

Chapter 2

Literature Review

In this chapter, we review existing works, highlighting their advantages and shortcomings, closely related to the two key problems addressed in this thesis: Problem 1, which focuses on *designing computing system for remote healthcare*, with an emphasis on real-time health data computation, latency and energy minimization, and prioritizing critical patient data, and Problem 2, which involves *developing learning system for remote healthcare*, focusing on the development and the integration of ML and FL models. To address these problems, we present a comprehensive review of key contributions, methodologies, and findings from the literature, while highlighting research gaps that form the foundation for the novel solutions proposed in this thesis.

The literature review is organized as follows:

- Designing Computing System for Remote Healthcare (see Section 2.1): This section presents a literature review focused on Problem 1, which is further divided into two sub-problems as follows:
 1. Designing Fog Computing-Enabled System for Remote Health Monitoring (see Subsection 2.1.1).
 2. Designing Energy and Latency-Aware Fog Computing-Enabled Smart Healthcare System (see Subsection 2.1.2).

- Developing Learning System for Remote Healthcare (see Section 2.2): This section provides a literature review on Problem 2, which is divided into three sub-problems as outlined below:
 1. Development of UAV-Assisted WBAN-based Federated Learning System for Smart Healthcare (see Subsection 2.2.1).
 2. Developing Energy-Efficient and Privacy-Preserving Blockchain-Based Federated Learning for Smart Healthcare Systems (see Subsection 2.2.2).
 3. Developing an Incentive Mechanism for WBAN User Selection in Multiple FL Systems for Smart Healthcare (see Subsection 2.2.3).

2.1 Designing Computing System for Remote Healthcare

In this section, we review existing research on computing systems for remote healthcare that enable real-time health data processing while prioritizing critical patient data. We also provide a comprehensive analysis of these works, highlighting the key challenges and gaps in existing approaches in the following subsections.

2.1.1 Fog Computing-Enabled System for Remote Health Monitoring

This subsection reviews closely related works on remote healthcare systems available in the literature, with a comparative analysis presented in Table 2.1.

In [32], the authors focused on improving haptic communications under three key factors- system stability, energy consumption, and network delay. Authors proposed a time-varying swarm algorithm to solve the formulated problem. However, they did not consider profit. Authors of [33] proposed a cost-aware medical cyber-physical system assisted fog computing model. In [34], authors primarily focused on resource allocation to minimize energy consumption and response time through dynamic-cluster algorithm. However, none of these works [32–34] considered criticality of patients’ health data while offloading it to a computing node.

Table 2.1: Related works on FC-enabled remote healthcare system

Problem Focus	Criticality	Profit	Beyond-WBAN	Utility Maximization
Resource allocation [32]	×	×	×	×
Task allocation [33]	×	×	×	×
Resource allocation [34]	×	×	×	×
QoS requirement [35]	×	×	×	✓
Data priority, latency [36]	×	×	✓	×
Criticality aware packet transmission [37]	✓	×	✓	×
Medical criticality [8]	✓	×	✓	×
Time-slot allocation, data priority [38]	✓	✓	×	×
Data-rate tuning [39]	✓	×	×	×

In [35], the authors investigated energy consumption, transmission delay, QoS requirement, power limit and wireless front-haul constraints in fog computing-based Internet of Medical Things (IoMT). However, this model did not consider criticalities of patients and profit of health service provider. Authors of [8] proposed a health monitoring system for IoMT considering criticality, energy and delay constraints. However, this work did not consider profit of MC while offloading the medical data to edge server. The authors of [36] proposed a queue-based transmission of time-sensitive medical data packets in beyond-WBAN using a non-cooperative game-based approach. In [37], authors proposed a criticality-aware dynamic management for medical data transmissions. However, the above works did not consider the profit for delay-sensitive medical data transmission. The authors in [38] proposed a priority-aware time-slot allocation in WBANs. They extended evolutionary game theory to solve the formulated problem. The authors of [39] proposed a Nash bargaining solution for a cooperative game based priority-aware data-rate tuning in WBAN model. However, these works did not consider beyond-WBAN scenario for priority-based data transmission.

In most of the existing approaches [32–35, 38, 39], only intra-WBAN transmission has been considered under latency and criticality constraints. Some works [8, 36, 37] have considered both intra-WBAN and beyond-WBAN transmission with latency and criticality constraints. However, none of the existing approaches has considered the

profit of the MC in their model. To address this research gap, Chapter 3 proposes a fog computing-enabled remote health monitoring system designed to maximize the MC's profit while minimizing patient latency and prioritizing critical patients' health data.

2.1.2 Energy and Latency-Aware Fog Computing-Enabled Smart Healthcare System

This subsection reviews closely related works on energy- and latency-aware remote healthcare systems in the literature, with a comparative analysis in Table 2.2.

In [33], the authors proposed a cost-aware fog computing-assisted medical cyber-physical system. Similarly, in [34], the authors designed a low-latency, energy-efficient fog computing-assisted healthcare system in collaboration with the cloud. However, these works [33,34] did not consider the criticality of patients' health data when transmitting it to a computing node for processing. In [40], the authors extended evolutionary game theory to prioritize time-slot allocation in WBANs, aiming to reduce packet drop rates and save energy. However, this work did not consider the health data computation model or the HSPs' profit.

In [35], the authors investigated energy consumption, transmission delay, QoS, power limits, and wireless front-haul constraints in a fog computing-based IoMT system, neglecting health data criticality and the HSP's profit. Work [39] applied cooperative game-theoretic approach for sensor data rate tuning based on health data criticality, without considering the computation of patients' health data. Authors of [41] introduced a blockchain and Internet of Things (IoT)-based health monitoring system to prevent data tampering and preserve privacy, but did not health data criticality during transmission and HSP's profit. Work [3] proposed a fog computing system for health monitoring, prioritizing critical patients; however, this work did not consider energy consumption during health data processing. Additionally, work [5] focused on multi-attribute caching mechanism for remote health monitoring system without addressing

Table 2.2: Related works on energy- and latency-aware FC-enabled healthcare system

Problem Focus	CR	HDR	PH	DY	UM	EC	LA	MFS
[33]	×	×	×	×	×	×	✓	✓
[34]	×	×	×	×	×	✓	✓	✓
[40]	✓	×	×	×	×	✓	×	✓
[35]	×	×	×	×	✓	✓	✓	✓
[39]	✓	×	×	×	×	×	×	×
[41]	×	×	×	×	×	×	×	✓
[3]	✓	×	✓	×	✓	×	✓	✓
[5]	✓	✓	×	×	×	×	×	✓
[8]	✓	×	×	×	✓	✓	✓	✓
[4]	✓	×	✓	×	✓	✓	×	×
[42]	✓	×	✓	✓	×	✓	×	×
[43]	×	×	×	×	×	✓	✓	×
[44]	×	×	×	×	×	✓	×	×
[45]	×	×	×	×	×	✓	✓	✓

Note- CR: Criticality, HDR: Health data relevance, PH: Profit of HSP, DY: Dynamic pricing, UM: Utility maximization, EC: Energy consumption, LA: Latency, MFS: Multiple FS.

energy consumption during monitoring or HSP's profit.

In [8], authors proposed an Mobile Edge Computing (MEC)-enabled 5G in-home health monitoring system for IoMT, considering criticality, energy, and delay constraints. However, this work did not consider HSP's profit under dynamic pricing scheme. Authors of [4] introduced a cooperative framework for partial offloading between MEC server and WBAN users to minimize MEC server energy consumption while maintaining WBAN users' QoS. Work [42] used a Stackelberg game approach for task offloading decisions in an MEC-enabled healthcare system. However, these works [4, 42] did not consider multiple MEC architectures or latency constraints in healthcare service delivering. Work [43] introduced D2D communication with next-generation wearables and a collaborative offloading framework for trustworthy health monitoring to reduce energy consumption and latency. Similarly, work [45] proposed a task offloading scheme to minimize energy consumption and latency in smart healthcare. Additionally, work [44] proposed an edge-enabled eHealth monitoring system to optimize storage and energy for IoT-based smart hospitals. However, these works [43–45] failed to address essential aspects of remote health monitoring systems, such as patients'

health criticality and HSPs' profitability.

Most existing works [33–35, 39, 40] have focused on health data transmission under latency and criticality constraints, with some addressing energy consumption [4, 8, 42] or privacy-preserving mechanisms [41]. Additionally, works such as [43, 45] focus on D2D health data processing for next-generation wearable, while works [5, 44] emphasize energy efficiency and caching mechanisms for smart healthcare systems. However, none of the existing works consider HSP's profit, along with patients' latency and energy costs, while prioritizing critical health data in a multi-FS architecture. To address this research gap, Chapter 4 proposes a fog computing-enabled WBAN-based system for real-time remote health monitoring, with a focus on improving latency and energy efficiency. It also introduces a dynamic pricing scheme for delivering remote health monitoring services based on the computational requirements of patients' health data.

2.2 Developing Learning System for Remote Healthcare

In this section, we review existing research on learning systems for remote healthcare, focusing on the systems designed for developing and integrating ML and FL models to improve the accuracy and efficiency of patient health predictions while ensuring data privacy and security. A comprehensive analysis is provided, highlighting key challenges and gaps in existing approaches, which are discussed in the following subsections.

2.2.1 UAV-Assisted WBAN-based Federated Learning System for Smart Healthcare

This subsection presents related works on learning systems, focusing on UAV-assisted WBAN-based FL frameworks, and provides a comparative analysis in Table 2.3.

In [46], the authors proposed an FL framework that balances FL time, computation, communication latency, and energy consumption over wireless networks. Work [47] optimized the number of global iterations under CPU, transmission delay, and model accu-

racy constraints. Work [48] proposed a decentralized privacy-preserving FL framework for training effective models using distributed healthcare data. However, works [46–48] focused on optimizing the FL model without considering RA for data transmission. In [49], the authors proposed a location-based FL model, utilizing reconfigurable intelligent surfaces to accurately determine the positions of computing nodes. However, this work did not consider computing energy or RA for data transmission. Y. Liu et al. [50] proposed an FL framework for UAV swarms that included joint training and RA to improve FL efficiency. However, this work did not consider PRB allocation and UAVs' revenue, altogether, despite addressing the interference issues among users.

Work in [51] proposed a Channel Allocation Algorithm (CAA) for disaster communication relief systems using UAVs. This work used Stackelberg game to derive a channel allocation strategy, considering mutual interference of users to improve network throughput. R. Duan et al. [52] proposed a Suboptimal Subchannel Assignment Algorithm (SSAA) to maximize system capacity by jointly optimizing sub-channel assignment, IoT node uplink transmit power, and UAV flying height. K-means clustering was employed to group IoT nodes into subsystems corresponding to the number of UAVs, and subchannels were assigned to each subsystem using an efficient many-to-many matching algorithm. Work [53] proposed a joint RA problem to minimize energy consumption for mobile devices and UAVs, considering the limited resources of UAVs and task delay. However, works [51–53] mainly focused on RA without considering the revenue for providing resources.

Existing works have attempted to address interference and RA in WBANs, but with certain limitations. For instance, a graph coloring-based approach was used in [54] to minimize interference among WBANs through channel reusability; however, it allocated only a single channel to each WBAN without considering the criticality of health data. Other works, such as [15], applied matching theory for RA in 5G networks based on service class, while [55] focused on minimum resource requirements for spectrum allocation

Table 2.3: Related works on UAV-assisted WBAN-based FL for smart healthcare

Problem Focus	FL	Energy	Revenue	RA	HD
FL via wireless network [46]	✓	✓	×	×	×
FL convergence [47]	✓	×	×	×	×
Decentralized FL [48]	✓	✓	×	×	✓
Location-based FL [49]	✓	×	✓	×	×
FL with UAV Swarm [50]	✓	✓	×	✓	×
Transmission capacity [52]	×	×	×	✓	×
Channel allocation [51]	×	✓	✓	✓	×
Resource allocation [53]	×	✓	×	✓	×
Channel allocation [54]	×	×	×	✓	×
Resource allocation [15]	×	×	✓	✓	×
Spectrum allocation [55]	×	×	✓	✓	×
Spectrum matching [56]	×	×	✓	✓	×

using matching theory. However, these approaches did not consider FL in UAV-assisted WBANs or prioritize critical patient data. Furthermore, none of the existing works have simultaneously considered the prioritization of critical patient data and the revenues of both WBANs and UAVs through RA, while accounting for resource demands and minimizing interference among WBANs. To bridge this research gap, Chapter 5 proposes a UAV-assisted WBAN-based FL framework that optimizes the revenues of both WBANs and UAVs through RA, while considering resource demands and minimizing interference among WBANs.

2.2.2 Energy-Efficient and Privacy-Preserving Blockchain Based Federated Learning for Smart Healthcare System

This subsection reviews related work on energy-efficient and privacy-preserving blockchain-based FL systems, with a comparative analysis presented in Table 2.4.

NVIDIA introduced Clara FL [57] for collaborative model training across multiple hospitals to develop a global model. In [58], a secure patient monitoring system using FL was proposed, where LDs perform training and send weight matrices to the server for aggregation. Similarly, privacy-preserving FL techniques have been employed in clinical and epidemiological research [59]. K. Wei et al. [60] proposed an FL framework

Table 2.4: Related works on energy-efficient, privacy-preserving, blockchain-based FL

Problem Focus	FL	DP	Encryption	Blockchain	Association	RE	HD
[57]	✓	×	✓	×	×	×	✓
[58]	✓	×	×	×	×	×	✓
[59]	✓	✓	×	×	×	×	✓
[60]	✓	✓	×	×	×	×	×
[2]	✓	×	✓	×	×	×	✓
[61]	✓	×	✓	×	×	×	✓
[62]	✓	✓	×	✓	×	×	×
[63]	×	✓	×	✓	×	×	×
[64]	✓	✓	✓	✓	×	×	×
[20]	✓	×	×	✓	✓	✓	×
[65]	×	×	×	✓	✓	×	×
[66]	×	×	×	✓	✓	×	×
[67]	×	×	×	✓	✓	×	×
[68]	✓	×	×	×	✓	×	×
[69]	✓	×	×	✓	✓	×	×
[55]	×	×	×	×	✓	✓	×

under DP by adding Gaussian noise to locally trained weights before sending them to the server. However, these works mainly focused on optimizing FL under DP by considering centralized model aggregation, without addressing incentives for the participants. In contrast, works [2] and [61] introduced FL frameworks for in-home health and activity monitoring that utilized HE and a cloud-edge architecture to mitigate privacy risks associated with model weights. However, these works failed to incorporate rewards for contributing health data in the FL process.

C. Li et al. [62] and K. Gai et al. [63] proposed a privacy-preserving data-sharing architecture for the Industrial Internet of Things (IIoTs) by merging FL and blockchain technology. Work [64] suggested a blockchain based privacy-preserving FL scheme that employs smart contracts instead of a central server for global model updates. Nevertheless, these approaches omitted considerations of incentives and energy consumption in local model computation and transmission. Work [20] introduced BlockFL, a privacy-preserving FL framework that eliminates the need for centralized global model aggregation but did not account for energy consumption or privacy-preserving techniques.

Several studies have delved into user association techniques, including intelligent user matching using blockchain for computation offloading in ultra-dense wireless net-

works [65], Gale-Shapley-based matching for node selection in blockchain based crowdsourcing [66], matching theory for spectrum allocation [55], and patient-physician matching to alleviate waiting times [67]. Works [20] and [69] introduced a random association scheme for clients and miners within the blockchain based FL framework. Additionally, work [68] proposed an edge association of LDs with edge servers for hierarchical edge FL. However, applying work [68] directly to our proposed approach is not feasible, given its lack of consideration for blockchain integration and incentives for participation in the FL process.

Existing research has predominantly focused on enhancing FL performance, neglecting incentives for WBANs actively engaged in the process. Nonetheless, it's imperative to compensate WBANs and miners for their participation, given the consumption of computational and communication resources. Moreover, none of the existing approaches address the joint integration of energy efficiency and privacy preservation in blockchain based FL, coupled with association and incentive mechanisms. To bridge this research gap, Chapter 6 introduces a smart healthcare system that leverages blockchain based FL, alongside incentive and association mechanisms, to effectively achieve energy efficiency and privacy preservation.

2.2.3 Incentive Mechanism for WBAN User Selection in Multiple FL Systems for Smart Healthcare

This subsection presents closely related works on incentive mechanisms for FL systems, along with a comparative analysis in Table 2.5.

Extensive research has focused on various aspects of FL, including incentive mechanisms and user selection [26, 29, 70–76], using approaches such as auction theory, contract theory, and Stackelberg games. These works typically focus on rewarding and selecting users based on amount of data [29, 70], privacy budget [71–73], training costs [74], model accuracy [75], and reputation [26, 76]. For instance, works [29, 70]

Table 2.5: Related works on incentive mechanisms in multiple FL for smart healthcare

Problem Focus	DA	ACC	CM	PR	RA	MFL	US	IM	SH
[29]	✓	×	✓	×	×	×	✓	✓	×
[72]	✓	×	✓	✓	×	×	✓	✓	×
[70]	✓	×	✓	×	×	×	✓	✓	×
[71]	×	✓	✓	✓	×	×	×	✓	×
[73]	×	✓	✓	✓	×	×	✓	✓	×
[74]	✓	✓	✓	×	×	×	×	✓	×
[75]	✓	×	✓	×	×	×	✓	✓	×
[76]	×	✓	✓	×	✓	×	✓	✓	×
[26]	×	✓	✓	×	✓	×	✓	✓	×
[77]	✓	×	✓	×	×	×	✓	✓	✓
[78]	✓	×	✓	×	×	×	✓	✓	✓
[79]	✓	×	×	×	×	✓	×	×	×
[80]	✓	×	✓	×	×	✓	×	×	×
[22]	✓	×	✓	×	×	✓	✓	×	×
[81]	×	×	✓	×	×	✓	✓	×	×
[82]	×	×	✓	×	×	✓	✓	×	×
[83]	×	✓	×	×	×	✓	✓	×	×
[25]	×	×	✓	×	×	✓	✓	✓	×
[21]	×	×	✓	×	×	✓	✓	✓	×
[27]	✓	×	✓	×	×	✓	✓	✓	×
[28]	✓	✓	×	×	×	✓	✓	✓	×

Note- DA: Data Amount, ACC: Accuracy, CM: Cost Model, PR: Privacy Requirement, RA: Reputation Aware, MFL: Multiple FL, US: User Selection, IM: Incentive Mechanism, SH: Smart Healthcare.

proposed incentive mechanisms based on the amount of data contribution. Due to the risk of privacy leakage during model transmission, the authors of [71–73] incorporated DP into the incentive mechanisms. Additionally, work [74] proposed an incentive mechanism that considers users’ training costs, while work [75] used local model accuracy as a metric for user contribution in the incentive design. Authors in [26, 76] designed an incentive mechanism and reputation-based selection approach using a multiweight subjective logic model to select reliable users with high-quality training data, thus improving FL performance. However, these works failed to simultaneously consider the amount of health data, privacy requirements, and reputation in scenarios involving multiple FL models. Moreover, recent studies explored incentives for FL in smart healthcare, with works [77, 78] proposing contract theory-based approaches. However, these studies overlooked the simultaneous training of multiple FL models while considering the privacy requirements of users.

While some progress has been made in the parallel training of multiple FL models, integrating incentive mechanisms has received limited attention. Recent research has aimed to enhance system efficiency and adapt to diverse application needs via parallel training of multiple models [22, 79–83]. For instance, work [79] aimed to minimize latency by using a matching game model for efficient FL model allocation to users. In [80], the authors proposed a multi-dimensional optimization framework to improve user selection and resource allocation, thus minimizing users' time costs. Work [22] introduced a framework for the parallel training of multiple FL models with intelligent scheduling for cost-effective user selection. Work [81] addressed the jointly selection of participants and optimization of learning topologies for concurrently trained FL models in edge clouds. Additionally, work [82] introduced a framework for optimizing resources and controlling hyper-learning rates across multiple FL services, focusing on user energy consumption and overall learning time. Work [83] proposed a two-tier resource allocation framework to minimize FL round duration by optimizing bandwidth distribution among clients within and across services. However, these works primarily focused on enhancing system efficiency and FL model performance, while neglecting critical aspects such as incentivizing participants and ensuring privacy.

Most existing work on multiple FL settings has focused on technical aspects, such as improving training efficiency or reducing energy costs. Only a few studies [21, 25, 27, 28] have addressed the design of incentive mechanisms for multiple FL models framework. In [25], the authors developed an auction-based trading market for multiple FL models in UAV-aided networks, concentrating on user clusters and using one-to-one matching for UAV assignments based on users' overall data size. Work [21] aimed to minimize social costs and design an incentive mechanism for selecting heterogeneous users in FL through procurement auctions, while considering FL completion time. Additionally, work [27] introduced a multi-leader-follower game-based incentive framework that incorporates a matching algorithm with incomplete preference lists, taking into account

the accuracy levels of users' local models. Furthermore, work [28] proposed a Stackelberg game-based mechanism for multi-task federated edge learning, jointly designing economic incentives and participation strategies based solely on the proportion of data provided by users.

While existing works have considered incentives in systems with multiple FL models, they have not addressed key factors such as privacy requirements and the reputations of WBAN users. Additionally, these studies did not model WBAN users' contributions based on accuracy, reputation, and the amount of health data, nor did they comprehensively consider the costs of data collection, computation, communication, and privacy. None of the existing approaches have integrated these factors into an incentive mechanism while considering the privacy requirements of WBAN users in a multiple FL model setting. To fill this research gap, Chapter 7 presents an incentive mechanism that selects reliable WBAN users for differentially private multiple FL models in smart healthcare, integrating cost models, accuracy, reputation, and the amount of health data to provide a more comprehensive and practical solution.

2.3 Research Gap

As highlighted in the above literature review, several key research gaps have been identified and summarized, outlining the critical issues that must be addressed to improve remote healthcare systems, which this thesis aims to address:

- As mentioned in Table 2.1, most existing approaches focused on intra-WBAN transmission under latency and criticality constraints, and while some considered beyond-WBAN transmission, none included the profit of MCs in their models. Therefore, there is a need for a system that not only prioritizes critical patients' health data and minimizes patients' latency but also balances these factors with the profit considerations of MCs.
- As highlighted in the comparative analysis Table 2.2, while many works have

primarily focused on health data transmission under latency and criticality constraints, others have explored energy consumption and privacy-preserving mechanisms. However, it is also important to account for HSP's profit, as well as patients' latency and energy costs, while prioritizing critical health data in a multi-FS architecture for an efficient and sustainable remote healthcare system.

- Most existing works, as shown in Table 2.3, have focused on minimizing interference through RA while considering minimum resource requirements for spectrum allocation. However, these approaches have not addressed UAV-assisted WBAN-based FL or the prioritization of critical patient data. It is also important to prioritize critical patient health data while optimizing the revenues of both WBANs and UAVs through RA in FL systems, considering resource demands and minimizing interference among WBANs.
- As highlighted in Table 2.4, although existing research on FL systems has primarily focused on improving performance, it has largely overlooked critical aspects such as energy efficiency, privacy protection, and the risk of a single point of failure. Moreover, the need for effective incentives for WBANs and miners, as well as association and incentive mechanisms, has not been adequately addressed. So, there is a need for an FL system that considers both energy efficiency and privacy preservation while offering incentives for WBANs and miners.
- Existing works on multiple FL models, as shown in Table 2.5, have not sufficiently addressed key factors such as privacy requirements and WBAN user reputation. Additionally, the contributions of WBAN users, including their accuracy, reputation, and the amount of health data they provide, have not been fully considered, nor have the costs related to data collection, computation, communication, and privacy been addressed, altogether. Thus, there is a need for an incentive mechanism that integrates these factors while addressing the privacy requirements of WBAN users in multiple FL model settings.

The above highlighted research gaps serve as the foundation for this thesis, which aims to address the limitations of existing works and improve remote healthcare systems. The subsequent chapters delve into the approaches used to address these limitations and enhance remote healthcare systems.