Mobile Learning New Trends in Emerging Computing Paradigms: An Analytical Approach Seeking Performance Efficiency

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Mobile learning (m-learning) adoption has increased and shall be demonstrated superior performance by implementing related computing paradigms, such as IoT, edge, mobile edge, fog, AI, and 5G. Mobile cloud architectures (MCAs) enable m-learning with several benefits and face limitations while executing real-time applications. This study investigates the state-of-the-art m-learning architectures, determines a layered m-learning-MCA obtaining numerous benefits of related computing paradigms, and expands m-learning functional structure. It evaluates m-learning performance across the four physical layer’s MCAs—distance cloud, cloudlet, operator-centric cloud, ad hoc cloud, and emerging computing architectures. Surprisingly, only distance-cloud MCA is adopted for developing m-learning systems by ignoring the other three. Performance evaluation shows m-learning gets terrific benefits and users QoE in related computing paradigms. Mobile edge computing offers ultralow latency, whereas the current architecture improves task execution time (1.87, 2.01, 2.63, and 3.97) for the resource-intensive application (i.e., 4.2 MB). Fog using AI algorithms is exceptional for more complex learning objects, IoT is superior for intelligent learning tools, and 5G ultrawideband services are more significant for intelligent video analytics. These findings help learners, educators, and institutions adopt an appropriate model for achieving their academic objectives across educational disciplines. The presented approach enables future research to design innovative architectures considering resource-intensive m-learning application execution requirements, such as video content analytics and virtual reality learning models.

1. Introduction

Mobile learning or just-in-time information delivery is a technology-based pedagogy. It facilitates m-learning actors, i.e., learners and teachers, to share learning contents [1]. It establishes itself as a complete learning delivery method and accessible using (MCAs) [2]. The m-learning models based on MCAs are time and place unconstrained in sharing learning resources [3]. m-learning frameworks and teaching strategies, such as guided learning, synchronous sharing, and contextual mobile learning, have evolved along with technologies [4]. m-learning architecture is one of the core components [5] of a learning management system (LMS) in delivering learning-teaching services efficiently [6]. The proliferation and the integration of communication and cloud technologies [7] advance m-learning models and usage. The advances in MCC technologies enable several optimistic affordances of m-learning [8] to actors in m-learning. Additionally, m-leaning systems developed on MCA (see Figure 1) are impacting the usage of m-learning enormously [1]. However, these systems face limitations, e.g., latency, security, and cost issues [9] and hence experience low-performance efficiency while accessing real-time learning content. The features of related computing paradigms attract the designers to incorporate their characteristics for promising benefits, such as connected learning,
cooperative learning, seamless learning, and interactive learning [10].

With the adoption of related computing paradigms, m-learning actors expose to a new learning experience. These paradigms are increasing learning efficiency in multiple dimensions, i.e., ubiquitous learning [11], collaborative m-learning [10], and ultralow latency [12]. Integrating these paradigms enables an enhanced interactive platform for m-learning actors to achieve their academic objectives. For instance, fog or edge-based m-learning allows flexibility to access educational resources with ultralow latency [13]. AI and machine learning [14] transform traditional m-learning [15] with more sophisticated approaches, i.e., virtual reality and mobile augmented reality learning objects [16]. In this context, the current study presents these paradigms’ features that facilitate m-learning actors in improving educational services delivery [1].

Mobile learners often need instantly accessible content with real-time intelligence using their institution’s mobile LMSs [1] and expect the desired performance efficiency. Nevertheless, most of the existing m-learning systems are developed on MCC [2, 3] and struggle performance efficiency while executing resource-demanding applications [7]. Besides, for m-learning, little attention is given to the existing four physical layer’s MCAs, i.e., distance mobile cloud, mobile cloudlet, operator-centric mobile cloud, and ad-hoc mobile cloud [17] (see Section 3.1). Moreover, m-learning systems have not been discussed for all existing MCAs in the literature. Most research has focused only on the distance mobile cloud [2, 3], ignoring the other three. Even the fast-growing technologies [12, 18] and the related computing paradigms [19, 20] get little attention. These computing paradigms and their characteristics should be considered for improving m-learning performance efficiency.

To the best of the authors’ knowledge, none of the studies considered the four physical layer’s MCAs [21] that shall be used to develop m-learning systems. Besides, studies that explore related computing paradigms’ characteristics for improving m-learning performance are absent (see Section 2).

The current study’s significance and contribution to scientific knowledge are summarized as follows:

(i) It is aimed at bridging the literature lacuna that needs attention as m-learning users experience performance efficiency issues when executing real-time applications, e.g., instant video interaction

(ii) Its novelty integrates the m-learning model with the four physical layer MCAs and determines a mobile cloud-based layered architecture towards obtaining the benefits of IoT, edge, mobile edge, fog, AI, and 5G

(iii) It evaluates the architecture performance for application execution time and across the emerging computing paradigms using SWOT analysis

(iv) It is finally aimed at answering the following research questions formulated on the knowledge gaps in context to m-learning performance

RQ1: What is the existing physical layer’s mobile cloud architectures potentially being used for m-learning system’s development?

RQ2: Is there any existing unified cloud-based m-learning architecture, and can it be extended to obtain the features of other related computing paradigms?

RQ3: How do the related computing paradigms, i.e., IoT, edge, mobile edge, fog, AI, and 5G network, impact the performance of existing cloud-based m-learning architectures?

2. Method and State-of-the-Art in Literature

The presented study discusses m-learning state-of-the-art into three aspects: (i) traditional m-learning, (ii) mobile cloud m-learning architectures, and (iii) m-learning opportunities in related computing paradigms. It applies different emerging architectures to extend m-learning application execution beyond the cloud datacentres and includes learning resources at the edge of the network. Finally, it evaluates m-learning performance across such architectures using SWOT analysis.

Mobile learning is a technology-based pedagogy that evolves along with technological advancement. [1] mentioned
several studies discussing TAM or the extended TAM in the context of technology adoption. They highlighted the usage of evolving technology, performance efficiency, and organization support. Henceforward, the presented study explores m-learning literature, identifies the knowledge gaps described in Table 1, and establishes the study’s objectives. Table 2 shows the acronyms and their description that were used across this paper.

2.1. Traditional m-Learning Architectures. The study [3] discussed the traditional m-learning features, e.g., learners acquire the learning content of multidisciplinary education via mobile devices. An m-learning architecture enables learning content to learners over portable devices, and its performance depends on its capability. Several approaches did call an m-learning model an architecture, a framework, and the application architecture. Generally, m-learning architecture classifies based on its abilities, such as context-aware, heterogeneity support, and adaptability provision. Another study [5] summarizes 11 context-aware architectures considering different implementation criteria of an m-learning system. It introduces a learning system and discusses its architecture’s layers, limitations, and implementation issues. It highlights the need for systems that support mobility, high bandwidth, location monitoring, and device heterogeneity. [6] highlighted limitations, such as device memory constraints, network connection cost, restricted processing power, and limited learning content. For overcoming these limitations, traditional m-learning needs to deploy on MCA and utilize cloud resources, such as high-performance computing, massive data storage, low cost, and service-on-demand [3].

2.2. MCAs for m-Learning. The MCA brings significant changes to traditional m-learning, and it is a dominant method of executing m-learning applications on resource-limited mobile devices, as illustrated in Figure 2. It facilitates dynamic interaction between m-learning actors using their mobile LMSs [1]. The MCA offers several benefits to mobile learners: context-aware (learner-centred), multiteniency (collaborative interactions), heterogeneity, and universal accessibility [10]. Studies [2, 3, 10] discuss MCAs improve m-learning performance. The paper [18] presents a survey on m-learning models based on MCC and underlines several traditional m-learning limitations that can be overcome by adopting MCC. It discusses that scalability and effective utilization of virtual resources can achieve through MCA. However, the study does overlook the other potential MCAs for m-learning adoption. Another study [2] presents a survey on m-learning frameworks, systems, and models. It emphasizes that MCAs’ characteristics help to overcome traditional m-learning limitations. It highlights MCA’s features, such as saving battery life, processing power, and scalability for better m-learning performance. As the computing technologies evolve, the m-learning architectures need to redesign to be more specific, e.g., hybrid m-learning architecture, augmented reality-based architecture [24], and agent-based collaborative m-learning architecture [10]. The agents of such systems are significant contributors in executing m-learning applications. Almost all mobile cloud-based m-learning applications migrate the resource-intensive execution tasks to the cloud during the execution cycle [3] and encounter latency issues.

2.3. m-Learning Applications and LMS. Traditional m-learning applications are limited in learning content, context, low transmission rates, and a high bandwidth cost [18] during execution cycles (see Figure 3). Further, these applications are tailored-made, challenging to customize, and incapable of handling resource-demanding tasks. For instance, such applications’ frameworks [21] are incapable of executing resource-intensive applications because the mobile devices are resource-constraints [7]. Additionally, resource-demanding applications, e.g., online video discussion, require rich cloud resources. During the application execution cycle, the intensive tasks offload to the cloud [2] for resource augmentation of mobile devices. Notably, MCC offers offloading schemes, such as context-aware, team-based, and collaborative learnings [10], that offload execution tasks to the cloud for performance optimization. Henceforth, the learning content based on multimedia and augmented reality platforms [24] have no longer been obstacles in a mobile cloud and context-aware m-learning systems.

The cloud-based m-learning systems are rich in learning content, increased availability, and low cost. The study [1] emphasizes the LMS’s features, such as instant messaging, video lectures, and online multimedia assessments, which support actors in m-learning. Moodle and Blackboard are very popular LMSs that can be downloaded on actors’ mobile devices and provide accessible platforms. Moodle is a widely used open-source system that facilitates institutions to deploy the LMS with reduced IT infrastructure cost [3, 20]. Blackboard learn is another Web-based LMS with a customizable open architecture that integrates with the institution’s other information systems, e.g., student information systems. An ITS is another context-aware mobile LMS that offers intelligent tutoring [14]. It consists of skills learning videos and supports students learning by recording their progress. It also facilitates teachers by generating students’ performance reports [20]. Besides, such systems enable Geolocation and Web Distributed Authoring and Versioning (WebDAV) capability for m-learning scenarios. The mobile LMSs allow learners independent learning [1], dynamic control for educators, and resource provisioning for the institutions.

2.4. m-Learning in Related Computing Paradigms. In recent times, cloud-related computing paradigms, e.g., mobile edge, fog, and mobile fog are being used to improve m-learning system’s performance, e.g., responsive m-learning [22]. The systems based on such paradigms offer many opportunities, such as context-driven m-learning [13], and improve m-learning efficiency. Edge-based learning opened new windows for processing data locally at multiple endpoints instead of centralized clouds [25, 26]. While AI-based ITSs teach course content using personalized methods [14], augmented reality mobile applications make learning conscious [27]. Besides, 5G network edge-cloud architecture [28] makes m-learning
speedier with uninterrupted video and voice calls, customized and learner-centric (see Section 3.4).

3. Results and Findings

3.1. Existing Physical Layer MCAs. (RQ1) The presented study found four physical layer MCAs [17, 29] and lots of application layer (AL) architectures (see Section 3.2) [5]. It integrates m-learning with the four MCAs that augment a learner’s mobile device capabilities by seeking cloud resources during execution [3]. Such integration enables more provisions to m-learning actors and designers. These MCA-based m-learning systems will be more efficient following the users’ requirements.

3.1.1. Distance Cloud m-Learning MCA. This architecture is merely generic MCA builds on four key components, mobile device, mobile operators’ core network, Internet, and cloud infrastructure provided by service providers [3, 17], shown in Figure 4. Each of the architecture’s components consists of subcomponents and performance parameters. Implementing this architecture, a learner requests an m-learning application execution using the institution’s LMS [18]. Subsequently, the connectivity establishes to the cloud infrastructure through wireless communication channels via the Internet. This architecture outsources the executable tasks to more powerful cloud resources and augments the learner’s mobile device resources [3]. It minimizes the consumption of device resources by running the application’s resource-intensive tasks in the remote cloud [7]. The architecture’s performance efficiency varies with the availability

Table 1: m-learning knowledge gap in literature.

| Study | m-learning emphasis | Mobile learning framework | Architecture type | Knowledge gap |
|-------|---------------------|--------------------------|-------------------|---------------|
| [3]   | (i) Distance cloud  | (i) Mobile cloud         | (i) PL-MCA        | (i) Did not consider emerging architectures |
|       | (ii) Context-aware  |                          | (ii) AL framework |               |
| [18]  | (i) Distance cloud  |                          | (iii) AL mobile agents |               |
|       | (ii) Context-aware  |                          |                   |               |
| [5]   | (i) Context-aware   | (i) Did not include      | (i) Application layer | (i) Did not include the framework |
| [6]   | (i) Research analysis | (i) Did not consider framework | (ii) PL architecture did not consider |
| [13]  | (i) Context-driven  | (i) Mobile cloud         | (i) PL-MCA        | (i) Did not mention AL and mobile edge for performance efficiency |
| [22]  | (i) Responsive m-learning | (i) Mobile cloud-fog   | (ii) Fog-cloud    |               |
| [12]  | (i) Fog-cloud       | (i) Fog in higher education | (i) Not available | (i) Did not discuss fog in m-learning |
| [23]  | (i) Autonomous m-learning model | (i) Mobile cloud | (i) Intelligent algorithm | (i) Discussed intelligent algorithm without considering application layer framework |
| This study | (ii) Cloudlet |                          | (ii) PL MCAs      | Study’s significance |
|       | (iii) Operator-centric cloud | (ii) Edge | (ii) Application layer |               |
|       | (iv) Ad hoc cloud   | (iii) Mobile edge        | (iii) IoT-based applications |               |
|       |                     | (iv) Fog                |                   |               |
|       |                     | (v) Unified framework    |                   |               |

Table 2: List of acronyms.

| Acronym | Description |
|---------|-------------|
| m-learning | Mobile learning |
| QoE | Quality of experience |
| MCAs | Mobile cloud architectures |
| LMS | Learning management system |
| MCC | Mobile cloud computing |
| PL and AL | Physical layer and application layer |
| IoT | Internet of Things |
| AI | Artificial intelligence |
| 5G | 5th generation mobile network |
| SWOT | Strengths, weaknesses, opportunities, and threats |
| TAM | Technology acceptance model |
| ITS | Intelligent tutoring system |
| RFID | Radio frequency identification |
| POCS | Performance optimization cloud stack |
| MEC | Mobile edge computing |
| ETSI | The European Telecommunication Standards Institute |
| ISG | Industry specification group |
| MCDM | Multicriteria decision-making |
| TOPSIS | Technique for order of preference by similarity to ideal solution |
of stable and fast connections between the learner’s device and the centralized cloud.

3.1.2. Cloudlet m-Learning MCA. According to [17], a cloudlet is an architecture that is usually installed in high-density areas, such as a library, coffee shops, and auditoriums, collocated with Wi-Fi hotspots [7]. Figure 5 illustrates the m-learning integration with the cloudlet-MCA, where m-learning actors connect through LMS to the cloudlet server via one-hop Wi-Fi/LAN access and offload the application’s execution tasks to consume the server’s resources. The tasks execute until the learner connects to the server in physical proximity. This architecture provides access to resource-rich learning content on the cloudlet, i.e., a datacentre in a box on-premises. It also enables high-bandwidth and low-latency [17] to the actors. The learners continue the application execution until they are in the one-hop Wi-Fi range and connected [7].

3.1.3. Operator-Centric m-Learning MCA. In this architecture, the designers bring cloud servers to the mobile operators’ network domain in physical proximity [7, 30], shown in Figure 6. This arrangement improves the learners’ content accessibility to the cloud resources and minimizes latency issues without affecting mobile communication services, such as handover, availability, and location privacy. The architecture’s characteristic, i.e., multicast traffic [17], is vital for executing resource-intensive m-learning applications, e.g., live video lectures.

3.1.4. Ad Hoc m-Learning MCA. Several mobile devices form an ad hoc MCA [31, 32]. This architecture includes components, such as LMS, requesting learner’s mobile device and P2P nodes, i.e., mobile devices of other learners [17]. The neighbouring devices in the physical proximity independently participate in executing m-learning applications by sharing their device resources. Figure 7 demonstrates a
mobile ad hoc Wi-Fi framework architecture, and its associated arguments improve the execution performance of the learner’s request. Here, a learner’s device requests the participating learners’ devices for sharing the burden of application execution. The requesting learner’s agent divides the execution task into subtasks and sends it to the participating learners’ devices. Later, the participating devices send the task’s results back to the requesting device. This process repeats for all executable tasks of the executing application and allows computing and networking [19] during the execution cycle. This ad hoc architecture can be used indoor and outdoor for students’ assignments, such as live video discussions and fieldwork.

3.2. Application Layer Architectures. The MCA at the application layer is responsible for determining the m-learning application execution tasks (see Figure 3) and complementary layer to the physical layer [17]. The application architectures estimate the task execution cost of a processing application, such as latency, energy efficiency, and execution time. Based on the cost estimation, application layer architectures offload the resource-demanding execution tasks to the intended cloud resources [7]. The paper [17] discusses several popular application layer architectures—CloneCloud and Cuckoo, and highlights different application groups, e.g., m-learning applications. Another study [5] compares 11 mobile learning application architectures that take several approaches to execute m-learning scenarios (see Section 2.3).

3.3. A Unified m-Learning MCA and the Reasons. (RQ2) The presented study investigates the state-of-the-art cloud-based m-learning models to discover any unified architecture that exists for improving m-learning performance. Several studies [2, 3, 5, 18, 24] did discuss MCA for m-learning models ignoring the uniformity in architecture standards. Besides, these studies have overlooked the other practising MCAs that can adopt for m-learning applications, since in the literature, less attention has been given to the standardization of m-learning MCA. Therefore, the current study determines a unified architecture based on the existing physical layer MCAs. Additionally, the architecture shall be extendable to obtain the features of other related computing paradigms [19].

3.3.1. Architecture Overview. For the unified m-learning MCA, this study recreates an MCA considering the physical layer’s components. Precisely, any physical layer MCA builds on four core components (CC): mobile device, wireless communication network, the Internet, and the cloud infrastructure [7]. These components integrate and execute interconnectivity during the m-learning application execution cycle. The current study defines the CC set as “a set of technically distinct and logically interconnected components forming integrated mobile cloud architecture.”
To execute a cloud-based m-learning application, it must deploy on a physical layer MCA. For designing a unified m-learning MCA, the following two policies should be considered [21]:

**Policy 1 (CC):** a physical layer MCA must build on the four core components that integrate to form a generic MCA.

**Policy 2 (application architecture-AA):** an m-learning application is an example of AA and deploys on the physical layer MCA to determine a functional architecture.

**MCA m-learning (MCA\textsubscript{ml}) unified model:** for the successful execution, essentially policies 1 and 2 need to integrate and perform a generic m-learning execution.

Equation (1) represents the unified m-learning MCA’s conceptual model. The equation includes the four core components of a physical layer, and the application layer’s components depend on the processing m-learning application’s computing paradigms. The integration of physical and application layers forms a basic MCA and performs generic functionality, shown in Figure 8.

$$MCA_{ml} = \sum_{j=1}^{4} (CC)_j + \sum_{j=1}^{n} (AA)_j, \quad (1)$$

### 3.3.2. Architecture Requirements and Strategies

A unified m-learning MCA needs to design on well-defined strategies and requires establishing learner’s device seamless connectivity to the learning content on the cloud via the Internet. It must execute the device’s native applications on the processing device and the m-learning application’s resource-intensive tasks on the cloud [3]. It has to facilitate rapid learning-content delivery, bandwidth management, and dynamic learning resource provisioning during the execution cycle [33]. From an institutional perspective, the architecture should enable a single integrated platform through LMS [34] and be accessible to the institution’s other information delivery system. It should provide tailored services to the users with changing requirements [35] and build on the following strategies:

(i) An intuitive architecture considering the significant factors of m-learning, distinctive institutional needs [1], and leverages interoperability standards

(ii) Capable of alignment with the educators’ and learners’ objectives [35] supports LMS’s tools and institution talent goals
(iii) Open to update the future learning needs without affecting the current learning activities and extensibility to configure the characteristics of emerging technologies

(iv) Improves security by keeping confidential institutional data in the local locations

3.4. Related Computing Paradigms and m-Learning Opportunities. (RQ3) m-learning has incredible momentum by incorporating the significant characteristics of related computing paradigms—IoT, edge, mobile edge, fog, AI, and 5G network. Researchers exemplify the opportunities by integrating these paradigms to enhance m-learning performance efficiency and improve an institution’s LMS acceptance [1]. The m-learning architectures build on such paradigms [13] will enable numerous benefits (e.g., ultralow latency and quick access time) to educators, learners, and educational institutions [12]. These architectures improve m-learning actors’ interactive communication [10], sharing learning contents, data processing and management, and robust performance. They also facilitate a context-aware learning process [5] and ultralow latency [33] with low cost. These paradigms out-compete the existing ones with innovative architectures [10] and superior performance. Therefore, teaching and learning have been tremendously responsive by encompassing such paradigms’ characteristics, e.g., fog-based m-learning applications [22].

Computing layers of IoT. Recent advancements in smart devices paved the way for the IoT. The IoT computing embeds with sensors and actuators, connected in a network, and renders their functionality using the Internet [20]. IoT has become more flexible and distributed and manages data in disparate points rather than in a central cloud. With the explosion of billions of connected devices, the cloud, fog, and edge platforms have seen a growing demand worldwide [19]. The integration of IoT with mobile computing opens incredible options for its users and controls IoT devices either remotely or in proximity. For instance, the processing application obtains sensor data to determine actuators for individualized decisions for the sensors and RFIDs in the same environment [20]. IoT computing offers several opportunities (see Section 3.4.1) to improve m-learning efficiency. Figure 9 illustrates a distributed m-learning layered architecture, i.e., performance optimization cloud stack (POCS) that includes the computing paradigms resources configure in the layer’s hierarchy. A processing m-learning application seeks these resources considering the requirements during the execution cycle.

3.4.1. m-Learning Applications and IoT. The deployment of m-learning applications on IoT platforms complements a solid education and has a massive impact on learning-teaching. For instance, the data generated from IoT devices in a learning scenario need to integrate [36] with the m-learning system to promote an intelligent m-learning environment. Such integration gives a real-time environment to the students and enables them the computation in reality [20]. Optimistically, the next-generation mobile LMS [1] build on IoT devices, as shown in Figure 10. In a mobile intelligent LMS [15], IoT devices, wearable sensors, and mobile applications are integrated to determine students’ moment detection and speech recognition while participating in online discussion forums [20]. Indeed, IoT-based m-learning is significantly more effective in medical education. For instance, wearable sensors and RFID tags are embedded into a patient’s body, and students’ mobile devices are equipped with RFID tags.

The mobile application displays the patient’s conditions on the students’ devices and displays students’ activity when they approach such patients. Similar information displayed on the teacher’s mobile device help the teacher monitor students’ physical assessment activities [20]. IoT-based m-learning applications are set to be performed more effectively in 5G networks. Following are some latest IoT-based m-learning applications [37] and their services.

SweetRush: it allows instructors customized options for learners’ training, real-time feedback, and multimedia animation that increase participation and retention.

Blackboard Mobile Credential: it enables authorized learners to Apple Watch and wallet for iPhone to access the institution’s resources and pay for services at ease.

LocoRobo: it provides a programming and robotics education environment where robots are used to teach coding languages like C, JavaScript, and Python. The other applications, such as Magicard and Kajeet, provide similar functionalities.

3.4.2. Edge Computing and m-Learning. Since the number of IoT devices and volumes of data is increasing rapidly in
academic institutions, edge computing has emerged to make the data computation faster but closer to the m-learning actors. Edge computing is a novel trend of decentralizing data processing at multiple endpoints instead of centralized datacentres or clouds [25, 26]. Edge is the immediate first hop from locally distributed IoT devices [19]. It ensures privacy, low latency, resource optimization, location-aware services, and reduced network traffic [25]. Hence, integrating m-learning, IoT devices, and edge computing enables highly efficient m-learning performance and promotes intelligent educational environments.

m-learning applications based on IoT-edge computing platforms are growing extensively, and they can be deployed and coupled with institutions’ micro datacentres [20, 22]. Edge-cloud m-learning applications are developed to facilitate resource-poor devices and support educational resources widely available [25]. Educational institutions utilize edge-cloud architectures to improve m-learning efficiency and QoS for m-learning actors [38]. The edge m-learning architecture requires a responsive LMS environment on mobile devices interacting with the local edge nodes. These architectures enable m-learning actors to access synchronous or and asynchronous learning opportunities, and they distribute the learning content among multiple edge nodes. Edge nodes handle data locally and reduce latencies for seamless execution of m-learning scenarios. Moreover, edge architecture scales resources and manages actors’ network connectivity to ensure uninterrupted performance [38].

3.4.3. Mobile Edge Computing and m-Learning. Mobile edge computing was introduced by the ETSI ISG [39], which enables the cloud computing characteristics within the radio access network (RAN) [33]. It provides an environment where m-learning actors get learning resources much closer to them at the edge of the network. The mobile-edge m-learning characteristics include ultralow latency, high bandwidth, and real-time experience for actors in m-learning. The MEC architecture, shown in Figure 11, recognizes as a key enabler for 5G network standard [20]. It enables the pathway towards the required communication network characteristics to deliver learning content efficiently. Further, it opens options to network operators to allow third parties (e.g., institutions) to deploy intelligent m-learning applications towards mobile learners. In the MEC environment, the m-learning actors connect to the mobile base station, and the architecture’s nodes deal with the processing applications to improve QoE [20] during the execution cycle.
3.4.4. Fog Computing and m-Learning. Since IoT devices produce massive data at their sources, the cloud architecture is scrambling to handle the influx of data. Processing volume of data back and forth creates delays between endpoint devices and the centralized cloud. The architecture needs to reconfigure and extended to minimize such delays [40]. For effective learning, academic institutions must shift their academic resources towards alternative infrastructures, e.g., the fog or edge, to utilize IoT devices appositely [20] and improve m-learning performance efficiency.

Cisco introduced fog computing in 2014 for real-time data processing and executing applications at the nearest server [33]. Fog is an emerging computing paradigm that enhances virtual learning architecture performance [36], facilitates ultralow latency access, analyses learners’ data quickly, and secures learning content within the cloud layer. Fog computing minimizes the m-learning service complexity, enhances context-driven m-learning [13], saves institutions’ bandwidth and network resources, and enhances the QoS [12, 22]. It also provides a platform to enable a 5G communication system and improves AI-based learning objects services.

Many educational institutions have already started relying on fog-edge computing paradigms for confidential and time-sensitive data [19], since fog computing helps in educational functions, supports agility [12], and brings the necessary computing power at the edge of the network [20]. Practically, institutions do not send all data to their main servers as such institutions have their cache to give replies from the servers. The institutions’ local servers fulfill the m-learning computing needs in collaboration with main cloud conglomerates, shown in Figure 9. These local servers or caches describe as fog nodes that facilitate the operation between IoT devices, edge devices, and cloud canters. The fog m-learning architectures enhance learning-teaching efficiency for live video lectures, online learners’ performance evaluation, and accurate educational big data stream analysis almost in real time [36].

3.4.5. Cloud Computing for m-Learning. The novel unification of m-learning and cloud offers numerous benefits, e.g., augments learners’ mobile device resources to improve m-learning application execution performance [3]. Traditional m-learning suffers from limited learning content, high network cost, and low transmission rates [2]. Integrating m-learning and cloud overcomes several traditional m-learning obstacles, such as massive learning content, easy-anywhere-anytime access, and high-performance dynamic execution [10, 18]. Notably, m-learning actors do not need to bother about mobile device hardware limitations and need not install necessary applications on resource-constrained devices. Hence, m-learning actors use Web-based platforms to execute the applications and access learning content using cloud service models [41]. Besides, the cloud provides an economic m-learning platform for institutions, and its architecture is open for adopting related computing paradigms’ features.

3.4.6. AI and m-Learning Applications. Artificial intelligence (AI) also recognizes as machine intelligence and includes multiple disciplines, such as philosophy, genetic algorithms, neural networks, computing, and robotics [15]. With various definitions in academic research, AI can be understood as creating human intelligence in the machine. It performs on knowledge data, natural language processing, and expert system and identifies patterns for a specific task from analyzing a massive data bundle. AI impacts higher education by applying the potential of fictions and robots [14]; it applies intelligent algorithms and creates an interactive learning environment by employing machine learning and deep learning. Today, AI has become an essential platform for researchers and educators, alters the learning process, and creates intelligence in learning applications and LMSs [1]. Intelligent tutoring systems (ITS) are getting popular because of their personalized and individual [14] approach for the learners. These ITS adopt various tutoring models, i.e., linear, dialogic, or more exploratory according to learners’ aptitude.

The AI-based m-learning applications provide an intelligent learning environment, advanced teaching methods, and learner easy access systems. For instance, mobile intelligent teaching expert systems [15] enable a platform where students have learning opportunities based on their knowledge, aptitudes, and individualized adaptive teaching. For example, Google very recently launches Socratic, an application [42] that enables a platform where learners ask questions in their voices. It determines the learners’ voices and provides the best answers from the educational content that the app finds on the Web. Further, the app is mighty AI dig up and very effective for learners for any academic course, explores various resources, and solves step-by-step math problems using the most powerful intelligent algorithms.
3.5. Fifth Generation (5G) Network. Communication and user-centric content management receive the most support from the emerging 5G network. 5G brings a significant change in network architecture and shifts the fundamental concept of network-aware application design to application-centric network provisioning [43]. The emergence of 5G network attracts researchers working on integrating 5G [44] with cloud-related computing paradigms, e.g., cloud-fog interoperation [45]. 5G wireless network is still relatively under deployment in many countries with speed up to 10–100 Gbps [40]. The 5G network advances IoT-based m-learning applications and executes them in an ultralow latency format. Hence, it supports high-speed Internet, facilitates the fastest learning video content streaming, and customized learner-centric content delivery in milliseconds. 5G will offer more efficient edge-based m-learning opportunities in the coming days. Besides, 5G will also provide highly effective services in learners’ density areas with efficient mobility performance [28].

4. Discussion and Result Analysis

The purpose of the presented study is to determine existing MCAs that did overlook for developing m-learning frameworks. It has discovered four physical layer MCAs [17] that researchers and application developers should consider when designing m-learning models. This study did consider the four MCAs and developed four m-learning MCAs that enable m-learning actors with different options for m-learning execution scenarios. The actors in m-learning should adopt these architectures following their virtual learning environment (RQ1). Further, this study proposes a unified m-learning-MCA that can be scaled to incorporate the features of related computing paradigms following the application execution requirements. The architecture consumes their resources and optimizes the m-learning performance (RQ2). The integrated m-learning architecture demonstrates numerous benefits, such as ultralow latency, quick access time, low-cost, security, and confidentiality [10, 13, 22], achieves performance efficiency, and provides QoE in m-learning across educational disciplines (RQ3).

This study reconfirms that several existing cloud-based m-learning architectures enhance m-learning performance by leveraging the cloud characteristics [3]. Such architectures offer several advantages: rich learning content resources, content sharing, independent learning, low cost, and energy-efficient while processing m-learning actor’s requests [2, 3]. Despite all these advantages, they suffer from substantial issues, such as high latency, security, and various service platforms. One of the issues, latency delay, affects m-learning performance and the learners’ acceptance and dilutes the system’s performance. The adoption of related computing paradigms addresses most of the earlier mentioned issues [12, 13, 38] and improves m-learning performance. This paper looks at the opportunities of such paradigms that optimize the m-learning system’s performance efficiency.

For instance, the MEC architecture significantly focuses on latency issues and provides ultralow latency for its users enabled by the 5G network standard [39]. The edge-based m-learning architecture with agility supports learners, educators, and educational institutions and impacts users’ acceptance and performance efficiency in real time.

4.1. The MCA-Based m-Learning Performance Analysis.

Table 3 shows the four physical layer MCAs and the m-learning SWOT analysis. The centralized cloud architecture is rich in resources and economical for intensive users. It accommodates rich learning content, reliable, comprehensive mobility, and improves m-learning performance. Cloudlet architecture offers low-latency services and quick access to the learning content. Operator-centric cloud architecture effectively uses user mobility and reduces m-learning access time during the execution cycle. In ad hoc mobile cloud architecture, peers’ mobile devices participate in task execution and leave the execution process independently. Here, the learners’ devices participate in collaborative tasks’ execution with the learner’s requested device.

4.2. m-Learning Performance in Related Computing Paradigms. Table 4 describes the m-learning performance and SWOT analysis across related computing paradigms and the emerging architectures [32]. The table shows that edge-based and fog-based m-learning architectures [22] have coherent performances, such as distributed services, locally accessible, and response time in milliseconds. Both share common characteristics and demonstrate similar performance efficiency [12, 13].

4.3. The POCS Implementation

4.3.1. Experimental Design. The envisioned architecture (see Figure 9) was designed for obtaining m-learning application execution performance efficiency. The designing approach considers the institution’s LMS capabilities and the architecture’s resources to improve performance efficiency. The integrated m-learning framework consists of four core components—m-learning actor’s device, LMS, POCS (edge-cloud, cloudlet, and mini data centre), and distant cloud.

(1) Implementation Setup. We deployed four learners’ the same brand smartphones (i.e., Lenovo K8 Note) with almost identical configuration: operating system (Android v7.1.1)-Bluetooth (v4.2) and Wi-Fi 802.11, b/g/n connectivity-Deca-core (dual core, 64-bit architecture, 2.3 GHz, Cortex A72+1.85 GHz, 4 GB RAM, Mali-T880 MP4 graphics, and MediaTek MT6797D chipset). For POCS, Two Dell PowerEdge T320 edge and cloudlet servers (Intel Xeon processor E5–1410, 16 GB RAM-6 DIMM slots)—Windows server 2012 OS. The university mini data centre was used, and for distance cloud, Amazon EC2 services were consumed through an SLA made by the university. CloudSim was used to evaluate the framework execution performance, and Cloud2Sim will be used for evaluating the architecture’s scalable resources distributed across its layers. Background irrelevant services were discarded during the execution.
Computation Requirements. The m-learning application executes on the Wi-Fi signal strength range (−30 dBm to −80 dBm) [7] and consumes architecture’s resources in the physical vicinity. The execution requests switch between POCS and the distant cloud considering the requirements of execution (task content) and the proposed algorithm decision (MCDM-TOPSIS).

Execution Profiling. It requires software (LMS tools and m-learning application), hardware (including learners’ devices), and network (wireless communication protocols). It includes application parameters’ performance measurement at the method level and determines the architecture’s resources following execution requirements.

Performance Efficiency Factors. The core factors, such as executable task workload (ETW), resource connection time (RCT), wireless network quality (WNQ), energy consumption (EC), and communication parameters (transmission, propagation, and processing delay), fluctuate and cause performance efficiency. These factors contribute to application execution and obtaining architecture’s resources, i.e., POCS and cloud. We have evaluated only task execution time for this article.

Prototype Testing. It includes the execution of three different size learning video content (see Table 5). The performance evaluation is done against execution time across POCS and distant cloud (see Figure 10). Network latency, turnaround time, and energy consumption are not the scope of the current study.

Cost estimation: the total computation time (TCT) is estimated using three components, task execution time (TET), request turnaround time (RTT), and transmission time (TT), and represented in Equation (2).

\[
TCT = TET + RTT + TT, \tag{2}
\]

\[
TET = \frac{N_{INT} \times CI_{CPI}}{PK_{MPS}}, \tag{3}
\]
4.3.2. Algorithm Design. The designed algorithm facilitates decision-making to offload execution tasks to the architecture’s POCS resources and the distant cloud. The decision is made on (i) offloading cost and (ii) multiple criteria (task workload, turnaround time, network quality, and energy consumption) using the MCDM-TOPSIS approach. We consider only task workload and execution time for the current paper to evaluate the performance. The cost is estimated using Equation (2), and the tasks offload considering Table 6 criteria. The learners’ devices obtain the resources based on these criteria.

4.3.3. Experimental Result Analysis. The m-learning performance is evaluated on (i) four physical layer MCAs and (ii) the POCS for execution time. Three content tasks (see Table 6) were executed to measure the performance efficiency. The learners’ devices are in the architecture’s vicinity and consume resources using one hop Wi-Fi access point and following the execution requirements.
Directions.

4.4. Challenges, Limitations, Implications, and Future Directions. For m-learning actors, it is challenging to adopt an efficient architecture as the application execution requirements are changing. Table 3 describes the MCAs’ features that should consider before adopting m-learning. The centralized m-learning MCA enables rich learning content but limited security and little control and involves service providers. Cloudlet m-learning MCA provides quick local access and improves security but with limited learning content and mobility. Operator-centric m-learning MCA reduces latency and improves secure content delivery, but the learners’ confidentiality is at risk and exposed to high network traffic. The ad hoc m-learning MCA faces certain limitations, such as radio access bandwidth range, application execution depending on participating devices, and sharing of task execution for an unspecified period. The mobile cloud m-learning performance efficiency varies considering the physical layer’s MCA and the application execution architecture. Before adopting any architecture, the users should consider the architecture model, LMS compatibility, and content delivery in heterogeneous platforms.

The presented study recreates a unified and integrated m-learning MCA, i.e., POCS that can be scaled up to incorporate related computing paradigms’ features and seek their characteristics. For instance, MEC-based m-learning architecture offers ultralow latency to the basic architecture during the execution of m-learning applications. However, it is challenging to guarantee the synchronization of MEC deployment into a network function virtualization environment. The architecture also experiences certain limitations, such as sustaining actors’ connectivity and radio access bandwidth, which remain potential challenges in obtaining latency efficiency. Further, the execution latency estimation and overhead of data portability are significant concerns when local network collectors or smart nodes fail. In fog-based m-learning architectures, fog tiers can support more complex data analysis using AI and machine learning algorithms, but such systems do not have standard service level agreements (SLAs) that facilitate control and monitoring [19].

The envisioned architecture has developed on the institution’s IT infrastructure and under the supervision of IT professionals. Despite some implications that need to be considered, the performance efficiency depends on latency delays, network connectivity (learners’ Wi-Fi connection) (signal strength range, i.e., −30 dBm to −80 dBm), and the management of the small cells (bandwidth). Further, optimizing performance efficiency depends on the architecture’s design, strategies, and the intended cloud resource, e.g., edge, cloudlet, and cloud. Additionally, the energy performance can vary and improve using the institution’s micro datacentre and cell zooming management. Besides, the architecture’s configurations, node security, and latent licensing costs may lurk. The m-learning stakeholders must be aware of these implications before adopting such systems.

Future research should consider LMS compatibility with the learning content, mobile platform interfaces, and actors’ device configurations while designing m-learning architectures and applications. The interface management that considers the emerging computing paradigm’s platforms and interface-aware protocols will be innovative. It will be significant to evaluate the architecture performance on multitier architecture by including an edge orchestrator. The current architecture can be redesigned for more complex use-cases, such as learning objects based on augmented and virtual reality. Several studies assume that fog nodes are fixed [19], and designing a mobility architecture for m-learning will be an incredible contribution. In a MEC hierarchy architecture [33], IoT, edge, and fog layers can be used for resource-demanding and AI-based m-learning applications. IoT is a power transforming environment and can explore emerging tools, e.g., smart speakers. The AI-based face recognition m-learning applications can help teachers identify learners’ authentications on course assessments.

| Application executable task type | Computation requirements | Target resource      |
|----------------------------------|--------------------------|----------------------|
| Low content                      | Low                      | Learner’s device     |
| Medium content                   | Medium                   | POCS                 |
| High                             | High                     | Distant cloud        |
| Low                              | Low                      | Learner’s device     |
| Medium                           | Medium                   | POCS                 |
| High                             | High                     | POCS                 |
| Low                              | Low                      | Distant cloud        |
| Resource-demanding content       | Medium                   | POCS/distant cloud   |
|                                  | High                     | Distant cloud        |

Figures 12 and 13 illustrate the execution performances of the architectures.

(i) POCS takes the execution time is principally much lesser than the distant cloud

(ii) The execution time for POCS is increasing in ascending order since the resources’ physical proximity is expanding, so the number of hops will be increasing. Therefore, execution time remains the same, but the transmission time will be increasing, and it impacts the network latency

(iii) Among POCS resources, edge-cloud execution time is faster than the other two for the task sizes (9.9 and 6.2 MBs). The task size of 4.2 MB is lesser in size, but it is resource-intensive (RI), which needs more computing iterations

(iv) Hence, POCS improves the m-learning system’s response crispness and optimizes the execution performance efficiency

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5. Conclusion

This study discusses three central points in the context of m-learning: (i) exploring existing physical layer’s MCAs that extent m-learning provisioning, (ii) determining a unified m-learning MCA to enhance performance efficiency, and (iii) the impact of IoT, edge, mobile edge, fog, AI, and 5G on cloud-based m-learning systems. It is found that only distance cloud is being used for m-learning implementation, whereas cloudlet, operator-centric, and ad-hoc mobile cloud architectures have been ignored for the adoption of m-learning application execution. The MCAs are significant contributors to m-learning performance, and their efficiencies vary with changing virtual learning environments. This study’s novelty recreates an integrated, scalable architecture that leverages the characteristics of related computing paradigms. The performance analysis demonstrates numerous benefits: ultralow latency, locally accessible learning content, millisecond response time, energy-efficient, improved user security and confidentiality, and optimized performance efficiency for m-learning actors. The POCS’s performance evaluation result shows that edge-cloud consumes less execution time (1.66, 1.04, and 1.87) for the task sizes (9.9, 6.2, and 4.2 MBs), respectively. Future research should consider the range of cloud capabilities, smart gateways, and data transmission rates for multiple learning resources. Edge-5G m-learning architectures will be significant for changing m-learning application requirements and the next-generation IoT-based learning applications. The integration of edge-fog opens the opportunities to deploy more complex and resource-intensive m-learning use-cases. AI-based m-learning models can execute latency-sensitive tasks locally or send data intelligently to either edge/fog or the cloud. The developers can deploy 5G ultrawideband service to meet learners’ instant interaction and intelligent video analytics requirements. The developers must know the related computing characteristics and the resource-intensive m-learning application execution requirements before designing the application architectures.
Data Availability

There is no separate data for this manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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