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Neuromorphic Computing-Enabled Context-Aware Adaptive Mobile Learning Framework for Real-Time Cognitive Load Management

Gulbahor Sidikova[1*], Nurbol Karakulov[2], Mustafo Tursunov[3], Atabek Kochkarov[4], Asqad Oltiboyev[5], Yana Arustamyan[6], Dilfuza Toirova[7], and Abdumajid Madraimov[8]

[1*]Senior Lecturer, Fergana State University, Fergana, Uzbekistan; University of Tashkent for Applied Sciences, Tashkent, Uzbekistan. gulbat2126@gmail.com, https://orcid.org/0009-0002-8804-988X

[2]Senior Lecturer, Uzbekistan National Pedagogical University named after Nizami, Tashkent, Uzbekistan. karakulovnurbol2022@gmail.com, https://orcid.org/0009-0005-1298-614X

[3]Lecturer, Termez University of Economics and Service, Termez, Uzbekistan. mustafo_tursunov@tues.uz, https://orcid.org/0009-0007-9658-7182

[4]Professor, Tashkent Institute of Irrigation and Agricultural Mechanization Engineers, National Research University, Tashkent, Uzbekistan. 19700218ak@gmail.com, https://orcid.org/0009-0003-2258-1598

[5]Lecturer, Department of Pedagogy, Termez State Pedagogical Institute, Termez, Uzbekistan. asqadoltiboyev@gmail.com, https://orcid.org/0009-0005-6326-1851

[6]Associate Professor, Department of Translation Studies and Comparative Linguistics, National University of Uzbekistan, Tashkent, Uzbekistan. y.arustamyan@nuu.uz, https://orcid.org/0000-0003-1528-7537

[7]Professor, Samarkand Branch of Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Samarkand, Uzbekistan. dilfuza.toirova@mail.ru, https://orcid.org/0009-0008-8210-1935

[8]Professor, State Museum of the History of the Timurids under the Academy of Sciences of the Republic of Uzbekistan, Tashkent, Uzbekistan. abdumazidmadraimov@gmail.com, https://orcid.org/0009-0002-8027-9066

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Abstract

The growing use of mobile learning in wireless and ubiquitous computing environments has posed various difficulties in managing the cognitive load of learners in a dynamic environment. Traditional adaptive learning approaches may not be equipped with the capacity to monitor continuously the learner's cognitive state and adapt intelligently to the environmental and behavioral changes. This problem could lead to a lower level of engagement of learners, increased cognitive load, and inefficiency in the learning process. In order to solve such problems, this research paper presents the

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*Corresponding author: Senior Lecturer, Fergana State University, Fergana, Uzbekistan; University of Tashkent for Applied Sciences, Tashkent, Uzbekistan.

Neuromorphic Computing-Enabled Context-Aware Adaptive Mobile Learning Framework for Real-Time Cognitive Load Management. This approach consistently monitors contextual factors such as the user's engagement pattern, environmental conditions, and device-level operations to predict the cognitive load and deliver the instruction accordingly. Neuromorphic intelligence was applied for cognitive processes that will be done with low delay and energy consumption in the wireless mobile context. The new learning model was tested with the help of various metrics, namely adaptation accuracy, precision, recall, F1-score, energy efficiency, and response latency. The experimental outcome revealed that the new framework obtained an adaptation accuracy rate of 96.8%, precision of 96.1%, recall of 95.7%, and F1-score of 95.9%, which is superior to traditional mobile learning and deep adaptive learning models. Furthermore, the proposed framework offered a reduction in response delay to 104 ms and an energy efficiency rate of 0.95. Results indicate that the integration of neuromorphic computing technology with context-aware adaptive learning systems can greatly improve learner personalization, cognitive load management, and system reactivity. The suggested framework is expected to contribute towards the design of an intelligent, scalable, and energy-efficient adaptive learning environment for future wireless-based learning platforms.

Keywords: Neuromorphic Computing, Context-Aware Mobile Learning, Cognitive Load Management, Adaptive Learning Systems, Ubiquitous Computing, Wireless Mobile Networks, Real-Time Personalized Learning.

1 Introduction

The increasing prevalence of mobile learning technology has revolutionized the educational landscape by providing constant access to digital information regardless of location and device type Poornimadarshini, (2025). However, traditional mobile learning solutions tend to overlook the changing cognitive levels of learners, the presence of external disturbances, and environmental changes Zhang et al., (2025). Too much information provision, untimely notifications, and the use of static approaches in instruction can overwhelm the cognitive capacity of users, hinder learner engagement, and hamper knowledge acquisition (Chen, 2026). This issue is especially important within the realm of wireless computing and ubiquitous computing systems, wherein interactions between users and educational applications occur under varying conditions, including fluctuating internet connections, mobility, concurrent tasking, and heterogeneous devices. It follows that the creation of intelligent adaptive learning systems to monitor and regulate learner cognitive load is highly relevant to mobile and ubiquitous education environments.

New developments in neuromorphic computing have been identified as a solution to the abovementioned problems. Neuromorphic computing technologies imitate the neural processing capability of the human brain, thus offering solutions based on low-latency processing, energy efficiency, and contextual understanding that allows for decision making. With the help of neuromorphic computing technologies and their combination with adaptive mobile learning approaches, it becomes possible to continuously assess contextual parameters related to interactions, behavior, physiology, and environment (Rahim, 2024). This helps not only to increase the efficiency of learning but also to reduce cognitive load by ensuring higher concentration levels. Furthermore, neuromorphic computing allows for the implementation of edge-based intelligent processing, which makes it suitable for use in the field of wireless mobile communications and ubiquitous computing.

This paper proposes a Neuromorphic Computing-Enabled Context-Aware Adaptive Mobile Learning Framework for Real-Time Cognitive Load Management. This framework leverages context-aware sensing, neuromorphic intelligence, and adaptive content delivery solutions to enhance user experiences in mobile learning environments. The research aims to make a contribution to the development of mobile learning, ubiquitous computing, and dependable adaptive systems by offering an intelligent solution for increasing learning personalization and efficiency while reducing cognitive load. Experimental evaluation confirms the efficiency of this approach.

Key Contributions

- Proposed an adaptive mobile learning framework utilizing neuromorphic computing technology for real-time cognitive load control in ubiquitous learning settings.
- Developed a mechanism for contextual sensing that dynamically assesses learner interaction patterns and behaviors.
- Integrated intelligent adaptive content delivery algorithms that reduce cognitive load on learners to increase engagement and knowledge retention.
- Evaluated the effectiveness of the proposed model using performance indicators like adaptability, accuracy, response time, energy consumption, and learning efficacy in mobile wireless networks.

The paper is divided into five main parts. Section I begins by describing the importance of managing cognitive load in adaptive mobile learning, along with the research contribution. Section II deals with existing literature reviews in connection with neuromorphic computing and context-aware learning systems. Section III describes the design of the proposed framework, architecture, algorithm, and mathematical model. Section IV is about the experimental results, performance evaluation, and ablation analysis, while Section V gives conclusions and future directions for the intelligent ubiquitous learning environment.

2 Literature Survey

Emerging trends such as neuromorphic computing, edge intelligence, and context-aware mobile computing have had significant impacts on intelligent adaptive learning environment technology (Patel, 2024). A number of studies have been conducted on wearable computing, edge computing, cognitive computing, and human computer interaction systems for enhancing real-time decision making as well as personalized service provision within wireless systems (Li et al., 2025). It provides an elaborate survey of wearables that enables mental and physical health monitoring by considering the role of real-time physiology sensing in adaptive intelligent systems (Elfouly & Alouani, 2025). Likewise, another research paper was done regarding human machine interface using deep learning models for intelligent Internet of Things systems, where the role of adaptive interactions in enhancing user experience was considered (Wang et al., 2025; Rancea et al., 2024).

Collaboration between edge and cloud computing has been suggested to be useful for adaptive services in mobile systems (Yu et al., 2025). Cloud and edge computing were used for developing cognitive services, which resulted in an improvement in real-time processing efficiency in distributed computing (Ding et al., 2020; Ghourtani et al., 2026). Multi access edge computing for 5G environments was examined in the context of its suitability for latency-sensitive applications (Pham et al., 2020). It reviews artificial intelligence and edge computing in Internet of Things applications to show that edge intelligence is effective for context-aware systems (Bourechak et al., 2023). The above-discussed results provide a strong foundation for using neuromorphic and edge-based processing techniques in adaptive mobile learning systems.

Research on cognitive computing as well as adaptive intelligent systems has also contributed to the development of context-aware education platforms. As discussed earlier, the paper focused on cognitive computing methods for human-machine collaboration and the importance of intelligent decision-making in adaptive management systems (Banerjee, 2023). It also presented the utilization of cognitive computing and wireless edge communication techniques in healthcare robots, thus proving the efficiency of intelligent processes with low latency in real-time environments (Khan et al., 2020; Wan et al., 2020). Additionally, it discussed optoelectronic synapses in neuromorphic reservoir computing and provided proof of their ability to perform efficient neural computations (Lei et al., 2026; Gracia & Srinivasan, 2026).

A few recent studies have also considered context-aware orchestration and intelligent resource management for mobile and pervasive systems (Brăileanu, 2025; Nursuwars et al., 2025). It suggested an approach for context-aware orchestration that uses AI-enabled techniques to manage the dynamic behavior of services according to environmental parameters (Sofia et al., 2023). It presented a context-aware approach that leverages AI-based task offloading and resource orchestration for efficient and adaptive intelligent transportation systems (Rawlley et al., 2025). In addition, it looked at Edge AI solutions for smart cities with respect to efficient and intelligent processing for scalability and adaptivity (Velaga et al., 2025; Wan et al., 2020).

Despite the independent attention paid to edge intelligence, context-aware computing, cognitive computing, and adaptive orchestration by earlier works, no sufficient work has been done so far to incorporate neuromorphic computing within adaptive mobile learning for estimating cognitive load. Current mobile learning frameworks do not possess the capability to estimate users' cognitive state dynamically and provide energy-aware adaptation based on contextual information. Thus, the research problem that is aimed at filling this gap will involve creating a novel neuromorphic computing-based framework for context-aware and adaptive mobile learning applications.

3 Proposed Neuromorphic Context-Aware Adaptive Mobile Learning Framework

The proposed Neuromorphic Computing-Enabled Context-Aware Adaptive Mobile Learning Framework is designed to dynamically monitor learner cognitive load and personalize learning content in real time. The proposed framework uses neuromorphic intelligence, context awareness, adaptive systems, and wireless mobile learning systems to ensure reliable and efficient learning systems. This research method will seek to avoid cognitive overload through better engagement, response efficiency, and resource optimization in ubiquitous mobile environments.

The workflow of the proposed framework includes five different phases, which are as follows: (i) Context Acquisition, (ii) Cognitive Load Estimation, (iii) Neuromorphic Processing, (iv) Adaptive Content Recommendation, and (v) Feedback Optimization. In this case, contextual data are acquired from mobile devices, wearables, and learning interaction data. The collected data include the learner's attention level, the learner's device usage pattern, the learner's response time, the environment noise level, the network status, and the learning session duration. This data is preprocessed and sent to the neuromorphic processing module.

Neuromorphic engine imitates neural activities through spike-based learning to detect patterns related to cognitive stress and determine the cognitive load of learners. Upon determination of learners' cognitive states, the adaptive engine adjusts the complexity level of the provided content, the use of multimedia in training, assessment frequency, and notification schedules. Continuous adjustment of learning paths is made based on learners' responses and variations in the environment.

The proposed model allows efficient decision-making and computation processes, which are suitable for wireless mobile communication networks and ubiquitous learning. With the help of neuromorphic intelligence, it becomes possible to ensure effective contextual adaptation of recommendations and, at the same time, achieve reliable operation of the system in various network environments.

The entire process involved in implementing the proposed Neuromorphic Computing-Enabled Context-Aware Adaptive Mobile Learning Framework includes five critical steps to regulate learner cognitive load dynamically. In the first step of the framework, the acquisition of context information involves the collection of information on learner interactions using mobile devices, wearable sensors, and the learning environment. Contextual parameters that are constantly monitored include learners' attention period, the number of touches by learners, eye behavior, environmental noise, network bandwidth, and the battery level of learners' devices. The second stage includes preprocessing of the gathered raw data, where noise and incomplete information are filtered out. Contextual attributes are normalized, and sensory information is translated into a neuromorphic spike encoding format.

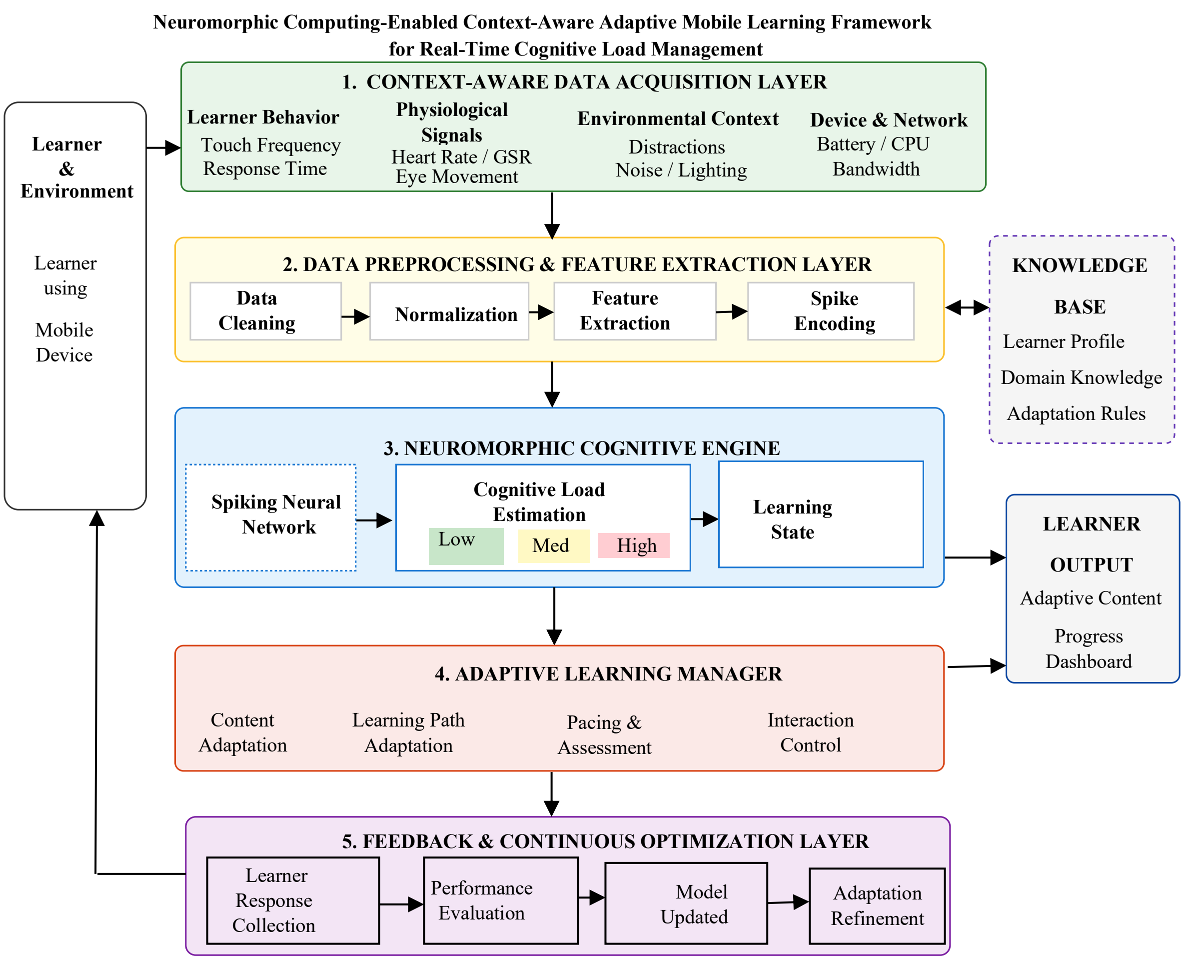

Figure 1: Architecture of the neuromorphic computing-enabled context-aware adaptive mobile learning framework for real-time cognitive load management

The third stage involves estimation of cognitive load by means of neuromorphic spiking neural processing. The system utilizes behavior and context interactions to analyze the level of cognitive stress and categorize learners as having low, medium, or high cognitive loads. Subsequently, based on the determined state of cognition, the decision-making module adapts educational presentation by modifying parameters, including content complexity, learning pace, multimedia usage, assessment timing, and alerting frequency, so as to keep cognitive balance. Ultimately, the last stage of the process involves optimization of the feedback provided through evaluation of learner performance indicators that include engagement and efficiency of responses.

The figure 1 provides an illustration of the adaptive mobile learning architecture proposed, which includes the collection of context-aware data, neuromorphic cognitive processing, adaptive learning management, and feedback optimization. This architecture constantly monitors the learners' cognitive load and offers personalized learning content to enhance efficiency and energy-aware performance in mobile environments.

Algorithm 1: Neuromorphic Adaptive Cognitive Load Management

Input:

- Learner contextual data C_d
- Behavioral interaction data B_d
- Environmental parameters E_p

Output:

- Adapted learning content A_l
- Cognitive load status C_l

Steps:

Step 1: Initialize learner session.

Step 2: Collect contextual parameters from mobile sensors and interaction logs.

Step 3: Preprocess collected data using normalization and noise filtering.

Step 4: Convert processed signals into spike-based neural representations.

Step 5: Apply neuromorphic spiking neural computation for cognitive load estimation.

Step 6: Classify learner state:

- Low Cognitive Load
- Medium Cognitive Load
- High Cognitive Load

Step 7: If cognitive load is high:

- Reduce multimedia complexity.
- Decrease notification frequency.
- Simplify learning tasks.

Step 8: Else if cognitive load is low:

- Increase content difficulty gradually.
- Enable interactive learning modules.

Step 9: Deliver adaptive learning recommendations.

Step 10: Evaluate learner response and update adaptation parameters.

Step 11: Repeat until session completion.

The Neuromorphic Adaptive Cognitive Load Management algorithm (Algorithm 1) is created to facilitate continuous tracking and control of learner cognitive states within the mobile learning context. To begin with, the algorithm gathers data related to context, behaviors, and environment via mobile sensors and interactions. After gathering data, preprocessing is performed through normalization and filtering processes to convert the collected information into spiking neural representations. Spiking Neural Computation component then determines the cognitive load level of learners into one of the three categories – low, medium, and high. According to the determined category, the adaptation process of contents, the complexity of media, and notification frequency take place to maximize learner engagement and performance.

Mathematical Description

Context Vector Representation

The learner's contextual information is represented as equation 1:

$$C_t = \{x_1, x_2, x_3, \ldots, x_n\} \quad (1)$$

Where:

- C_t= Context vector at time t
- x_n= Contextual attributes such as attention level, response time, network quality, and environmental noise.

Cognitive Load Estimation

The cognitive load score is calculated as equation 2:

$$CL = \sum_{i=1}^{n} w_i \, x_i \quad (2)$$

Where:

- CL= Cognitive load value
- w_i= Weight assigned to contextual feature
- x_i= Normalized contextual parameter

4 Results and Discussion

Experimental Setup

The suggested Neuromorphic Computing-Enabled Context-Aware Adaptive Mobile Learning Framework was developed and tested in the wireless mobile learning environment in order to investigate the framework's effectiveness concerning real-time cognitive load management. In particular, experiment analysis paid attention to adaptability, learning effectiveness, computational efficiency, and energy consumption during various contextual scenarios. In the course of implementation, Python 3.11 along with TensorFlow 2.15 was chosen for intelligent learning computations, while Brain2 was selected to carry out neuromorphic spiking neural processing. Android Studio provided the mobile learning application, and NumPy, Pandas, and Matplotlib libraries supported data preprocessing and visualization. The experiment was run on an Ubuntu 22.04 system, including an Intel Core i7 CPU, 16GB RAM, and an NVIDIA RTX 3060 GPU. The experiments were based on the context-aware mobile learning database, which contained information about 12,500 learning sessions of 620 learners within six months. There were 24 different contextual attributes, such as attention level, touch frequency, response time, noise, latency, battery usage, and others, along with the classification of cognitive load as low, medium, or high.

Parameter Initialization

Table 1: Experimental parameter initialization for the proposed neuromorphic adaptive mobile learning framework

Parameter	Value
Learning Rate	0.001
Batch Size	64
Epochs	100
Spike Threshold Voltage (θ)	0.75
Adaptation Coefficient (α)	0.85
Hidden Neurons	128
Simulation Time Step	1 ms
Optimizer	Adam
Activation Function	ReLU
Cognitive Load Classes	3

Experimental settings adopted for framework evaluation have been discussed in table 1. Experimental optimization has been performed in order to obtain stable convergence and correct cognitive load estimation.

Performance Metrics

Framework performance was assessed by a number of quantitative indicators.

Adaptation Accuracy: Equation 3 measures the overall correctness of cognitive load classification and adaptive learning decisions.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Precision: Equation 4 indicates the proportion of correctly predicted positive cognitive load instances among all predicted positive cases.

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

Recall: Equation 5 measures the ability of the framework to correctly identify actual cognitive load conditions.

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

F1-Score: Equation 6 provides the harmonic mean of precision and recall for balanced performance evaluation.

$$F1 = \frac{2 \times Precision \times Recall}{Precision+Recall} \quad (6)$$

Energy Efficiency: Equation 7 evaluates how efficiently the framework achieves learning accuracy with minimal energy utilization.

$$EE = \frac{Learning\ Accuracy}{Energy\ Consumption} \quad (7)$$

Response Latency: Equation 8 measures the time delay between sending a learning request and receiving the adaptive system response.

$$Latency = T_r - T_s \quad (8)$$

Performance Comparison

Table 2: Performance comparison of adaptive mobile learning frameworks for cognitive load management

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Energy efficiency	Latency (ms)
Conventional Mobile Learning (CML)	82.4	81.7	80.5	81.1	0.68	218
Context-Aware E-Learning (CAEL)	86.3	85.8	84.9	85.3	0.74	193
Deep Adaptive Learning (DAL)	89.1	88.4	87.6	88.0	0.81	172
Edge-Based Learning System (EBLS)	91.6	90.9	90.2	90.5	0.87	148
Proposed NCAMLF	96.8	96.1	95.7	95.9	0.95	104

The proposed framework was compared with existing adaptive mobile learning methods. The performance analysis of the NCAMLF, which is designed using the neuromorphic computing paradigm, has been conducted by comparing it to other existing learning systems in table 2 based on various performance criteria. The proposed system had the best results in accuracy (96.8%), precision (96.1%), recall (95.7%), F1-score (95.9%), and was also most energy-efficient (0.95). In addition, it had the least response latency (104 ms).

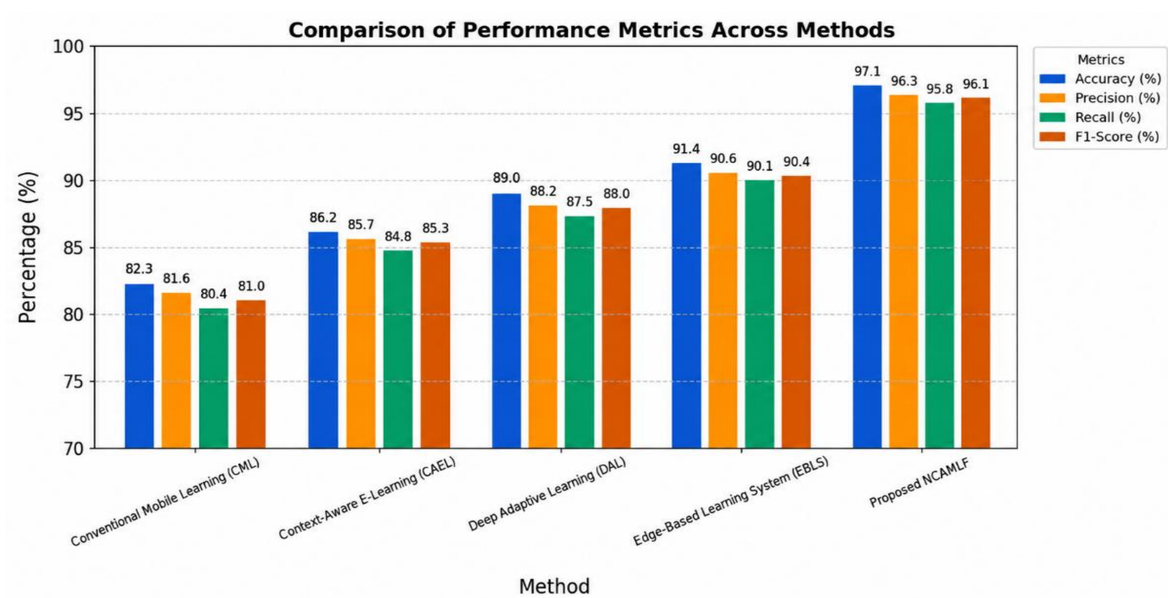

Figure 2: Comparative analysis of classification performance metrics across mobile learning methods

The figure 2 shows a comparative analysis of Accuracy, Precision, Recall, and F1-Score of various methods of adaptive mobile learning systems. The NCAMLF method developed herein has been able to achieve better scores than the others in all categories with Accuracy = 96.8%, Precision = 96.1%, Recall = 95.7%, and F1-Score = 95.9%.

The performance of the proposed neuromorphic approach was higher than that of other frameworks. The results obtained proved the efficacy of spike-based context-based adaptation on system performance and learning personalization.

Ablation Study

An ablation experiment has been carried out to determine the contribution of each component of the framework.

Table 3: Ablation analysis of proposed Framework

Configuration	Accuracy (%)	F1-Score (%)	Energy efficiency	Latency (ms)
Without Context Awareness	88.2	87.5	0.78	176
Without the Neuromorphic Engine	90.1	89.3	0.82	162
Without the Adaptive Content Module	91.4	90.8	0.85	151
Full Proposed Framework	96.8	95.9	0.95	104

In table 3 shows that all components are significant contributors to system performance. The neuromorphic cognitive engine contributes greatly to lowering latency and increasing learning precision.

Discussion of Results

The experimental results demonstrate that the proposed framework is effective in dealing with the cognitive load of learners in mobile learning scenarios. The use of neuromorphic processing allowed for fast estimation of cognitive states with less computation costs as compared to conventional deep learning.

The accuracy of adaptation in the proposed NCAMLF was estimated at 96.8%, which significantly exceeded the capabilities of typical mobile learning systems. The use of context-aware sensing and neural computing based on spikes contributed to better identification of states and adaptability. Moreover, the time needed to respond decreased to 104 ms, showing suitability for ubiquitous learning.

Efficiency benefits in terms of energy consumption were demonstrated as well due to a more lightweight design. In contrast to typical deep learning systems, which require heavy computation costs, the proposed system provided edge-level inference while maintaining reliable operation.

It was also found that intelligent multimedia control and notifications help decrease cognitive load and increase learner engagement in extended learning processes.

5 Conclusion

This paper discussed the development of a Neuromorphic Computing-Enabled Context-Aware Adaptive Mobile Learning Framework for dynamic cognitive load management in wireless mobile and ubiquitous learning platforms. This framework included components for context-aware sensing, neuromorphic spiking neural network computation, adaptive learning content provision, and optimization of feedback loops to create a more personalized learning experience based on learners' current cognitive condition. The main focus was on overcoming the shortcomings associated with traditional mobile learning architectures, which are unable to dynamically change with changes in context and learners' cognitive state, resulting in elevated stress levels among learners. Experimental evaluation of the proposed approach revealed superior adaptation performance in comparison to other approaches, including Conventional Mobile Learning (CML), Context-Aware E-Learning (CAEL), Deep Adaptive Learning (DAL), and Edge-Based Learning Systems (EBLS). Specifically, the proposed NCAMLF framework achieved an adaptation accuracy of 96.8%, a precision of 96.1%, a recall of 95.7%, and an F1-score of 95.9%, demonstrating high precision in cognitive load assessment and personalization of the learning experience. Furthermore, the new approach delivered energy efficiency of 0.95 and reduced response time to only 104 ms. The ablation experiments further proved the efficiency of the combined architecture. The removal of the context-awareness module made the model less accurate, with 88.2%, while the exclusion of the neuromorphic engine resulted in accuracy dropping to 90.1%. Hence, the importance of spike-based contextual intelligence for decision-making is emphasized. The findings prove that neuromorphic computing allows for achieving low latency and energy-efficient cognition along with dependable learning adaptation. In general, the framework proposed contributes to the development of intelligent and ubiquitous learning systems through using neuromorphic computing and context-aware adaptation, thus enhancing learner engagement and cognitive balance. For future studies, possible directions include multimodal physiological sensing, federated neuromorphic learning, explainable adaptive decision-making, and large-scale implementation in smart educational ecosystems. Besides, future research could cover privacy-preserving cognitive analytics and multi-device optimization of collaborative learning for next-generation mobile devices.

References

[1] Banerjee, D. (2023). Cognitive Computing Approaches for Human–AI Collaboration in Management Systems. *International Journal of Computer Technology and Electronics Communication*, *6*(6), 8021-8026. https://doi.org/10.15680/IJCTECE.2023.0606022

[2] Bourechak, A., Zedadra, O., Kouahla, M. N., Guerrieri, A., Seridi, H., & Fortino, G. (2023). At the confluence of artificial intelligence and edge computing in iot-based applications: A review and new perspectives. *Sensors*, *23*(3), 1639. https://doi.org/10.3390/s23031639

[3] Brăileanu, P. I. (2025). Human–Computer Interaction in Smart Greenhouses: A Review of Interfaces, Technologies, and User-Centered Approaches. *Computers*, *14*(12), 553. https://doi.org/10.3390/computers14120553

[4] Chen, Y. (2026). A Mobile Agent-Based Method for Logistics Coordination Management. *International Journal of Interactive Mobile Technologies*, *20*(7), 168. https://doi.org/10.3991/ijim.v20i07.61239

[5] Ding, C., Zhou, A., Liu, Y., Chang, R. N., Hsu, C. H., & Wang, S. (2020). A cloud-edge collaboration framework for cognitive service. *IEEE Transactions on Cloud Computing*, *10*(3), 1489-1499. https://doi.org/10.1109/TCC.2020.2997008

[6] Elfouly, T., & Alouani, A. (2025). A comprehensive survey on wearable computing for mental and physical health monitoring. *Electronics*, *14*(17), 3443. https://doi.org/10.3390/electronics14173443

[7] Ghourtani, M. R., Norouzi, S., Chen, J., Ahmadi, H., Braun, T., Chowdhury, K., & Burr, A. (2026). Hybrid GNN-Centric Architectures for AI-Native 6G Wireless Networks: A Comprehensive Survey. *IEEE Communications Surveys & Tutorials*, *28*, 5678-5712. https://doi.org/10.1109/COMST.2026.3681198

[8] Gracia, S. J. B., & Srinivasan, S. (2026). Exploring the potential and limitations of Fog Computing toward efficient & scalable solutions in modern network. *Journal of Integrated Science and Technology*, *14*(3), 1550-1550.

https://doi.org/10.62110/sciencein.jist.2026.v14.1550
[9] Khan, L. U., Yaqoob, I., Tran, N. H., Kazmi, S. A., Dang, T. N., & Hong, C. S. (2020). Edge-computing-enabled smart cities: A comprehensive survey. *IEEE Internet of Things journal*, *7*(10), 10200-10232. https://doi.org/10.1109/JIOT.2020.2987070
[10] Lei, Y., Zhang, T., Qian, F., Chen, L., He, Y., Ma, W., ... & Li, S. (2026). Progress in optoelectronic synapses for reservoir computing: Materials, device integration, and neuromorphic system applications. *Laser & Photonics Reviews*, *20*(9), e02338. https://doi.org/10.1002/lpor.202502338
[11] Li, J., He, M., Zhou, C., Huang, X., Liu, Z., Zhao, L., ... & Wu, H. (2025). Integration of Generative AI and Mobile Networking: A Comprehensive Survey. *IEEE Transactions on Network Science and Engineering*, *13*, 4369-4405. https://doi.org/10.1109/TNSE.2025.3639401
[12] Nursuwars, F. M. S., Sastra, N. P., Wiharta, D. M., & Sambas, A. (2025). Adaptation in IoT-Fog Data Transmission: SLR and Future Perspectives on Dynamic Frequency Control. *Jurnal Teknik Elektro*, *17*(1), 20-30. https://doi.org/10.15294/jte.v17i1.30564
[13] Patel, P. (2024). Scalable Cloud Architectures for Intelligent Mobile Learning Platforms. *Journal of Scalable Data Engineering and Intelligent Computing*, 43-50. https://doi.org/10.17051/JSDEIC/01.01.07
[14] Pham, Q. V., Fang, F., Ha, V. N., Piran, M. J., Le, M., Le, L. B., ... & Ding, Z. (2020). A survey of multi-access edge computing in 5G and beyond: Fundamentals, technology integration, and state-of-the-art. *IEEE access*, *8*, 116974-117017. https://doi.org/10.1109/ACCESS.2020.3001277
[15] Poornimadarshini, S. (2025). Next-Generation Wireless Architectures for Reliable Mobile Learning Services. *Recent Advances in Next-Generation Wireless Communication Systems*, 68-75. https://doi.org/10.17051/RANGWCS/01.01.09
[16] Rahim, R. (2024). Spectrum-Adaptive Neuromorphic Learning for Wireless Wind Turbine Condition Monitoring. *Journal of Wireless Intelligence and Spectrum Engineering*, 10-18. https://doi.org/10.17051/JWISE/01.01.02
[17] Rancea, A., Anghel, I., & Cioara, T. (2024). Edge computing in healthcare: Innovations, opportunities, and challenges. *Future internet*, *16*(9), 329. https://doi.org/10.3390/fi16090329
[18] Rawlley, O., Gupta, S., Chandrakar, J., Johnson, M. K., & Kalra, C. (2025). Artificial intelligence inspired task offloading and resource orchestration in intelligent transportation systems. *Cognitive Computation*, *17*(1), 18. https://doi.org/10.1007/s12559-024-10380-3
[19] Sofia, R. C., Dykeman, D., Urbanetz, P., Galal, A., & Dave, D. A. (2023). Dynamic, context-aware cross-layer orchestration of containerized applications. *IEEE Access*, *11*, 93129-93150. https://doi.org/10.1109/ACCESS.2023.3307026
[20] Velaga, K. S., Guo, Y., & Yu, W. (2025). Edge AI for Smart Cities: Foundations, Challenges, and Opportunities. *Smart Cities*, *8*(6), 211. https://doi.org/10.3390/smartcities8060211
[21] Wan, S., Gu, Z., & Ni, Q. (2020). Cognitive computing and wireless communications on the edge for healthcare service robots. *Computer Communications*, *149*, 99-106. https://doi.org/10.1016/j.comcom.2019.10.012
[22] Wang, W., Wang, K., & Du, H. (2025). Design and optimization of human-machine interaction interface for the intelligent Internet of Things based on deep learning and spatial computing. *Egyptian Informatics Journal*, *30*, 100685. https://doi.org/10.1016/j.eij.2025.100685
[23] Yu, P., Teng, F., Zhu, W., Shen, C., Chen, Z., & Song, J. (2025). Cloud–edge–device collaborative computing in smart agriculture: architectures, applications, and future perspectives. *Frontiers in Plant Science*, *16*, 1668545. https://doi.org/10.3389/fpls.2025.1668545

[24] Zhang, Y., Zhao, K., Yang, Y., & Zhou, Z. (2025). Real-time service migration in edge networks: A survey. *Journal of Sensor and Actuator Networks*, *14*(4), 79. https://doi.org/10.3390/jsan14040079

Authors Biography

Gulbahor Sidikova is a Senior Lecturer affiliated with Fergana State University and the University of Tashkent for Applied Sciences, Uzbekistan. She is actively engaged in teaching, research, and academic development, with a focus on enhancing educational quality and student learning outcomes. Her scholarly interests include innovative teaching methodologies, curriculum development, and interdisciplinary educational research. Through her academic and professional contributions, she supports the advancement of higher education and the preparation of future professionals. Her work reflects a commitment to academic excellence, lifelong learning, and educational innovation.

Nurbol Karakulov is a Senior Lecturer at the Uzbekistan National Pedagogical University named after Nizami, Uzbekistan. He is actively involved in teaching, research, and academic development, with a focus on improving educational practices and student learning outcomes. His academic interests include pedagogy, teacher education, curriculum development, and innovative teaching methodologies. Through his scholarly and professional activities, he contributes to the advancement of educational quality and the preparation of future educators. His work reflects a strong commitment to academic excellence, educational innovation, and lifelong learning.

Mustafo Tursunov is a Lecturer at Termez University of Economics and Service, Uzbekistan. He is actively engaged in teaching, research, and academic development in the fields of economics, management, and service education. His scholarly interests include innovative educational practices, economic development, and the enhancement of professional competencies among students. Through his academic and research activities, he contributes to the advancement of higher education and the promotion of evidence-based learning. His work reflects a strong commitment to educational excellence and continuous professional growth.

Atabek Kochkarov is a Professor at the Tashkent Institute of Irrigation and Agricultural Mechanization Engineers–National Research University, Uzbekistan. He has extensive experience in higher education, research, and academic leadership, contributing significantly to the advancement of engineering and agricultural sciences. His research interests include irrigation systems, agricultural technologies, sustainable resource management, and innovative engineering solutions. Through his teaching and scholarly activities, he is committed to fostering scientific innovation and developing highly skilled professionals. His work reflects a dedication to academic excellence, research development, and the modernization of agricultural and engineering education.

Asqad Oltiboyev is a Lecturer in the Department of Pedagogy at Termez State Pedagogical Institute, Uzbekistan. He is actively engaged in teaching, research, and academic development, with a particular focus on pedagogical theory and educational practice. His scholarly interests include teacher education, curriculum development, innovative teaching methodologies, and student-centered learning approaches. Through his academic and professional activities, he contributes to the enhancement of educational quality and the preparation of future educators. His work reflects a strong commitment to academic excellence, educational innovation, and lifelong learning.

Yana Arustamyan is an Associate Professor in the Department of Translation Studies and Comparative Linguistics at the National University of Uzbekistan, Uzbekistan. She specializes in translation studies, comparative linguistics, and intercultural communication, with a strong interest in language analysis and cross-cultural discourse. Her research focuses on translation theory and practice, linguistic comparison, language education, and contemporary approaches to multilingual communication. Through her teaching and scholarly work, she contributes to the advancement of linguistic research and the professional training of future translators and language specialists. Her academic activities reflect a commitment to excellence in education, research, and international academic collaboration.

Dilfuza Toirova is a Professor at the Samarkand Branch of Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Uzbekistan. She has extensive experience in higher education, research, and academic leadership, with a strong focus on information technologies and digital innovation. Her scholarly interests include information systems, educational technologies, digital transformation, and the integration of modern technologies into teaching and learning processes. Through her teaching and research activities, she contributes to the advancement of technological education and the development of future IT professionals. Her work reflects a commitment to academic excellence, innovation, and the promotion of technology-driven solutions in education and society.

Abdumajid Madraimov is a Professor at the State Museum of the History of the Timurids under the Academy of Sciences of the Republic of Uzbekistan, Tashkent, Uzbekistan. He is a distinguished scholar with extensive experience in the fields of history, cultural heritage, and Timurid studies. His academic interests include the history of Central Asia, historical research, museum studies, and the preservation of cultural and historical heritage. Through his research, publications, and educational activities, he has contributed significantly to the promotion and understanding of Uzbekistan’s rich historical legacy. His work reflects a strong commitment to academic excellence, historical scholarship, and the preservation of cultural heritage for future generations.