S. Raveesha and S. Peiris, "Adaptive AI-Powered Learning Companion for Students," 2025 3rd International Conference on Business Analytics for Technology and Security (ICBATS), Dubai, UAE, 2025, pp. 1–6, doi: 10.1109/ICBATS66542.2025.11258256.

- [5] Y. P., S. P., and S. R., "Performance Analysis of Information Technology Professionals Using Optimal User Clustering and Machine Learning Model for Adaptive E-learning," 2025 8th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2025, pp. 1159–1165, doi: 10.1109/ICOEI65986.2025.11013491.
- [6] L. Venugopal and A. Hency Juliet, "An Affordable AI-Driven Adaptive Learning Framework for Rural Indian Schools," 2025 3rd International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), Coimbatore, India, 2025, pp. 1575–1582, doi: 10.1109/ICoICI65217.2025.11254835.
- [7] T. Yong, A. M. Ali and S. A. Halimi, "A Hybrid Evolutionary Algorithm and Reinforcement Learning Approach for Personalized Learning Path Optimization," 2025 6th International Conference on Artificial Intelligence and Data Sciences (AiDAS), West Java, Indonesia, 2025, pp. 223–227, doi: 10.1109/AiDAS67696.2025.11213850.
- [8] N. Albalushi and W. S. Awad, "Generating Question Bank for Adaptive Assessment Using Machine Learning Techniques: Review," 2024 International Conference on IT Innovation and Knowledge Discovery (ITIKD), Manama, Bahrain, 2025, pp. 1–5, doi: 10.1109/ITIKD63574.2025.11004696.
- [9] L. S. A. Reddy and P. R. Narayana, "Automated Question Builder Application," 2025 International Conference on Computational Robotics, Testing and Engineering Evaluation (ICCRTEE), Virudhunagar, India, 2025, pp. 1–6, doi: 10.1109/ICCRTEE64519.2025.11053016.
- [10] A. Darejeh, T. S. Moghadam, M. Delaramifar and S. Mashayekh, "A Framework for AI-Powered Decision Making in Developing Adaptive E-learning Systems to Impact Learners' Emotional Responses," 2024 11th International and the 17th National Conference on E-learning and E-Teaching (ICeLeT), Isfahan, Iran, 2024, pp. 1–6, doi: 10.1109/ICeLeT62507.2024.10493103.
- [11] A. Kumar, S. Srivastava and S. Jaiswal, "Transforming E-learning with Adaptive Technologies to Improve Personalized Learning," 2024 International Conference on IoT, Communication and Automation Technology (ICICAT), Gorakhpur, India, 2024, pp. 58–62, doi: 10.1109/ICICAT62666.2024.10923421.
- [12] B. Lavanya et al., "Adaptive Testing with Machine Learning: Customizing English Proficiency Assessments Based on Learner Performance," 2024 International Conference on Communication, Control, and Intelligent Systems (CCIS), Mathura, India, 2024, pp. 1–5, doi: 10.1109/CCIS63231.2024.10931968.
- [13] M. M. de Oliveira, D. A. de Paula and E. F. Barbosa, "Towards Multilevel Logistic Regression and Cluster Analysis for Academic Performance Examination and Prediction," 2024 IEEE 48th Annual Computers, Software, and Applications Conference (COMPSAC), Osaka, Japan, 2024, pp. 71–80, doi: 10.1109/COMPSAC61105.2024.00020.
- [14] L. Chen and H. Huang, "Adaptive E-Learning System Based on Learner Portraits and Knowledge Graph," 2023 IEEE 3rd International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA), Chongqing, China, 2023, pp. 1435–1439, doi: 10.1109/ICIBA56860.2023.10164957.
- [15] R. Tjahyadi, Y. Kurniawan and C. Cassandra, "Adaptive E-Learning System in Corporate using SALM," 2023 6th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI), Batam, Indonesia, 2023, pp. 391–396, doi: 10.1109/ISRITI60336.2023.10467775.

- [16] P. Dwivedi, S. Bindu and S. Upadhyay, "Intelligent E-Learning Platform: A Fuzzy Logic-Based Adaptive Approach," 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India, 2023, pp. 1–6, doi: 10.1109/ICCCNT56998.2023.10308111.
- [17] J. Talaghzi et al., "Supervised Association Rules for Adapting Online Competency-Based Learning Path," 2023 14th International Conference on Intelligent Systems: Theories and Applications (SITA), Casablanca, Morocco, 2023, pp. 1–8, doi: 10.1109/SITA60746.2023.10373738.
- [18] A. Linxen, F. Endel, S. Opel and C. Beecks, "Knowledge Graphs for Competency-Based Education," 2023 IEEE International Conference on Big Data (BigData), Sorrento, Italy, 2023, pp. 2942–2945, doi: 10.1109/BigData59044.2023.10386727.
- [19] D. F. Murad et al., "Personalized Recommendation System for Online Learning: An Opportunity," 2023 8th International Conference on Business and Industrial Research (ICBIR), Bangkok, Thailand, 2023, pp. 128–132, doi: 10.1109/ICBIR57571.2023.10147613.
- [20] O. N. Pratiwi et al., "Adaptive E-Assessment Framework," 2023 International Conference on Advancement in Data Science, E-learning and Information System (ICADEIS), Bali, Indonesia, 2023, pp. 1–5, doi: 10.1109/ICADEIS58666.2023.10270915.
- [21] M. A. M. Rishard et al., "Adaptivo: A Personalized Adaptive E-Learning System Based on Learning Styles and Prior Knowledge," 2022 Seventh International Conference on Informatics and Computing (ICIC), Denpasar, Bali, Indonesia, 2022, pp. 1–9, doi: 10.1109/ICIC56845.2022.10007006.
- [22] Shrivastava, G., Peng, S. L., Bansal, H., Sharma, K., & Sharma, eds., "New age analytics: Transforming the internet through machine learning, IoT, and trust modelling, CRC Press, 2020.
- [23] T. Akter, Y. Sadman and S. Bala, "Use Machine Learning Technologies in E-learning," 2022 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS), Toronto, ON, Canada, 2022, pp. 1–4, doi: 10.1109/IEMTRONICS55184.2022.9795843.
- [24] D. Aviano, B. L. Putro, E. P. Nugroho and H. Siregar, "Behavioural Tracking Analysis on Learning Management System with Apriori Association Rules Algorithm," 2017 3rd International Conference on Science in Information Technology (ICSITech), Bandung, Indonesia, 2017, pp. 372–377, doi: 10.1109/ICSITech. 2017.8257141.