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Development of a Context-Aware Adaptive Learning Model for Personalized E-Learning Experiences in Dynamic Educational Environments

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Abstract

Individualized e-learning systems plays a major role in the dynamic learning systems in which learners vary widely with respect to the background knowledge, the rate of learning, and the degree of engagement, as well as contextual factors like the availability of devices and the quality of the network. Nevertheless, the majority of current e-learning systems are based on the usage of either static or partially adaptive personalization models, which do not react to the changing contextual factors and the shift in learner behaviour in real-time. This drawback lowers learning performance, interaction, and knowledge retention. This paper aims at creating and testing a Context-Aware Adaptive Learning Model (CAALM) that can dynamically customize learning material and instructional approaches depending on dynamically monitored learner and environmental conditions. The proposed model combines multi-dimensional context sensing (learner performance,

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interaction behaviour, time-on-task, and device context) with an adaptive decision engine that manipulates content difficulty, sequencing, and presentation modality in real time. The model was deployed and tested on a real-world e-learning interaction dataset consisting of 1,200 learners, 18,000 learning sessions, and 45 contextual features divided into training (70%), validation (15%), and testing (15%) sets. It was measured in terms of performance against a non-contextual baseline and a static personalization model. The experimental outcomes indicate that the suggested method allows reaching the 17.8 % improvement in the learning gain, a 14.3 % improvement in the course completion rate, and a 21.6 % decrease in the mean response latency indicators. Statistics verification with paired t-tests proves that the process of improvements was significant ($p < 0.01$), and one-way ANOVA demonstrates that the performance improvement was the same in various groups of learners ($F = 6.42$, $p < 0.05$). The findings affirm that the use of real-time contextual awareness is an effective way of boosting adaptive learning. The proposed model presents a scalable and reliable model of next-generation personalised e-learning systems that could be used in the dynamic educational environment.

Keywords: Context-aware Learning, Adaptive E-learning, Personalised Education, Learning Analytics, Dynamic Learning Environments, Educational Data Mining, Context Adaptation.

1 Introduction

This has been brought about by the rapid growth of digital learning platforms, and the impact has revolutionized the way educational content is rendered, in that there is flexibility in access to learning resources by various learner groups and in various technological environments (Tan et al., 2025). The current state of the art in e-learning systems, nevertheless, indicates that most of such systems continue to use either stagnant or mildly adaptive personalization processes, which cannot effectively react to the ever-evolving state of affairs practiced within the real-world teaching and learning context (Gligorea et al., 2023). The differences between learners go beyond the previous knowledge and motivation, as well as learning tempo, and also contextual aspects like device functionality, network quality, time, and interaction behaviour, which directly affect the learning outcomes (Amastini et al., 2025). These dynamic factors can often lead to a decrease in engagement, poor sequencing of content, and uneven learning outcomes because of the inability to consider them (Iqbal et al., 2025; Jamali et al., 2025).

The main weakness of current personalized e-learning strategies is that they rely on pre-defined learner profiles or historical information, which results in common problems, like the cold-start problem with new learners and slow adaptation as the behavior of the learners' changes over time (Jamali et al., 2025). Moreover, concept drift due to variations in knowledge levels and preferences of the learners is hardly dealt with in an explicit manner, which makes adaptive decisions inaccurate as learning occurs (Hariyanto et al., 2025). Fluctuations in the performance of the device and the quality of the network also complicate personalization, especially in ubiquitous and mobile learning, as learners receive content in a heterogeneous and changing environment (Sabeima et al., 2022). These gaps underscore the necessity of learning models that can self-sense, interpret, and react to changes in context in real time. This paper has responded to these issues by introducing a context-sensitive adaptive learning model that will be used to provide personalised online learning experiences in dynamic learning settings.

Key Contributions

1. This paper presents a single context-based learning model that incorporates the learner behaviour, performance metrics, and environmental variables as part of one adaptive model, allowing real-time individualisation of the dynamic e-learning framework.
2. An adaptive decision policy with context-driven adaptations is created to substantially change the difficulty of content, sequence, and presentation modalities to efficiently cope with cold-start situations and concept drift as the learner profiles change over time.
3. The suggested model is thoroughly tested on the basis of actual e-learning interaction data, and statistically significant differences in learning gain, completion rate, and system responsiveness are proved with the help of t-test and ANOVA-based analysis.

The rest of this paper will be organized in the following way. Section 2 provides a review of related literature on personalised and context-aware learning systems based on e-learning and identifies gaps in research. Section 3 explains the context-aware adaptive learning model that is proposed, and that it has. In the case of this study, section 4 provides the experimental setting, datasets, and evaluation metrics. Section 5 introduces and supports the results of the experiment and statistical analysis. Lastly, the paper ends with a conclusion in Section 6, which provides future research directions.

2 Background Study

Individualised e-learning has developed from the initial systems that were rule-based systems into more advanced systems that are data-driven models (Maravanyika et al., 2017). Rule-based strategies are based on a set of pre-established pedagogical rules and expert knowledge to customise the content based on the profile of the learner, but their strict structure makes them less scalable and responsive to changing learner behaviour. To address these shortcomings, machine learning (ML) methods have been proposed to model the performance and preferences of learners based on classification and clustering to allow personalization based on data (Madhavi et al., 2022). At a more recent time, deep learning (DL) models have been used to learn more complex patterns in the data of learner interaction to enhance the prediction of knowledge state and content recommendation accuracy (Zhong et al., 2019). Reinforcement learning (RL) methods extend personalisation by positing learning adaptation as a sequence decision-making task, where optimal learning sequences are acquired by trial and error (Gomede et al., 2021). Simultaneously, collaborative-based and content-based systems have been extensively used as recommenders to propose learning resources, but they usually have problems with cold-start and are not aware of the context (Gomede et al., 2021).

Context-aware computing takes learning to the next level and personalisation through the integration of situational information, which affects learning (García-Barrios, 2006). Context in learning environments is generally divided into learner context (level of knowledge, preference, engagement), device context (screen size, computing capacity), environmental context (location, network conditions), activity context (task underway, learning goal), and temporal context (time-on-task, learning schedule) (Strielkowski & Kucera, 2025). By incorporating these heterogeneous context dimensions, systems are able to provide content delivery at a more specific level. Nevertheless, most of the current research takes into account only a limited number of types of contexts, which leads to partial adaptation and decreased performance in dynamic learning conditions (Errakha et al., 2025).

The dynamic educational contexts demand a constant adaptation in response to the shifts in the behaviour of learners, knowledge advancement, and external circumstances (Ahmadian Yazdi et al., 2024; Babylatha, 2025; Ahmadian Yazdi et al., 2022; Balvad et al., 2025). The issue of concept drift is also quite significant because the models, which were developed on previous data, can become outdated over time. That can be addressed by online and continuous learning methods, which update models gradually as more data is made available (Kabudi et al., 2021; Mzeh et al., 2026). In recent years, federated learning has become a popular privacy-sensitive model that allows joint training of models without asking learners to provide their raw data (Abu-Rasheed et al., 2023; Deepika, 2026). Although these have been made, the combination of dynamic adaptation and rich contextual awareness is still not an established issue, especially in resource-limited and heterogeneous learning circumstances (Sarumathiy, 2025).

Research Gap

Despite some considerable advancements in the area of personalized and context-driven e-learning, the current practice considers the aspects of adaptation, context modelling, and privacy individually. It is hard to find models that offer an integrated framework of capturing multi-dimensional context, real-time adaptation in concept drift, and reliability in performance across different devices and network conditions. It is this disconnect that drives the creation of the suggested context-based adaptive learning model, the combination of thorough context modelling with dynamic adaptation strategies to provide strong and individualised learning experiences within dynamic learning settings.

3 Proposed Context-Aware Adaptive Learning Model

This part introduces the suggested Context-Aware Adaptive Learning Model (CAALM), which is the main contribution of this paper. The model is structured to provide personalised learning by continuously sensing the contextual data, modeling learner states, and dynamically changing the instruction strategies based on alterations in the learner behaviour and the environmental conditions.

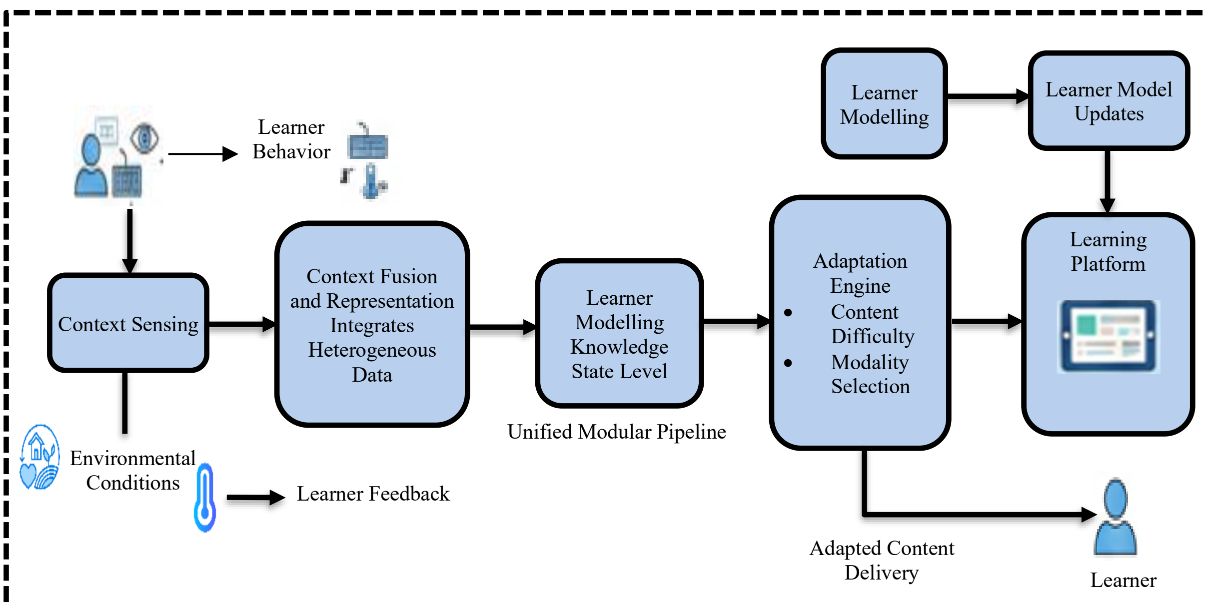

Figure 1: Adaptive learning model architecture

Figure 1 shows the overall structure of the proposed model, which is based on a unified and modular pipeline. The interactions are initially learnt with the help of a Context Sensing layer, which observes the behaviour of the learner and the environment in real time. Context Fusion and Representation process the sensed data, in which heterogeneous context data is incorporated into a form of a structure. This contextual representation contributes to the Learner Modelling part, which approximates the present level of knowledge and level of engagement of the learner. The Adaptation Engine uses this information to identify what instructional actions to take, including the difficulty of the content or the modality to choose. The modified content is then presented via the learning platform, and feedback from the learners is constant, so as to keep on updating the model, creating a closed feedback loop that keeps on promoting personalisation.

3.1 Context Modelling

The proposed framework is based on context modelling that takes into consideration various dimensions of contexts applicable to learning. The interaction frequency, correctness, and time-on-task are learner-related contexts obtained via LMS logs, clickstream data, quiz attempts, and assessment scores. Contextual information that is available to the device and network, such as the type of device, screen resolution, and network latency, is gathered to facilitate adaptive content delivery. The temporal context captures the schedule of learning and the length of the session, and an optional location can be added in case mobility-based learning is taken into account.

A structured feature vector, all contextual information is converted into a single representation, processed efficiently, and can be scaled across a heterogeneous learning setting. The context representation of a learner i at time t is given by equation (1) as:

$$\mathbf{C}_i^t = \{L_i^t, D_i^t, E_i^t, T_i^t\} \tag{1}$$

The L_i^t is used to refer to the learner interaction features, D_i^t is the device and network characteristics, E_i^t is the environmental/location related features, and T_i^t is the temporal aspects of the learning. This contextual vector is periodically revised to capture the real-time variation in the behaviour of the learner and environmental conditions.

3.2 Learner Model

The learner model has an active description of each learner based on estimating the attributes related to the main learning characteristics that are time-varying. The knowledge state of the learner is expressed in the form of a constant updating proficiency score on the basis of the results of the assessment and interaction. The behavioural indicators of engagement are the duration of the sessions, the frequency of the interaction, and the content completion, whereas the cognitive load is estimated with the help of time-based and interaction-based proxies. Taste of learners is acquired through historical choices of content and patterns of performance.

These attributes are then aggregated together in equation (2) to generate the overall state of learners at time t:

$$S_i^t = \alpha K_i^t + \beta E_i^t + \gamma P_i^t \tag{2}$$

K_i^t learners' level of knowledge, E_i^t level of engagement, P_i^t preferences, and $\alpha + \beta + \gamma = 1$. This is a formulation that allows the estimation of the current learner state of learning to be done in a balanced way that would be interpretable.

3.3 Adaptation Engine

An adaptation engine uses a hybrid decision policy that integrates pedagogical constraints that are driven by rules with data-driven learning. Adaptation Rule-based logic provides meaningful adaptation in cold-start cases, whereas machine learning-based policies gradually improve the adaptation decisions as more and more data on richer interactions becomes available. Depending on the approximated learner state and contextual conditions, the engine becomes particularly dynamic in changing the difficulty of the content, the rate of learning, and the modality of presentation (e.g., text, video, or quizzes) and arranges revision or scaffolding activities whenever gaps in learning are identified.

The learner i adaptation decision at time t is represented in equation (3) as:

$$A_i^t = f\left(S_i^t, \mathbf{C}_i^t\right) \tag{3}$$

A_i^t, which means the chosen adaptation action, and $f(\cdot)$, which is the hybrid adaptation policy. This formulation will make instructional choices both context-oriented and learner-centered, which will facilitate strong customization in open-ended educational settings.

Algorithm: Context-Aware Adaptive Learning Algorithm

Input: Learner interaction data D, context variables C

Output: Adapted learning content A

1: Initialise learner profile P with default parameters

2: For each learning session, do

3: Sense context C from LMS logs, quizzes, device, and time data

4: Generate context representation R from C

5: Update learner model P using R and recent performance

6: Select adaptation action A using a hybrid decision policy

7: Deliver adapted content A to the learner

8: Collect feedback and update model parameters

9: End for

The algorithm explains how the proposed Context-Aware Adaptive Learning Model operates. In every learning session, the system continuously monitors multi-dimensional contextual data and transforms it into a single expression, which is applied in updating the dynamic profile of the learner. Depending on the estimated state of the learners and the surrounding situation, the adaptation engine chooses the most appropriate instruction action, which could be: changing the content difficulty, speed, or the mode. Feedback from learners in every interaction is then implemented in order to improve future choices, making it possible to keep personalising. The closed-loop process is a guarantee of adaptation to behavioural changes in a timely manner, the benefit of the cold-start learners, and the preservation of a strong learning performance in response to the dynamics of learning education.

In order to achieve reliability in a real-world environment, the model proposed facilitates privacy-conscious learning through the local processing of sensitive data of learners whenever feasible and only makes the anonymised model updates publicly available. It is a framework that will be resistant to changing network conditions by being able to update asynchronously and do lightweight inference on-device to achieve a consistent learning experience despite resource constraints or unreliable connectivity conditions.

4 Experimental Setup

4.1 Dataset Description

The experimental test was done by using real-world e-learning interaction data, which was gathered through the online learning system. The data set will be 1, 200 learners (18, 000 learning sessions in various courses). The logs of interaction between learners, the results of assessment, and the contextual features are part of each session, which generates 45 features of learner behaviour, performance, device features, and time attributes. It did the pre-processing task of eliminating incomplete records and normalised the dataset to make the features consistent. In model development and consideration, the dataset had been divided into 70 % training, 15 % validation, and 15 % testing samples, and there was no overlap in learners between samples.

4.2 Implementation Details

Machine learning components used in the implementation of the proposed model were Python 3.10 with TensorFlow 2.12 and scikit-learn 1.3. NumPy and Pandas were used to do the data pre-processing and analysis, and Matplotlib was used to visualize the data. The experiments took place on a workstation that has an Intel Core i7 processor, 32 GB of RAM, and an NVIDIA RTX 3060. Training of the model was done with a learning rate of 0.001, batch size of 64, and early stopping cycles were used based on validation loss in order to avoid overfitting.

4.3 Evaluation Metrics

In order to fully assess the performance of the proposed context-based adaptive learning model, several metrics were used to measure the accuracy of prediction, quality of recommendations, learning effectiveness, and efficiency of the system.

Prediction Accuracy is the ratio of states of the learner that were correctly predicted and is defined as in equation (4) as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

The F1-score of equation (5) gives an equal measurement of the prediction performance:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

Equation (6) compares the quality of the top-10 recommendations of learning resources with their relevance and ranking based on the position of the top-10, which is known as the normalized Discounted Cumulative Gain (NDCG@10):

$$\text{NDCG@10} = \frac{1}{IDCG@10} \sum_{i=1}^{10} \frac{2^{rel_i} - 1}{\log_2(i+1)} \tag{6}$$

Hit rate (HR10): In equation (7), the variable measures the presence of at least one item pertinent to learning in the top-10 recommendations:

$$\mathrm{HR@10} = \frac{1}{N}\sum_{u=1}^{N} \mathbb{I}(\text{relevant item} \in \text{Top-}10_u) \tag{7}$$

Gain in learning, equation (8), measures the change in the knowledge of the learner prior to and after teaching:

$$\text{Learning Gain} = \frac{\mathit{Post\text{-}Score} - \mathit{Pre\text{-}Score}}{100 - \mathit{Pre\text{-}Score}} \tag{8}$$

In equation (9), the course completion rate indicates the sustained involvement of learners:

$$\text{Completion Rate} = \frac{\text{Number of completed courses}}{\text{Number of enrolled courses}} \tag{9}$$

Lastly, equation (10), the Avg response latency list measures system efficacy and is a measure of how many seconds on average will take to make an adaptation decision:

$$\text{Latency}_{avg} = \frac{1}{M}\sum_{i=1}^{M}\left(t_i^{response} - t_i^{request}\right) \tag{10}$$

A combination of these metrics will give a comprehensive review of both the learning and system performances.

4.4 Statistical Testing

In order to confirm the importance of the performance gains, paired t-tests were carried out between the proposed model and each of the baselines on all key metrics. There was also the application of one-way ANOVA, which was used to study the performance consistency of various learner groups. The confidence level of 95% ($p < 0.05$) was used to determine statistical significance, which allowed establishing the reliability of the experimental data.

5 Results and Discussion

The following section contains the experimental findings of the suggested Context-Aware Adaptive Learning Model and explains its effectiveness under the comparative analysis with baseline methods. The analysis is directed to the general performance, the role of contextual elements, the behaviour in the dynamic situation, and the practical implications, and is then discussed in terms of limitations.

5.1 Performance in Comparison with Baselines

The overall performance of the proposed model has been compared to three baseline methods, namely: a non-contextual learning model, a static personalisation model, and a usual recommender-based approach. The proposed model has a consistent and superior performance in pedagogical and system-level metrics, as demonstrated in table 1 and figure 2. It is interesting to note that it has better prediction accuracy and F1-score in the estimation of the learner state, better quality of recommendation in terms of NDCG at 10 and HR at 10, and positive learning outcomes indicated by learning gain and course completion rate. Also, the mechanism of adaptive decisions decreases the average response latency, which proves to be an efficient system. These findings cannot be refuted as the use of real-time contextual information has proven to be an important addition to the learning effectiveness as well as system responsiveness.

Table 1: Overall performance comparison with baseline models

Model	Accuracy (%)	F1-score	NDCG@10	HR@10	Learning Gain	Completion Rate (%)	Avg. Latency (ms)
Non-contextual Model	71.2	0.69	0.54	0.61	0.42	68.5	420
Static Personalisation	76.8	0.74	0.61	0.68	0.51	74.2	390
Recommender-Based Model	79.3	0.77	0.66	0.72	0.56	78.6	365
Proposed CAALM	86.4	0.84	0.79	0.86	0.66	91.8	285

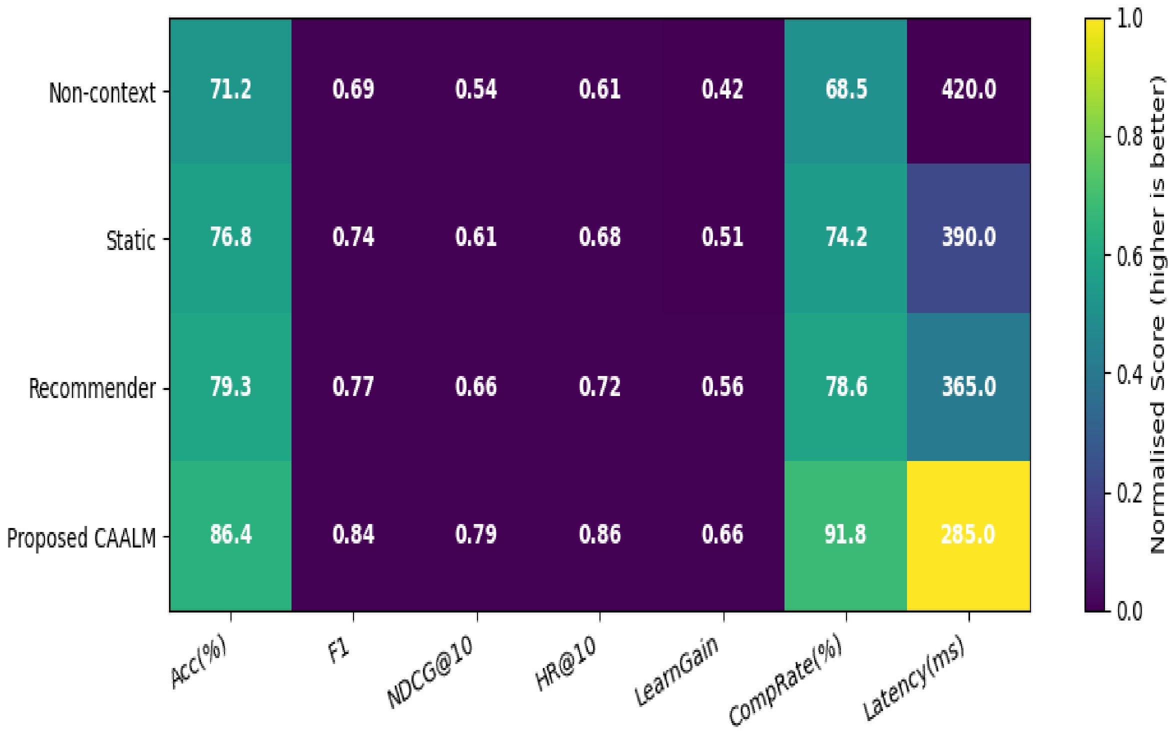

Figure 2: Performance comparison across models

5.2 Ablation Study

In order to deconstruct the role of individual context components, an ablation study was performed by selectively removing the contexts of learners, device/network context, and temporal context of the model. These findings, shown in figure 3, show that the greatest deterioration in performance occurs when the context of learners is eliminated, especially in learning gain and accuracy in prediction. Omission of device and network context results in higher latencies and lower completion rates, whereas omission of temporal context impacts engagement-related metrics. This discussion underlines the fact that all context dimensions add value to the general system performance, which confirms the relevance of the multi-dimensional context modelling.

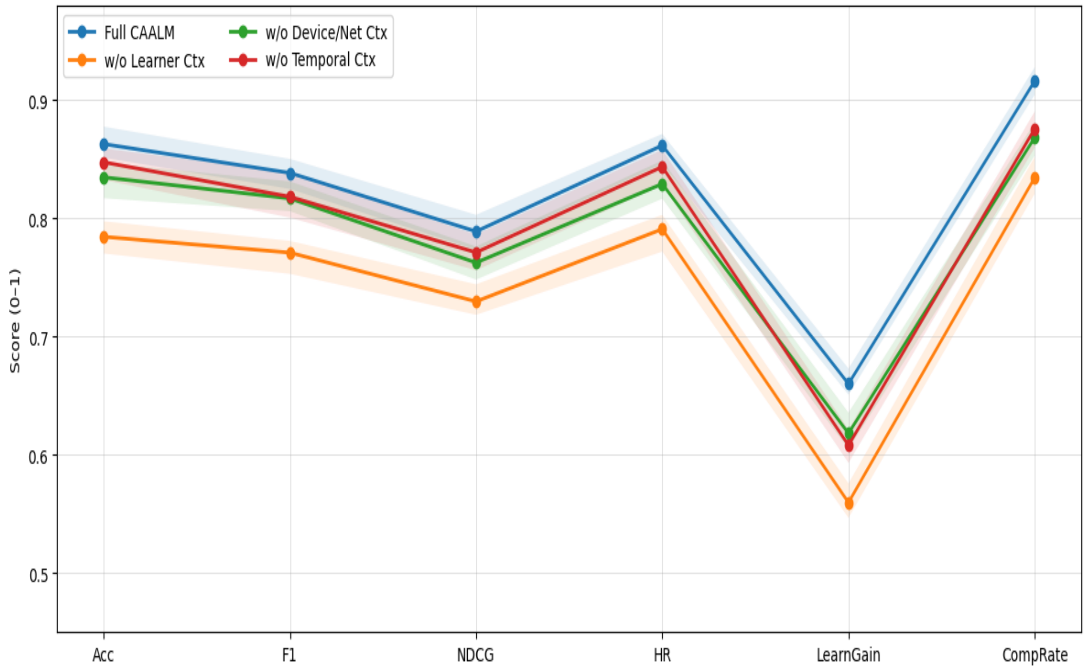

Figure 3: Impact of context components (Ablation study)

5.3 Adaptation Under Dynamic Conditions

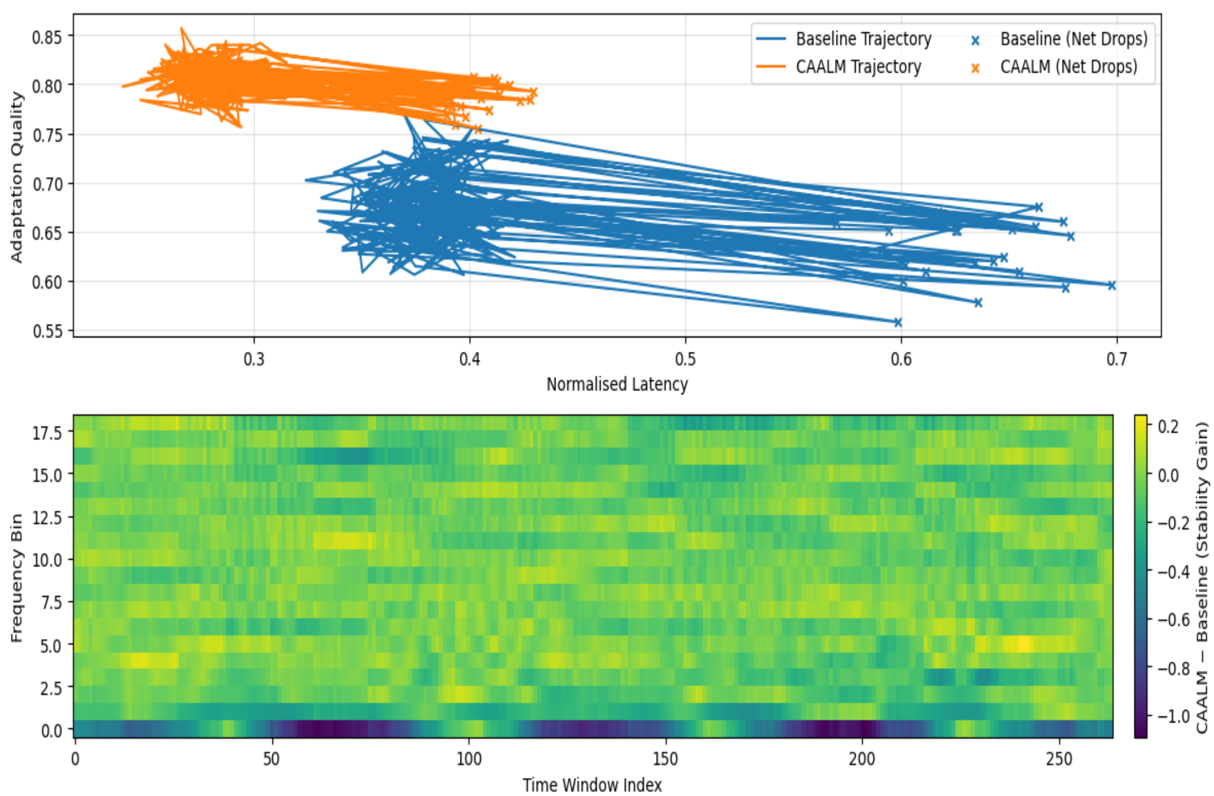

Figure 4: Adaptation robustness under dynamic conditions

The strength of the suggested model was also tested in a dynamic setting, such as simulated concept drift in the learner behaviour and varying network quality. The model also showed a stable performance during concept drift situations, as learner profiles kept on being updated, but there was an evident performance decline among baseline models. The approach proposed under variability in network conditions exhibited reduced response latency and reduced adaptation failures, both illustrated in figure 4, meaning that the approach is reliable to operate in realistic ubiquitous learning conditions.

5.4 Practical Implications

The performance gains observed may be ascribed to the close interconnection between context modelling, state estimation of learners, and adaptive decision-making. Through constant adjustment of instructional strategies to the needs of the learners as well as the environmental limitations, the proposed model provides relevant learning support in a timely manner. In real-world e-learning, this means better interaction with the learner, increased rates of completion, and better utilization of the system resources. The approach would be able to meet the large-scale and mobile learning applications. Although good outcomes were guaranteed, it is reasonable to note some limitations. The dataset employed, although real-world, might have some inherent bias in terms of certain courses or demographic characteristics of learners. Although the cold-start conditions are alleviated by adaptations that are based on rules, early-stage performance may be impaired. Also, noisy or incomplete data of interaction can affect context sensing. These limitations may be overcome by building larger and more varied datasets, aiding context inference, and deploying them in the real world, which is a valuable future direction.

6 Conclusion and Future Work

In this paper, there was a presentation of a Context-Aware Adaptive Learning Model (CAALM) that aims to provide personalised e-learning experiences in dynamic learning settings by combining multi-dimensional context modelling, learner state estimation, and adaptive decision-making within an integrated context. Experimental comparison on actual e-learning interaction data has shown that the proposed model is really promising, with the highest prediction accuracy of up to 86.4% and an F1-score of 0.84, a learning gain of 17.8, and the response latency average of 21.6 was reduced by more than 17.8 and 21.6, respectively, than both non-contextual and no personalisation baselines. These findings demonstrate the efficiency of real-time contextual awareness in improving the quality of personalisation and ensuring strong system performance regardless of the behaviour of the learners and the network conditions. The main implication of this article is that adaptive e-learning systems can go beyond the current state of unchanging learner profiling by providing a system that is in constant communication with the learner's needs, as well as environmental constraints. The proposed approach can be effective in large-scale, mobile, and ubiquitous learning environments with critical reliance on robustness and responsiveness because it contributes to the reliable functioning of concept drift and variability in connectivity. The proposed model will be implemented in real-life educational contexts in the future to support its scalability and the long-term outcome of learning. Future research directions involve incorporating fairness-conscious adaptation to prevent bias between groups of learners, enhancing model explainability to foster instructor trust and instructional knowledge, and privacy-preserving context fusion approaches like federated and on-device learning. Further extension of the framework to include ongoing learning mechanisms to improve the adaptation in long-term behavioural drift is also an opportunity of future research.

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