PROPOSING A HIERARCHICAL ARCHITECTURE FOR EFFICIENT MOBILE LEARNING AND ACCEPTABLE DELAY

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Abstract

The emergence of new computing paradigms like mobile cloud, mobile edge computing, fog computing, artificial intelligence, and 5G opens up opportunities to enhance mobile learning outcomes across various subjects. By relocating processing capabilities to the network's edge, where mobile-learning agents can readily access them, this study explores the potential of these paradigms. A novel mobile computing hierarchical architecture is proposed to revolutionize mobile learning effectiveness. This architecture offers benefits such as reduced response times, minimized delays, and on-site data processing. This local data processing lessens the demand on radio access bandwidth, enhances data privacy, and enables uninterrupted app functionality even during network disruptions. This adaptable framework can be customized, reconfigured, and integrated with other computing approaches. While designing IoT-based mobile learning use cases, learner-specific resource requirements must be considered. Incorporating complex use cases will expand the architecture's foundation, boost the adoption of MEC-based learning models, and reshape the dynamics of education across disciplines.

Keywords: Mobile learning, Cloud computing, Edge computing, IoT, Delay.

1. Introduction

Using smart mobile devices in a mobile setting, Mobile Learning actors (i.e. students and instructors) can accomplish learning and teaching goals. It creates a system that includes Mobile Learning actors, Mobile Learning content, and Mobile Learning technologies for delivering education [2]. Learning materials and actor interactions can be accessed at any time and from any location [3]. Users can make use of a number of Mobile Learning's promising affordances thanks to the widespread dissemination and integration of communication and cloud technologies [4]. The remarkable features of new technologies inspire and illustrate new forms of mobile education [5]. Guided learning, synchronous sharing, and contextual mobile learning [3] are just a few examples of novel methods of education that are made possible by the development of new technology. In addition, there are significant advantages that Mobile Learning students can make use of learning, collaborative learning, seamless learning, and interactive learning [3] with the use of cutting-edge computing paradigms. For instance, the resource augmentation of mobile devices and energy-efficient application performance are both made possible by the mobile cloud computing paradigm [6]. Students who are constantly on the go have an increased demand for rapid communication and content exchange through their registered learning management system (LMS) [7]. mobile learning platforms hosted in the cloud [8] improve location-aware, context-aware, and situated learning [2], but struggle to enable real-time communication like video chats because of delays in data transmission. Edge, mobile edge, and fog computing are all examples of emerging computing paradigms (ECPs) that have desirable qualities for addressing delay problems [9]. Therefore, the current research endeavors to understand more about these

computing paradigms and how they may be integrated into Mobile Learning platforms.
The efficiency of Mobile Learning applications running in the cloud on mobile devices is highly dependent on the quality of your wireless connection to the cloud [4], using a wireless connection means your performance efficiency will fluctuate. Due to the cloud-based nature of the processing, Mobile Learning actors here have unreliable network connections and have less say over the actual execution of the training [10]. Resource-intensive processes, such as the distribution of multimedia learning information, are difficult to execute due to delay concerns in the execution process. Furthermore, security and privacy violations might occur during the execution cycle, compromising actors' private information [11,12]. Indeed, delay is a major issue and an important factor affecting the performance of the Mobile Learning system. To the best of the authors' knowledge, none of the studies has taken delay into account as a major factor for optimizing Mobile Learning performance. Recently, edge-based architecture opened up opportunities for performing data processing and resource-intensive operations locally at several endpoints rather than in centralized clouds [13,14]. There is also a lack of research into performance optimization using novel designs like mobile edge/fog.
The researchers and developers of mobile learning applications need to understand that the edge is where computing is headed in the future. They need to think about the features of developing computing paradigms [16] and the capabilities of freshly emerging architectures [15] to improve Mobile Learning results. The Internet of Things, the edge, the mobile edge, and the fog are all examples of such paradigms that provide many tools for raising productivity. Indeed, combining these computing paradigms allows a platform to have access to resource-rich educational information, run applications in real-time, and analyze data locally in milliseconds [9]. In addition, the 5G network creates a reliable method of operation for Mobile Learning applications based on AI, such as VR. Mobile Learning architectures built on such principles allow actors in Mobile Learning scenarios to experience ultra-low delay and fast response time. Thus, this study takes into account the research demands for enhancing the quality of learning-teaching dynamics.
To improve Mobile Learning's efficacy and users' quality of experience, this research delves into the features of new computing paradigms. By proposing a layered design [11] based on the ETSI MEC ISG framework [17,18], it fills a gap in the existing literature. The efficiency of the design is tested by running a real-time use case on it. The findings demonstrate that ultra-low delay, and short access time, affect actors' adoptability intentions, and raise Mobile Learning usage from dissatisfactory [5] to a satisfying level. In addition, it does a SWOT analysis of Mobile Learning performance on cutting-edge architectures. This study uses the gaps in knowledge to inform the research questions discussed in Sections 3 and 4.
RQ1. How do new forms of computing, such as the Internet of Things, the edge, mobile edge, fog, artificial intelligence, and the 5G network, interact with cloud-based Mobile Learning architectures?
RQ2. To what extent do new architectures remove constraints from mobile learning while also enhancing performance for mobile learning actors?

2. Method

The research presented here investigates potential Mobile Learning applications in new forms of computer architecture. Section 3 explains how this approach explores the potential properties of various paradigms and merges them into a layered design to improve performance. It does

things like run a real-world use case, analyze strengths and weaknesses, and test out new designs.
Possibilities for Mobile-Based Education in ECPs

New computing paradigms improve the effectiveness of cloud-based mobile learning in several ways [19], including enhancing functionality, altering the learning experience, and introducing new measures of success. These theories form the basis for cutting-edge Mobile Learning architectures, advance communicative interactivity, refine data processing, and tackle issues of quality assurance [20]. They also provide low delay, context-aware processing, and high performance [9]. Indeed,

The benefits to Mobile Learning actors are substantial [20,22], and the integration of these paradigms provides tremendous momentum [21]. The productivity of Mobile Learning systems is maximized by their integrated Mobile Learning frameworks and the efficient application of LMSs [7]. For instance, Mobile Learning architectures embedded in the fog or on the edge reduce delay and increase access to educational resources [22]. Intelligently analyzing learning data is made easier by AI with machine learning [23]. It is expected that Mobile Learning data would be processed efficiently and locally by fog and edge computing in 5G networks [24].

(i) Mobile Learning on the Cloud: Mobile cloud computing (MCC) offers various beneficial aspects that effectively extend to ubiquitous learning, overcoming the limits of conventional Mobile Learning systems. Mobile cloud computing (MCC) is a paradigm that combines mobile devices and cloud storage [4]. To run a Mobile Learning application, mobile cloud architecture (MCA) must be used by the Mobile Learning models that MCC is based on. By moving resource-intensive application execution duties to highly-resourced cloud infrastructure, the MCA enhances the computation and communication capabilities of mobile devices [25]. It's the standard approach to running power-hungry programs on low-powered gadgets. The MCA provides Mobile Learning actors with context-aware (i.e. learner-centered), multitenancy (collaborative learning), hetero-genes, and universal accessibility [11]. Through MCA, mobile learning actors can efficiently scale and make use of virtual resources [10]. Save battery life, boost processing power, add more storage space, and expandability are just some of the benefits of the MCA [26]. Furthermore, Mobile Learning models, such as hybrid Mobile Learning, Mobile Learning based on augmented reality [27], and Mobile Learning based on mobile agents [11], need to be redesigned to be more specialized.

(ii) Mobile cloud Mobile Learning systems: These systems improve the learning-teaching process in general, and multi-media learning content in particular, on the go. These programs improve system accessibility, content availability, the quality of educational materials, and user-friendliness. LMSs like Moodle and Blackboard, for example, are widely used because of the many advantages they present in a variety of academic fields. Since Moodle is freely available, its deployment in educational institutions requires less money and resources in terms of hardware and software [8,9]. Nonetheless, Blackboard Learn is another sophisticated LMS with open architecture customization and adaptable teaching methods [28]. It's a fully dynamic platform, it has tools for delivering courses, and it helps Mobile Learning actors succeed in their studies. In the same vein as other mobile LMSs, intelligent tutoring systems (ITS) provide instruction in both general and specialized computer use. It helps both students and teachers by keeping track of their development and providing updates on that progress [9].

(iii) Applications for mobile learning that take advantage of the Internet of Things: Deploying such applications on IoT platforms and integrating them with IoT devices are in their infancy. During application execution, Mobile Learning systems must include the data supplied by IoT learning devices. Such integration provides students with a first-hand look at computing in action [9]. For instance, medical education makes extensive use of mobile IoT and learning applications.

Patients and students alike now have RFID tags and wearable sensors built into their bodies and mobile devices. When students approach patients, their mobile devices will show information about the patients' conditions. Teachers' mobile devices also show similar data, allowing them to keep tabs on students' physical assessment activities [9]. Next-generation learning management systems (LMSs) will revolve around Internet of Things (IoT) devices, necessitating compliance with integration principles for IoT devices and mobile learning activities in a digital setting. Systematic evaluations of students' recognizing spoken phrases and capturing spontaneous moments while engaging in a variety of digital lessons.

(iv) Mobile edge-based Mobile Learning: The cloud computing characteristics within the radio access network (RAN) [29] are made possible by mobile edge computing (MEC), which was introduced by the ETSI ISG on MEC [17]. Recent years have seen a surge in data volume [18] due to the proliferation of intelligent end devices and interactive applications. With the proliferation of Internet of Things (IoT) devices in the Mobile Learning ecosystem, edge computing has developed as a means to run Mobile Learning applications locally, where they may be used most efficiently. Edge computing is a new approach to data processing that is becoming increasingly popular [13,14] in place of traditional data centers and the cloud. The edge nodes lower latencies for a continuous and improved learning experience [16], and the edge is the instant first hop from locally distributed IoT devices. Indeed, an edge-based Mobile Learning architecture boosts seamless connectivity, privacy, delay, reduced network traffic [13,45], and the quality of life for actors at the moment. For example, it facilitates the deployment of cutting-edge Mobile Learning apps in a school setting and the efficient delivery of multimedia learning content. As network traffic increases, its capacity increases [30], its services are distributed over several edge nodes, and a responsive LMS is necessary for optimal performance.

It is acknowledged as a critical enabling factor for 5G and several important uses of the 5G system are determined [31].

(2) Mobile Learning and fog computing The volume of data produced and processed by IoT devices causes delays between the edge nodes and the cloud. Minimizing lag time and making optimal use of Internet of Things (IoT) devices is what fog is all about. Fog computing was first created by Cisco in 2014 to process data in real-time and have it executed on the nearest server [32]. Fog computing is now being used by academic institutions for data processing [21]. Institutions process data in tandem with major cloud conglomerates, but they do not upload everything to the cloud. These storage nodes are analogous to a fog that makes communication between edge devices used by learners and cloud data centers more efficient. Fog-cloud architecture-based mobile learning applications consider execution requirements [22] and run across learners' devices, fog nodes, and the cloud. Mobile context-aware and adaptive learning applications that run according to the instructions of the learners benefit greatly from such an architecture. Not only are these architectures compatible with 5G, but they also facilitate services like low delay, improved context awareness, and heightened operational efficiency and quality of service [20] for actors.

Artificial intelligence (AI), also known as machine intelligence (MI), encompasses several different fields of study (Q [33]). AI-based Mobile Learning systems and 5G are two such examples. It has ramifications for academia by tapping into the power of fiction and artificial intelligence [23]. When applied to learning applications and LMSs, AI uses machine learning and deep learning to revolutionize the educational experience and add intelligence to the process [34]. Because of the unique needs of each student, intelligent tutoring systems (ITS) are growing in popularity [23]. These ITS provide students with customized learning opportunities that are tailored to their specific needs. Tutors use a variety of approaches—linear, dialogic, and exploratory—based on the abilities of their students. Socratic, an app developed by Google that allows students to record themselves asking questions, was released recently [35]. This program analyzes the students' speech and returns relevant results culled from the internet's wealth of educational material. The software also uses sophisticated, intelligent algorithms to help users step-by-step answer arithmetic problems, and it is a tremendous AI dig-up that can learn in any academic course.

Innovative mobile learning tools built on the latest in computing paradigms are anticipated to perform better in the 5G network. Many countries are beginning to roll out 5G networks with speeds of 10–100 Gbps [24]. An efficient platform for data-heavy educational content can be found in the new architectures being deployed on 5G [18]. Video content lectures, multi-media content streaming, and instant video interaction are just a few examples of how these technologies can benefit greatly from this advancement. It will pave the way for cutting-edge possibilities in Mobile Learning applications that leverage IoT/edge/fog/artificial intelligence to enhance operational effectiveness. For Mobile Learning actors' in densely populated locations or those constantly in motion, this will be a game-changer [18].

3. The proposed framework

Cloud-based Mobile Learning systems face difficulties with real-time data transfer due to delay (F [36]).

Alternate architectures that take into account the features of the new computing paradigms can be designed to avoid these setbacks. The MEC is a model that uses induced computing resources at the network's edge to reduce delay delays [18]. To achieve optimum efficiency in Mobile Learning performance, an envisioned Mobile Learning architecture design must incorporate MEC elements.

In Fig. 1, the authors suggest an edge-cloud layered architecture that acquires layer-specific computing resources for the needs of running Mobile Learning applications. There are three primary components: (i) the edge devices (the devices used by the actors), (ii) the local edge, which is the infrastructure that supports the application and network workloads, and (iii) the cloud. It processes data in real-time, does computations at the edge, and keeps processing insights as it moves up the architecture's many levels. It incorporates mobile edge APIs [17,18] and 4G wireless network standards, expanding on the work of the ETSI MEC ISG. It enables ultra-reliable low-delay communication and provides millisecond-predictable low-delay services. Also, it enables resource-intensive Mobile Learning scenarios like video content distribution, VR/AR apps, and more by providing enhanced mobile broadband (eMBB). The parts of the architecture are as follows.

(1) Requirements and approaches to architecture: The network's requirements and the protocols it uses must be dynamically accommodated by the design. The server must be able to transmit

content quickly, manage bandwidth effectively, provide a virtualized environment for MEC applications, and make the most of every millisecond of available time [29]. It should be a unified system that can accommodate various learning management systems (LMSs) while also catering to individual academic institutions' requirements and desired outcomes in terms of student development and potential. It provides a gateway for incorporating new and emerging pedagogical requirements into ongoing projects.

(2) The fundamental building blocks of architecture: It is a hierarchical, multi-layer architecture where the physical and application levels provide access to the available resources.

Layer one is the physical layer, and it includes things like gadgets (IoT, edge, fog), network nodes, and cloud servers. Here, Mobile Learning and mobile-edge apps are hosted locally on the edge nodes. Edge gateways redirect data from student devices to local edge servers, bypassing the cloud entirely. APIs allow the server to process the students' requests in real-time and return the results to their devices[46, 47.48].

To execute mobile edge native and Mobile Learning-specific apps such as context-aware and delay-sensitive applications and improve users' interactions, the application layer provides APIs, distributed educational modules, and MEC application platform services.

Typically, network administrators avoid using physical Equipment in the network for each user. In this situation, most of the switches and routers that make up the network layer are owned by the university [49, 50].

Figure 2 depicts the edge computing layer and its sub-layers, and it outlines the evolution of the architectural layer at the mobile base station. Furthermore, it demonstrates how its parts may be broken down into three distinct levels—the ME system level, the ME host level, and the network level [18]. The top-level system provides an overarching perspective on the ME infrastructure and the UEs' availability. The virtualized environment and the potential for deploying ME applications are both provided by the host level. The 3rd Generation Partnership Project (3GPP) cellular network, local access network, and external network [29] are all within the purview of the network level, where connectivity needs are managed.

(1) The practicality of the building's design: The design facilitates efficient Mobile Learning performance, learner-centric services, and extremely low-level delay. In the current mobile cloud architecture setup, the MEC server is deployed at the edge, closer to the actors' proXimity, and where the following processes may be verified.

The functionality can be evaluated while the program is running. The MEC server examines execution requests from actors and, if necessary, forwards them to higher layers via a layer profile request (LPR) message to access more powerful computational resources.

Communication between the MEC server and the higher-layer computing resources is established through the execution of multiple components, including the local protocol identifier (LPR), message field identifier (MFI), requesting profile server hash value (RPSHV), transmission timestamp, profile acknowledge message (PAK), and profile-based component. In addition, the layer profile message (LPM) identifies the job definition, complete with a service determiner and a unique identifier.

To ensure actors receive their requested content, the architecture executes sophisticated content delivery and management tasks when they request the MEC server. The server then either (i) delivers the requested content via the caching function, or (ii) forwards the request message to the resourceful upper tiers, depending on what it finds during its content lookup. Similarly, the architecture deals with any actor's request following the needs of execution.

3.1 Experimental Design and Procedures

The following conditions must be met for the suggested model to be widely implemented: (i) the mobile devices (Android smartphones) of the actors and (ii) the teachers' knowledge of the deployed system and responsibility for high-quality educational content. It was believed that the preexisting mobile cloud infrastructure would serve as the basis for the first pass at implementing the plan. The MEC server was pre-configured, and a performance efficiency test based on profiles was run before deployment. The services were analyzed for resource efficiency and adapted to fit the various Mobile Learning programs. The test was run with two sets of students, and the MEC server processed the requests for execution according to the specified compute and service parameters.

3.1.1 System Configuration

On the college campus, close to the edge computers, we set up the following components that would be used to carry out the use case.

The application was launched on the edge server(s). To get the application duties done, many agents on the students' devices talked with the server. On the other hand, the server kept tabs on the processors and received data from them when necessary.

a more advanced processing layer.

Dell OptiPlex 9010/7010 model, Intel i7 3770 at 3.4 GHz, 16 GB RAM, 1 terabyte hard drive, AMD Radeon HD 7470 graphics card, Intel 82,579 LM Gigabit network adapter. Wireless DW 1530 NW LAN with Windows 10 Pro as the operating system.

Edge workloads from students' devices are computed and distributed by the server, which is a server capability. It organizes computing activities, manages resources, and combines results.

To execute native computations, host and run programs, and include intelligent computing resources, students' mobile devices serve as edge devices (actors' devices). To divide up execution duties, these devices coordinate with a central server.

Edge node: any device, such as an edge gateway or edge server, that participates in and aids edge computing.

An edge cloud is a private cloud that can also function in a public cloud environment. When devices' calculation needs exceed their capabilities, this system makes available a novel computing platform at their disposal. As a result, bandwidth issues are resolved, and delay between processing devices is drastically reduced. Applications and network workloads that can be deployed to various edge nodes are managed by the orchestration features.

An on-campus data center that oversees local resources, data analytics, and dashboards to boost workload performance is what we call a "hybrid multi-cloud" in the world of higher education. It makes use of Amazon Web Services and Google Cloud Platform infrastructure following service-level agreements.

Liberal Arts and Sciences The LMS (Blackboard) is a treasure trove of educational programs and resources. It runs the learning program, such as MagicPlan (iOS/Android), and an accompanying Android app, allowing the authorized Mobile Learning actors to carry out their duties. The layer-based edge infrastructure is where the learning application is deployed.

3.1.2 Prerequisites for Carrying Out Use Cases

In this research, an Mobile Learning use case was implemented on the institution's mobile cloud infrastructure via a MEC on-premises strategy, small cell networks, and the 4G network standards. Using the MEC platform, students' devices, a variety of virtual network functions (VNFs), and MEC software, this method represents a private deployment option. The deployment ensures the highest quality of experience (QoE) and real-time content delivery by making use of the radio conditions offered by MEC (specifically, the RNIS). Connectivity, VPN, and MEC services are orchestrated by the facilitators and consumed via APIs [37].

Practical Example: Thirty civil engineering students were given a deadline to use the mobile LMS to take measurements of two campus buildings still in the development phase. They were required to finish the measurements, compile a comprehensive report on the two structures, and hand it to their teacher. Students worked in groups of 10 and 20, and each utilized a mobile camera to take measurements using an architecture program like MagicPlan (iOS/Android). During the process, students were involved in a video conference, factors of dissemination, and usability.

3.1.3 Flowchart of Architecture-Based Use-Case Execution

First, students use their mobile devices to log into the Mobile Learning platform (see Fig. 3).

Second, the system's MEC server receives request messages (request profile) that contain the information and computational demands created by the students' devices.

Third, the MEC server examines the learner's request message profile, figures out what computing resources it needs, and carries out execution duties according to the request message profile (on the same layer).

Fourth, the MEC server transmits the completed task's results via the requested result profile. This process is carried out for each profile of a request message.

Step 5: Neighboring servers (edge cloud) in the same layer or the higher tier of the architecture hierarchy (currently not covered under this article) receive the request message profile that requires intense processing resources and exceeds the MEC server capabilities.

3.2 Appraisal of Efficiency

The scientific evaluation was based on two factors: (i) a series of simulations with a varying number of students, and (ii) a real-time application execution with 30 students. Several MEC simulation programs, such as EdgeCloudeSim, iFogSim, and others described in Ref. [38], were considered for the implementation. CloudSim and Clou- dAnalyst [39] are two examples of mobile cloud framework simulation tools that have been investigated. But EdgeCloudSim and CloudSim were used to model the system and gauge its efficiency. The performance measures of delay, reaction time, and energy efficiency were examined after initially considering certain ISO/IEC 25023 standard measurements.

We designed a multi-hop overlay network (MEC) topology with three tiers of egress nodes. At the top level of the architecture, one wireless router connected all MEC servers, with an expected throughput of 80–100 Mbps. Each server's capabilities were taken into account, and a maximum of 200 migration requests were determined to be an optimal number of actors. To quantify the difficulty of a computation, a target number of central processing unit cycles was established. For instance, each MEC server could have to execute a migration request requiring one gigacycle of computing power in as little as 0.4 seconds. Thus, we compare the efficiency of execution between the following architectures: (i) a flat MEC, (ii) a MEC with a series of hierarchical levels, (iii) a mobile cloud, and (iv) the proposed design.

Figures 4 and 5 depict typical delay behavior and time-to-student requests for simple computations made to the server-based functional architecture. It is important to note that the following designs only take into account the server processing time for migrated requests when calculating the average delay time.

In a flat MEC architecture, the MEC server is set up close to the buildings from which students send computation requests for assigned tasks across a wireless network. For migrating tasks, it conducts computation with minimal delay, while for new computations, the average delay grows. When the amount of computation required exceeds the server's computing capacity, the requests are forwarded to the next available MEC server.

As more and more computation is offloaded to the more reliable upper layers of a hierarchical MEC, it can offer lower delay than its flat counterpart.

When compared to the other two architectures, the mobile cloud has a longer average delay time since the mobile data center is further away

from the learners' devices that are issuing computation migration requests .

Although average delay times are on the rise, the proposed architecture nevertheless delivers ultra-low delay services by moving the growing amount of computational requests to the higher levels of the network. To achieve low delay on average, the moved jobs locate more potent computing MEC servers across the hierarchy layers. It solves the slowness of other designs' computations by avoiding round-trip delays.

Learners' average response time for downloaded content is depicted in Fig. 6. Using a digital library (or learning management system), students request the processing infrastructure necessary to obtain video lectures. We have measured how long it takes for the following architectures to respond on average when downloading the necessary content.

By connecting to the closest MEC server, Flat MEC can provide mobile edge services, such as caching capabilities, at a faster rate than MCA.

Multiple tiers of MEC: it responds to requests for content migration from students and faces growing difficulty keeping up with demand. The performance of MEC varies with an increase in content transmission requests and is increasingly burdened by demands from neighboring MEC servers, which slow down the architecture due to delays in searching for neighboring servers.

Content requests are fulfilled by the mobile cloud according to the resources available in the mobile cloud data of the requests made by the students to the framework, and as the number of requests increases, the downloading time also increases.

The proposed architecture places more responsibility for computing at the upper levels of the system. The requested content can be downloaded quickly from the MEC server because of its content caching capability. If that fails, queries from students are forwarded to a nearby MEC server or higher in the architecture stack. It has a faster download speed than the other three since its response time is lower.

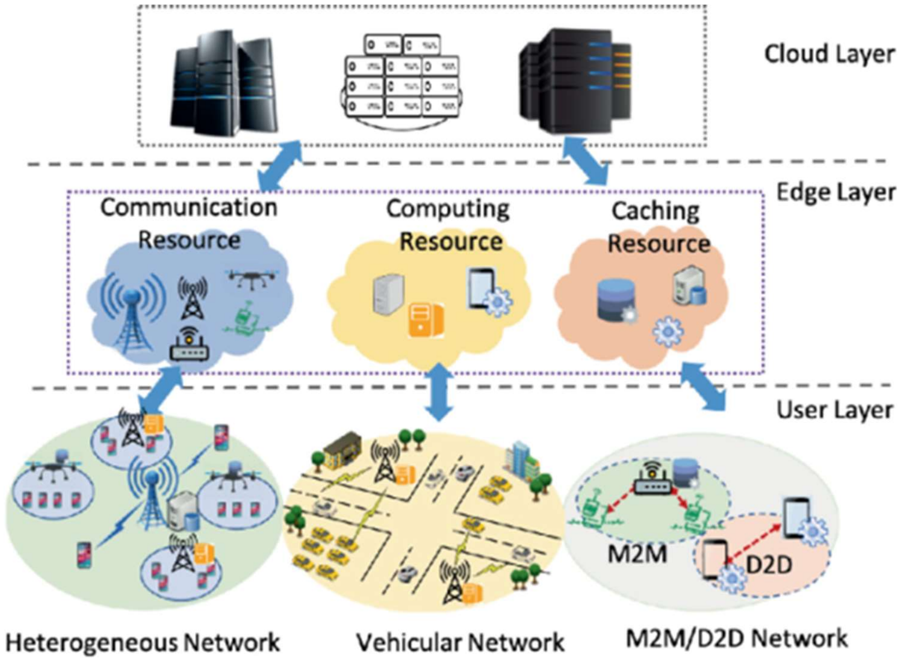

Fig. 1. MEC Mobile Learning layered architecture overview

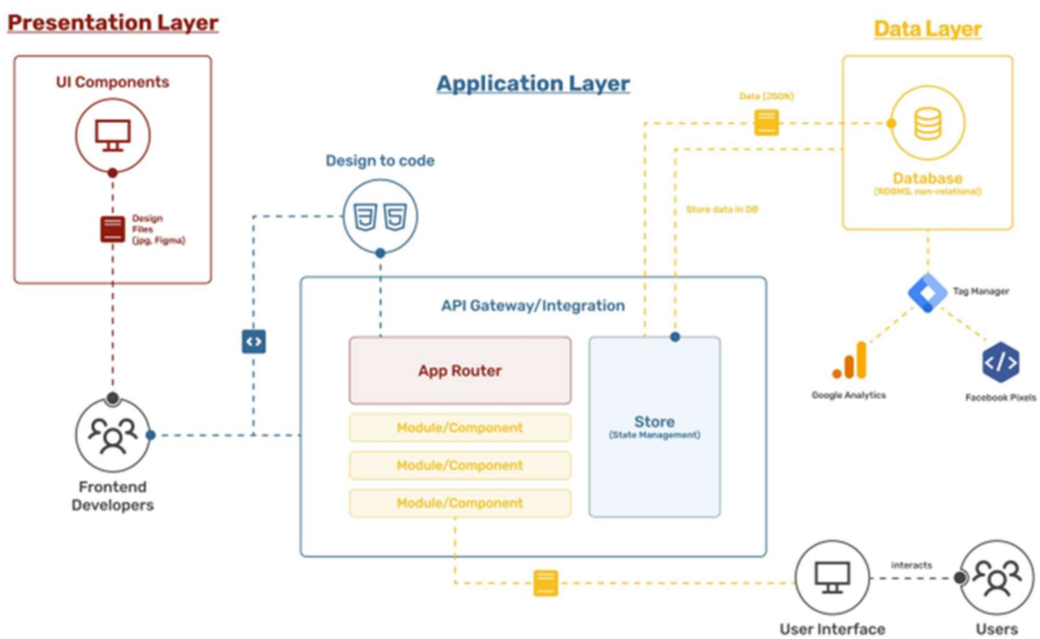

Fig. 2. The fundamental architectural layers

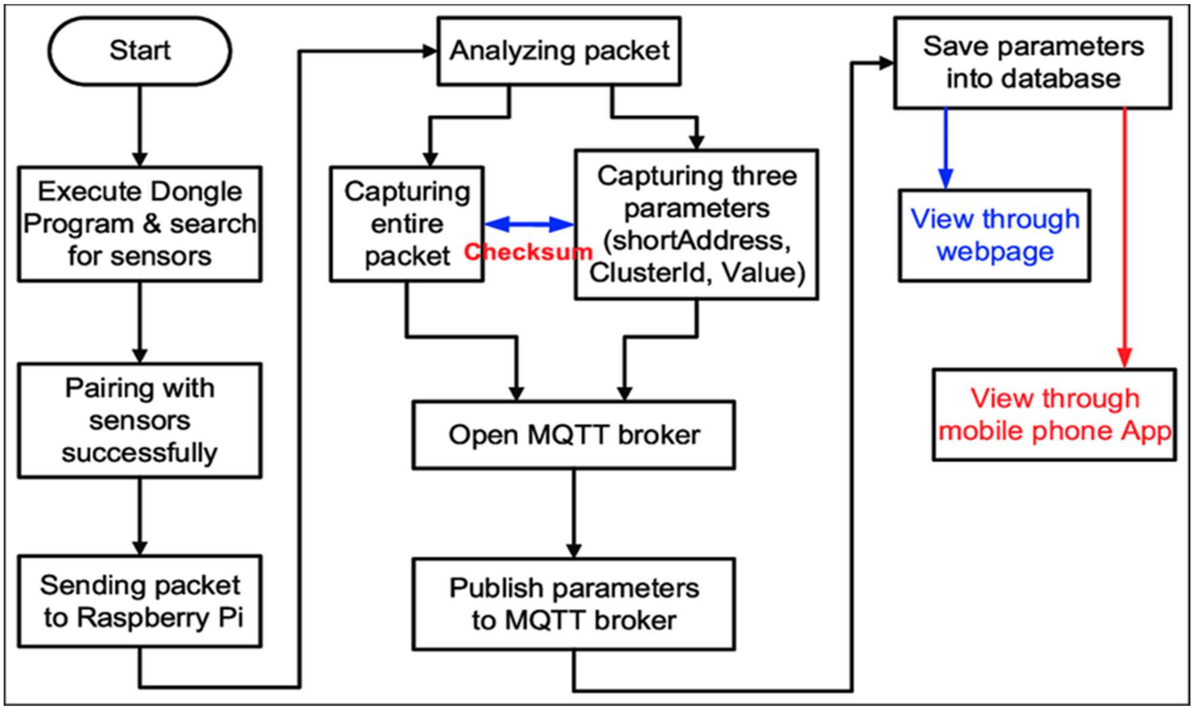

Fig. 3. use cases might play out in the proposed architecture.

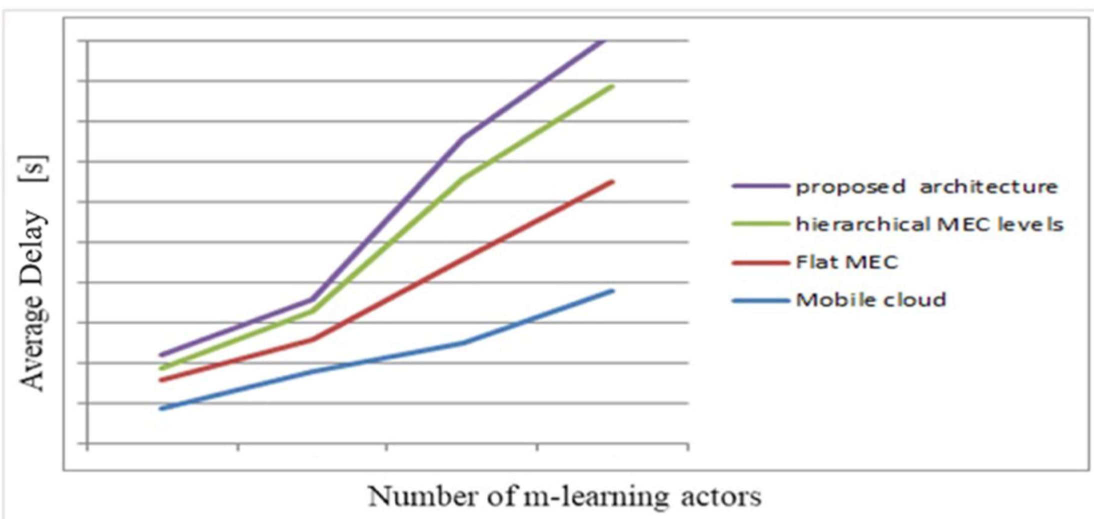

Fig. 4. Testing the effectiveness of delay.

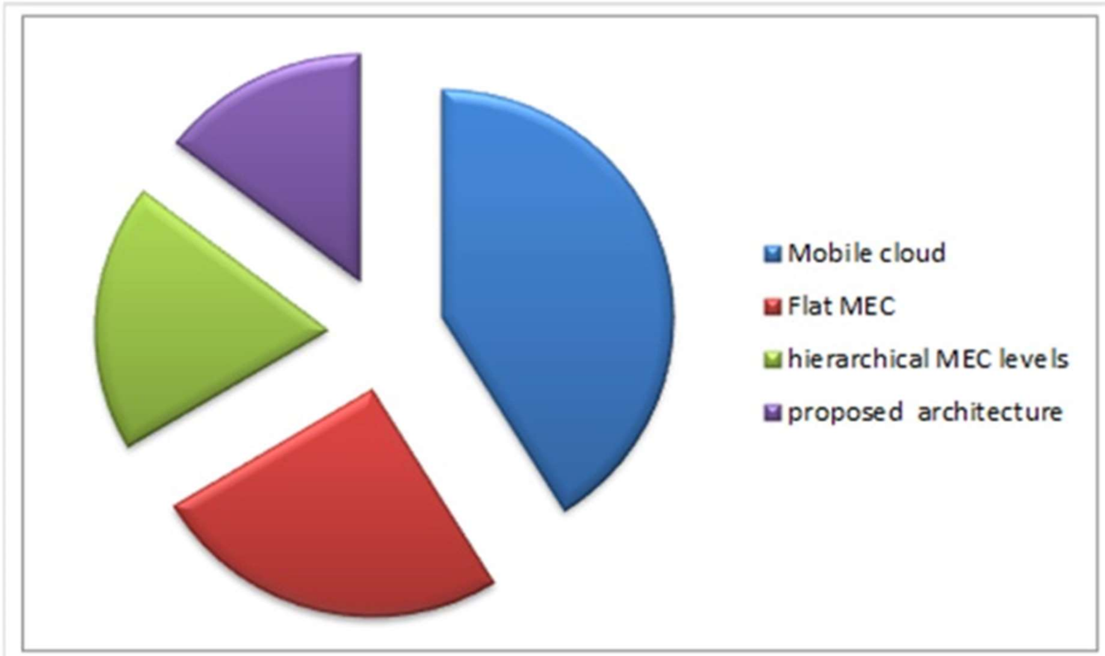

Fig. 5. Monitoring and analysis of delay in real-time.

4. Result and Discussion

4.1Newness in Architectural Design

The suggested architecture is the purpose of this research is to identify potential applications for machine learning in cutting-edge technologies including the Internet of Things (IoT), edge-fog architectures, artificial intelligence (AI), and the 5G network (Research Question 1). In addition, we want to investigate how edge-cloud computing affects the effectiveness of m-learning processes (RQ2). The study also shows the proposed design to enhance performance efficiency for its users across subject areas.

This research reaffirms the notion that existing cloud-based m-learning designs improve m-learning performance by taking advantage of cloud features [8]. These architectures can process requests from actors in an efficient, reliable, low-cost, and energy-saving manner [26]. Despite these benefits, these models have serious drawbacks, such as poor delay, security, and platform support from a wide range of service providers.

The performance of m-learning and its adoption by its users are both negatively impacted by delay delay. The efficiency of the system and the effectiveness of m-learning are degraded by the presence of delay delays. Most of these problems could be solved by the development of ECPs [21,22,30]. Education is already benefiting from edge-fog computing [21]. The purpose of this research is to investigate such opportunities for improving the effectiveness of m-learning. Computing paradigms like multi-access edge computing architecture [17] pay special attention to the delay problem and provide consumers with ultra-low delay.

Supporting m-learning actors, instructors, and educational institutions while also influencing user acceptability is what MEC is now doing.

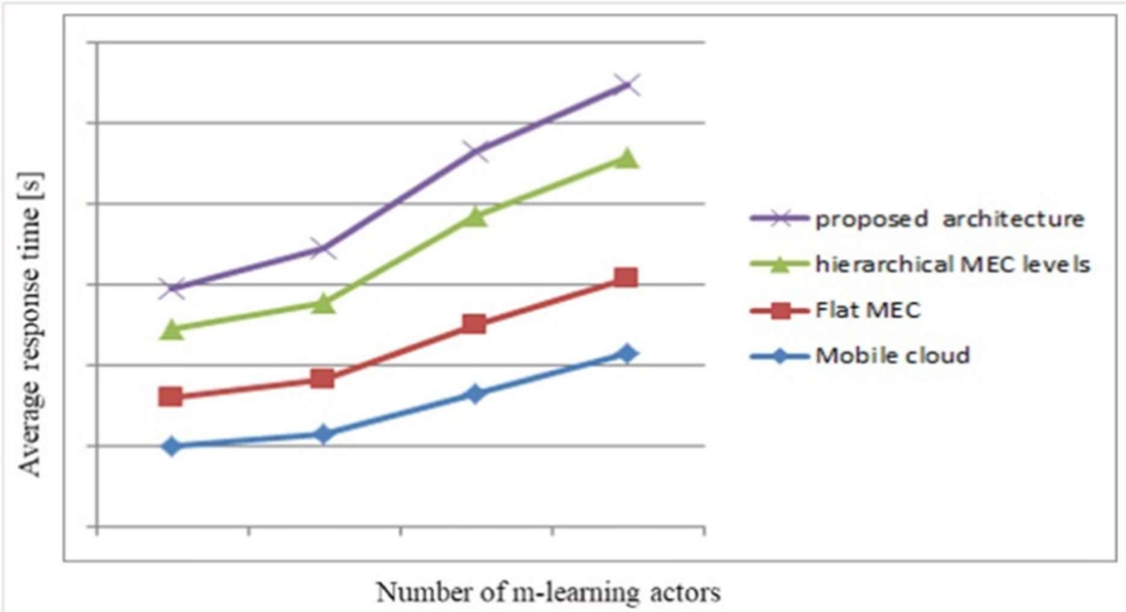

Fig. 6. Analysis of content download speeds.

first of its sort to our knowledge, as it combines the advantages of edge computing with a lightweight design for use in a more traditional institutional setting. It provides quick connectivity to the MEC server of the layer and the institution's mini data centers. It provides significantly faster response times, less strain on radio access capacity, and shorter response times. It's efficient in all areas of study, helps protect sensitive information, and keeps applications running even if the network goes down. When m-learners visit the learning management system (LMS) during peak scenarios, for instance, the institution's ability to handle the volume of requests is tested. As a result, it increases the system's workload, networking requirements, delayed responses, and diluted performance. The current architecture is remarkable in that it minimizes data about travel, processes data locally, deals with traffic, and maximizes productivity. Because of its decentralized nature, the MEC server can be placed nearer to the devices being used by students. It improves the quality of experience, impacts user acceptance, and executes computations locally by avoiding the main data center. It enables a service domain through the employment of small power cell stations near edge resources.

4.2 Analyzing the Outcomes of Implementation

Use case execution analysis and architecture performance against performance metrics. It was discovered that the mobile cloud's Flat MEC and HMEC levels performed poorly in terms of delay, with the proposed architecture bearing ultra-low delay outperforming both. Learners can expect faster computations and less waiting time using the proposed architecture. It guarantees satisfactory results by involving students in individualized learning through interactive lessons and challenging laboratory work. On the other hand, thanks to the LMS's ability to orchestrate a variety of academic solutions, teachers can track their student's progress in a dynamic, collaborative setting [34]. Detailed use cases, like intelligent video analytics, are encouraged by the outcomes of use case execution on the planned architecture.

SWOT analysis of m-learning performance across ECPs. Since the suggested and edge-based m-learning architectures exhibit similar traits, this demonstrates that they both deliver consistent performance. Although fog-based systems have unique promise for m-learning applications, this research will not be focusing on them.

4.3 The originality and benefits of architecture

By adding unique techniques and deploying only one MEC server at the edge cloud, taking the observed use case into account, the suggested architecture differentiates itself from the flat MEC, which deploys multiple MEC servers at the same level. It provides ultra-low delay and rapid reaction time by doing away with the server's searching time of the flat MEC. It validates the functional needs of an edge-based architecture by putting the planned strategies into action. In other circumstances, where more resources are required, such as virtual reality and augmented reality-based mobile learning applications, it has drawbacks and ramifications. The following advantages are provided, and a comprehensive and prospective mobile learning model should be taken into account.

4.3.1 From an architectural point of view

Delay, round-trip time, security, numerous hops, and bandwidth consumption are only some of the issues that mobile cloud architecture attempts to solve [10, 40].
Features cutting-edge implementations of QoE enhancements, such as localized social ecology, adaptive learning, and real-time computation.

4.3.2 The views of students and educators

Creates a unified system that uses common protocols, and supplies the software and educational materials needed to get started.
An institutional learning management system (LMS) facilitates two-way contact between students and instructors and content delivery to students' edge devices.
Motivates students more makes the most of multimedia interactions, and maximizes the use of learning resources.
Offers insightful metrics for learners and dynamic, upgradable content for performers.

4.3.3 The View from the Institutional Level

Facilitates high dependability of the institution's LMS learning applications and supplies consolidated learning performance metrics and analytics for institutional uses; integrates with the existing institution's IT infrastructure and leverages interoperability standards.
Saves money on bandwidth by processing data on-site, and boosts safety by storing sensitive data at the institution's physical facilities.

4.3.4 How Do Learning Management Systems Work?

An LMS is a database that houses your company's online training courses, resources, and data. Users can access the system with the specified credentials. User permissions are a standard element of most LMSs, letting admins decide who gets to use which parts of the system and which courses.
Once training has begun, managers can track employee progress and performance using online tests and surveys to ensure everyone is staying on track. This information can be analyzed in the

LMS itself, or synchronized with an HRIS or other talent management tools, to find connections between training and things like job satisfaction, promotion opportunities, and turnover Fig. 7 shows the top future of LMS.

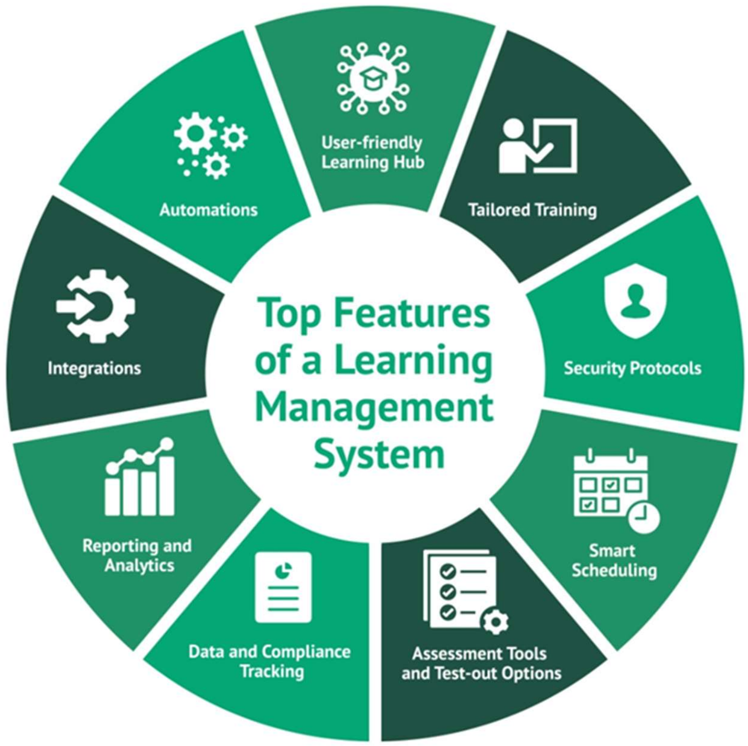

Fig. 7. The top future of LMS

5. Issues, Restriction, Implications, and Prospective Paths

Even at this early stage of development, the use case implementation verifies the goals of the proposed architecture, namely, the acquisition of ECPs features to enhance m-learning performance. It establishes a foundation for running more involved use cases that call for ECP capabilities. For instance, real-time video analytics with AI and ML algorithms will make substantial use of fog levels. However, obstacles and restrictions have been encountered during use case execution.

Challenges: Finding a good spot on the college campus and setting up the MEC server at the network's edge have been the first orders of business ever since the idea for the study was conceived. To ensure the synchronization of MEC deployment into an NFV environment, there is required to be strong between execution scenarios and ETSI NFV. Since the number of m-learning actors was growing, the difficulty became more severe during the actual implementation in real-time. Potential obstacles include an expanding cast of characters, connections, radio access bandwidth, license, and setup. Additionally, the execution delay estimation and data portability costs were serious problems when nodes in the local network were able to collect data or make decisions[41][42].

The existing architecture has limitations due to its immaturity and its layered nature. At the most basic level of the infrastructure, a single MEC server was set up. University learning management system (LMS) interoperability, delay, and reaction time were primary design considerations in

the architecture [43].
The architecture has far-reaching implications, as it provides ultra-low delay and improves execution efficiency. The efficiency was evaluated based on the given requirements for the use case and varies depending on the network's connectivity and how the small cells are managed [44]. By adhering to the architectural design principles, MEC can enhance the performance of delay and response time. Designers need to consider these consequences when making new kinds of buildings [45 ,46].
The Way Forward: There is room for improvement in the current architecture to accommodate new computing paradigms like fog [47]. In the future, it will also include round trips to the MEC server when measuring the same metrics, but for now, it just takes into account the time it takes for students to make a request. Additionally, a number of MEC servers, including the flat MEC with its privileged communication, mobile orchestration, and other IoT devices, can be placed at the edge layer. Cell zooming management enables the institution's tiny data center to maximize its potential for saving money on energy costs [48 ,49].
The mobility model's decision-making interfaces and interfaces are currently under integration. MEC platforms and interface-aware protocols can be used to create an interface management system. A multi-tire evaluation of the architecture's performance is made possible by the incorporation of an edge orchestrator [50]. To meet the demands of increasingly sophisticated use cases, mobile workloads, an edge data center for actors' learning analytics, and the need to scale out in terms of available resources, this advancement will be crucial [51]. The present framework and MEC-based learning models will be affected by the inclusion of mobility and connection functions[52, 53].
If students' gadgets are incompatible, cost-cutting measures regarding computers and programs can be investigated.

6. Conclusion

The research described here focuses on the possibilities of new computing paradigms to reduce the prevalence of drawbacks to m-learning, such as delay and slow response times. This research contributes new knowledge by proposing an edge-based m-learning architecture and deploying a single MEC server at the edge layer by ETSI MEC ISG requirements. It uses the school's mobile cloud to power the learning management system (LMS) and any other necessary learning apps, such as MagicPlan (iOS/Android). The students were using video conferencing on their devices with the program running on those devices to take measurements of the building's facilities. A rapid response time and ultra-low delay in transmitting video material are just two of the benefits that have been demonstrated by early implementation results. It allows for excellent quality of experience for m-learning actors, maintains sensitive data in local storage, and delivers insightful learning analytics. However, the efficiency of performance depends on the actors' connectivity to the server, the architecture's design approach, and the administration of the small cells. Delay and response time are solely taken into account by the design when it comes to requests made by students to the MEC server. The flexibility of the architecture will allow for the incorporation of various interfaces and decision-making processes, and the performance of the mobility model will increase as a result. Simulation experiments appear to support the claim that the proposed architecture can improve response times by 15% to 40% for tasks where the level of response increases with the number of computing requests, thanks to the migration of these requests to higher, more powerful layers. The addition of an edge orchestrator affects MEC-based m-learning models and broadens the scope of the underlying architecture. IoT-based m-learning use cases are supported, and the architecture's flexibility makes it possible to implement a wide range of advanced applications.

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