

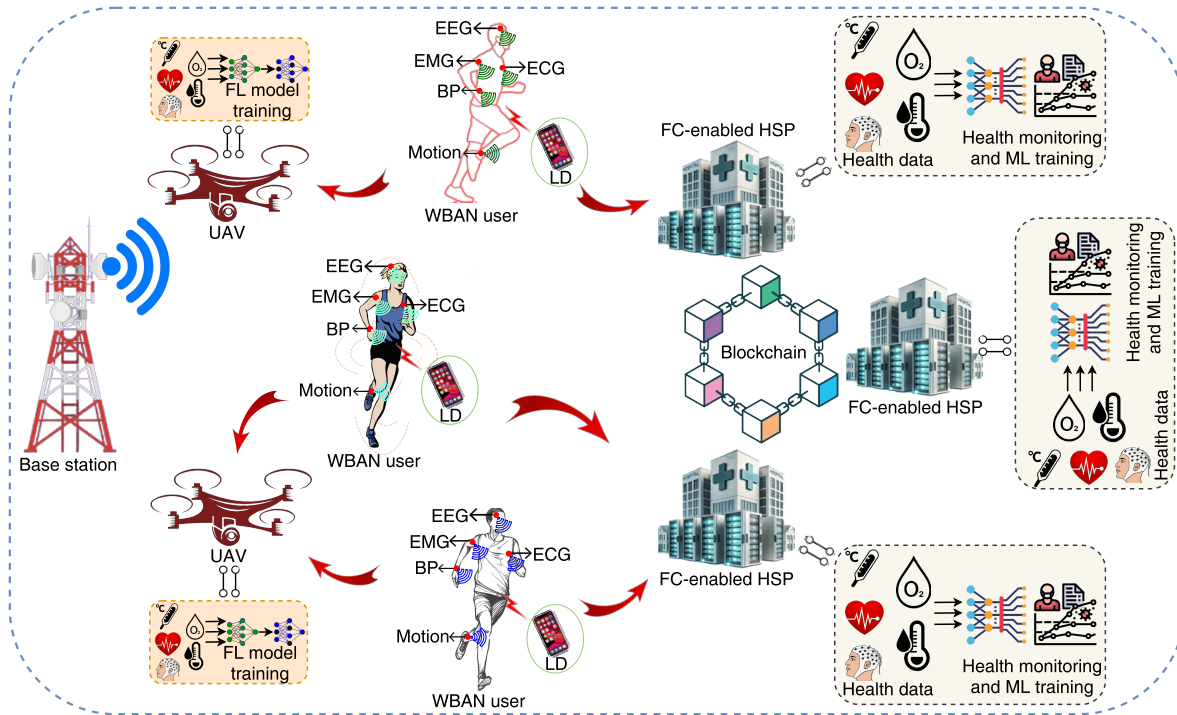
# Chapter 1

## Introduction

**A**ccording to the World Health Organization (WHO), the global population of individuals aged 60 or older is expected to reach 1.4 billion by 2030 [1]. As this population increases, individuals are becoming increasingly vulnerable to chronic illnesses, such as cardiovascular diseases, diabetes, and mental health disorders. The growing population of vulnerable individuals is placing immense pressure on healthcare systems, which are already facing resource shortages and declining quality of care [2]. Consequently, there is an urgent need for innovative technological solutions that can address these challenges while ensuring high standards of patient care. One promising solution is the employment of Wireless Body Area Networks (WBANs)<sup>1</sup>, which comprise multiple on-body physiological sensors and a Local Device (LD) (such as a smartphone, tablet, or laptop) to transmit the gathered sensor data to a server for analysis, enabling continuous remote health monitoring [3], as illustrated in Fig. 1.1. WBAN-based systems enable real-time tracking of vital health parameters, such as heart rate, body temperature, and activity, facilitating timely interventions and helping healthcare providers manage the growing burden of chronic diseases in aging populations. Additionally, these systems offer effective solutions in emergency situations where patients

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<sup>1</sup>The terms “WBAN,” “WBAN user,” and “patient” are used interchangeably throughout this thesis to refer to individuals utilizing WBANs.



**Fig. 1.1.** Remote healthcare system.

may not receive immediate medical attention until reaching a healthcare facility, as WBANs can monitor and transmit real-time health parameters during transit.

Due to its critical nature, real-time monitoring is important, especially for time-sensitive healthcare applications such as post-surgery monitoring, real-time athlete fitness tracking, and remote surgery, where any delays can have severe or even fatal consequences [4]. Additionally, patients with chronic conditions, such as lung and heart diseases, require continuous monitoring, and their data must be prioritized over other conditions. However, processing such critical health data often exceeds the capabilities of resource-constrained LDs, which typically have limited computational power and energy resources, while still meeting the desired delay constraints [4, 5]. A promising solution is Fog Computing (FC), which brings computing services and storage closer to patients, supports computation-intensive healthcare applications, and enhances Quality of Service (QoS), thereby enabling real-time remote health monitoring [6, 7]. Although fog computing effectively reduces latency, energy consumption in WBANs remains a sig-

nificant issue. In remote healthcare applications, maintaining continuous connectivity to Fog Servers (FSs) is crucial for real-time, reliable services; however, it substantially increases the energy consumption of LDs [4]. Furthermore, the diverse functions supported by LDs contribute to higher energy usage, which ultimately limits the lifespan of the health monitoring system [8,9]. To mitigate this, offloading data processing to FSs can significantly reduce the energy burden on LDs. However, as the number of WBAN users seeking healthcare services grows, the computational load on FSs rises, raising concerns about timely service delivery [5]. Additionally, to encourage Health Service Providers (HSPs) or Medical Centers (MCs)<sup>2</sup> to offer remote healthcare services and ensure their continued participation, it is vital that HSPs are adequately compensated.

With the growing utilization of WBANs for collecting patient health data, researchers have harnessed this substantial dataset to develop robust Machine Learning (ML) models for various healthcare applications [2]. Moreover, the growth of 5G network has led to the use of Unmanned Aerial Vehicles (UAVs) to address the complex WBAN infrastructure, leveraging their agility, flexibility, and mobility [10]. UAVs play a crucial role in supporting resource-constrained WBANs, especially in outdoor events and remote areas, by collecting physiological data from WBANs and performing model training for applications, such as Human Activity Recognition (HAR) [11] and disease detection [12,13]. Nevertheless, conventional ML approaches necessitate the transmission of patients' health data to a central server, consequently raises privacy vulnerabilities. To enhance the inference model, independent UAV companies can collaborate by sharing collected physiological data from WBANs for model training [10]. However, sharing data from multiple sources to a central server faces challenges due to limited network resources, resulting in data islands. To this end, we propose the adoption of a Federated Learning (FL) [14] approach to enable privacy-preserving collaborative ML across independently owned UAVs. However, this framework faces several challenges

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<sup>2</sup>The terms "Health Service Providers (HSPs)" and "Medical Centers (MCs)" are used interchangeably throughout this thesis.

due to limited 5G radio resources, i.e., Physical Resource Blocks (PRBs)<sup>3</sup>, which affects the QoS in Healthcare Domain (HD) [16, 17]. Moreover, there is a need to prioritize Resource Allocation (RA) strategies based on the criticality of the data. For instance, patients with heart disease require continuous monitoring, where heart rate, blood pressure, and blood sugar level detection take priority over body temperature data. Hence, it is crucial to allocate minimal resources for transmitting critical data while allocating maximum resources to WBANs for transmitting complete data if the required resources are available. However, the growing number of WBANs with varying PRB demands for transmitting physiological data to UAVs may result in interference, presenting a unique challenge in 5G for real-time smart healthcare applications.

Although UAVs help overcome the limitations of WBANs by offloading tasks such as FL model training, they also introduce privacy risks, making them vulnerable to unauthorized access or transmission breaches. A promising solution to mitigate privacy risks is local model training on LDs. However, due to WBANs' limited energy capacity, both computation and transmission energy must be carefully considered in the FL process. To reduce energy consumption associated with the computation and transmission of local models, researchers have proposed adopting Quantized Neural Networks (QNNs) operating at reduced precision levels. Although WBANs transmit only model weights to the aggregation server, the prospect of privacy breaches remains, as adversaries might exploit these weights to infer original data [18]. To mitigate privacy concerns in the FL framework, strategies like Differential Privacy (DP) [19] and Homomorphic Encryption (HE) [18] have been employed. Furthermore, the conventional FL framework relies on a single server, which presents a single point of failure. To address this limitation, blockchain technology has been integrated with FL to create a secure decentralized platform for model aggregation [20].

Due to privacy concerns and the costs associated with using their own computational

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<sup>3</sup>PRB is the smallest unit of radio resource in cellular 5G networks, comprises a 0.5 *ms* time slot and a 180 kHz frequency band [15].

and communication resources for FL training, users are often hesitant to participate [21]. As a result, a comprehensive incentive mechanisms is crucial to encourage data sharing and ensure efficient FL training. Additionally, most research focuses on single FL models, addressing aspects such as incentive mechanisms and user selection, but single FL models involve only a subset of WBAN users, leaving others idle and reducing overall efficiency [22]. However, multiple FL models, can enhance efficiency by training several models simultaneously with diverse health data from WBAN users [22]. As demand for ML-powered healthcare applications grows, training multiple FL models is becoming more practical. For instance, models for HAR, fall detection, and gait analysis - used to monitor Parkinson's patients - can be trained simultaneously in the FL paradigm, addressing privacy concerns [23, 24]. Moreover, FL models have varying learning requirements, such as model structure, deadlines, and economic value [25], while WBAN users vary in computing power, communication capabilities, privacy concerns, and data quality, resulting in different learning costs. Furthermore, unreliable WBAN users may submit low-quality models, which can negatively affect the global FL model [26]. Therefore, selecting reliable and suitable WBAN users based on their attributes and the specific requirements of each FL model is also crucial for maximizing economic value (discussed in Section 7.2, Chapter 7). However, research on incentive mechanisms for multiple FL models [21, 25, 27, 28] often fails to consider important factors like privacy needs, user reputations, and the criticality of health data, which significantly affects WBAN users' willingness to share their data [29].

The design and the development of remote healthcare systems face several challenges and issues that need to be addressed, as discussed in the following section.

## 1.1 Key Challenges in Remote Healthcare Systems

Despite the potential of WBAN-based remote healthcare systems for continuous patient monitoring, several key challenges persist that limit their effectiveness. The following

are some of the key challenges that this thesis aims to address:

1. A major challenge in remote healthcare systems is managing real-time monitoring, particularly for serious conditions like heart disease, where even minor delays in data transmission or processing can have serious consequences. Additionally, WBANs often lack the computational power necessary for time-sensitive healthcare applications, leading to latency issues. As the number of WBANs increases, FSs face growing computational demands, further increasing delays and hindering the efficiency of data processing. These delays in processing critical health data can result in slower medical responses, putting patients' lives at risk. Therefore, allocating appropriate FC resources is crucial for ensuring timely healthcare delivery, facilitating the rapid detection and response to urgent medical needs.
2. Continuous connectivity required for WBANs to communicate with FSs significantly increases the energy usage of LDs. This presents a significant challenge in remote healthcare, as it can reduce system up-time, leading to delays in medical responses, especially in critical cases where timely interventions rely on real-time data, posing serious health risks. Moreover, the varying needs of patients and their diverse QoS requirements highlight the importance of dynamic pricing schemes to improve healthcare delivery. Therefore, ensuring the profitability of HSPs while minimizing latency and energy costs for patients is crucial for the long-term sustainability and accessibility of the healthcare system.
3. In remote healthcare systems, managing network resources effectively is crucial due to the limited availability in 5G networks, which can affect the QoS for critical health data transmission used in the FL process. As the number of WBANs transmitting data for FL model training increases—particularly when UAVs are used for data collection—interference becomes a major challenge, requiring effective management to ensure timely and accurate data transmission.
4. As sensitive health data is transmitted to a central server for processing, privacy

concerns become critical, especially since traditional ML models rely on centralized data for training. Although FL allows local model training without the need to transmit health data to a central server, it still poses privacy risks through model parameter inference. Furthermore, resource-constrained WBAN devices face challenges with energy- and computation-intensive ML training, which may result in interrupted learning cycles and incomplete or delayed model updates, thereby reducing FL performance. To tackle these challenges, it is essential to adopt ML techniques that allow LDs to train models efficiently while minimizing energy consumption during local computations and transmissions in FL. Additionally, traditional FL frameworks pose a single point of failure, a vulnerability that blockchain-based approaches aim to mitigate. However, the high energy demands of blockchain mining and the lack of incentives for WBAN users complicate the deployment of these systems, highlighting the need for an approach that encourages participation while maximizing efficiency.

5. A critical challenge in FL systems using WBANs is user reluctance to participate in model training, driven by privacy concerns and the computational and communication costs of local training, which poses significant barriers to widespread adoption of FL in healthcare. Additionally, WBAN users are highly heterogeneous in terms of their computational capabilities, communication resources, and data quality, which complicates user selection for FL. Moreover, unreliable users may provide low-quality model updates, negatively affecting the overall performance of the global model. Existing research mainly focuses on single FL models, neglecting the advantages of simultaneously training multiple models with diverse user data—a strategy that is becoming crucial due to the rising demand for ML-powered smart healthcare applications. To address these challenges and encourage participation, it is crucial to design efficient incentive mechanisms that consider privacy concerns, user reputation, and other key attributes.

Motivated by the key challenges mentioned above, this thesis aims to address critical issues in the design and development of remote healthcare systems. It specifically focuses on enhancing real-time data processing, energy efficiency, privacy, user incentives, and communication resource management. Driven by these challenges, the research objectives of this thesis are presented in the following section.

## 1.2 Research Objectives

The primary objective of this thesis is to enhance WBAN-based remote healthcare systems by optimizing latency, energy efficiency, and privacy preservation, while also considering rewards for various participants and prioritizing the health data of critical patients. By leveraging intelligent optimization techniques and computational methods, this thesis addresses the critical challenges faced by WBAN-based remote healthcare applications. Specifically, it investigates the following five key problems aimed at improving the efficiency and effectiveness of WBAN-based remote healthcare systems:

1. Design an intra-WBAN and beyond-WBAN fog-computing system for remote health monitoring, focused on optimizing MC's profit and patients' latency costs, while introducing a flat-pricing scheme to effectively measure the MC's profit. To achieve this, an optimization problem is formulated that maximizes system utility, defined as a linear combination of the MC's profit and the patients' latency costs. Additionally, a flat-pricing scheme is introduced to measure the MC's profit, and a swapping-based heuristic is proposed to maximize system utility.
2. Design a fog computing-enabled WBAN-based system for real-time remote health monitoring, aimed at improving latency and energy efficiency, while considering HSP's profit by introducing a dynamic pricing scheme and prioritizing critical health data. To achieve the above research objective, an optimization problem is formulated that maximizes system utility by considering HSP's profit, patients' latency, and energy costs, with an emphasis on prioritizing critical health

data. Additionally, a dynamic pricing scheme is introduced, and a matching- and exchange-based sub-optimal algorithm is proposed.

3. Develop a UAV-assisted WBAN-based FL framework for smart healthcare applications, focused on maximizing revenue for both WBANs and UAVs through RA, while minimizing interference among WBANs. To accomplish the objective of developing a UAV-assisted WBAN-based FL framework for smart healthcare applications, we first formulate an optimization problem that aims to maximize revenue for both WBANs and UAVs through efficient RA, while minimizing interference among the WBANs. Furthermore, we propose an efficient sub-optimal solution that employs stable matching [30, 31] and graph coloring techniques to address the revenue maximization problem.
4. Develop a decentralized blockchain-based FL framework that enhances energy efficiency and privacy in collaborative training across multiple WBANs, while optimizing both WBANs' and miners' rewards. To achieve this objective, we formulate an optimization problem that maximizes utility by considering energy consumption, WBAN rewards, miner revenue, and FL loss. Furthermore, we propose a stable WBAN-Miner association algorithm that maximizes utility and integrate QNN to reduce energy consumption, while strengthening privacy using DP and Paillier HE techniques.
5. Design an incentive mechanism for selecting reliable WBAN users with high-quality health data for differentially private federated learning models in smart healthcare applications, considering factors such as costs, local model accuracy, user reputation, and the amount of health data. To accomplish this, we propose an auction-based incentive mechanism that selects WBAN users with high-quality health data for multiple FL models, considering key factors such as local model accuracy, user reputation, and data volume.

## 1.3 Contributions

This section provides a summary of the key contributions and organisation of the thesis (Fig. 1.2). The primary contributions of this thesis focus on the design, development, implementation, and comparative analysis of novel approaches to address critical challenges in remote healthcare systems. The thesis is organised into multiple chapters that build upon each other. Chapter 2 offers a detailed literature review of existing works, while Chapter 8 concludes the thesis by summarising the findings and discussing future research directions. Chapters 3 to 7 present the major contributions of the thesis. The contributions and organisation of the thesis are outlined as follows:

Chapter 2 reviews existing works, highlighting their advantages and shortcomings in remote healthcare systems. The literature review is categorized into two key problems: designing a computing system for remote healthcare and developing a learning system for remote healthcare. Each of these problems is further divided into two and three sub-problems, respectively. To address these challenges, we propose solutions that address each of these sub-problems in the subsequent five chapters.

Chapter 3 proposes an intra-WBAN and beyond-WBAN-based fog-computing system for remote health monitoring. An optimization problem is formulated to maximize system utility, defined as a linear combination of the MC's profit and patients' latency costs, which is NP-hard, and a flat-type pricing scheme is offered to measure the MC's profit. Additionally, a swapping-based heuristic is presented to maximize system utility under latency constraints for the computation of patients' health data with polynomial time complexity. Our extensive simulations and real-world data analysis demonstrate that the proposed heuristic achieves an average utility of 94.5% of the optimal solution, highlighting its effectiveness and efficiency in practical applications.

Chapter 4 proposes a fog computing-enabled WBAN-based system for real-time remote health monitoring, aimed at improving latency and energy efficiency. An optimization problem is formulated to maximize system utility by considering the HSP's

profit, patients' latency, and energy costs, with a focus on prioritizing critical health data. To solve this, we introduce a dynamic pricing scheme and propose a matching and exchange-based sub-optimal algorithm that operates in polynomial time complexity. The effectiveness of the proposed algorithm is demonstrated through experiments and simulations with real-world data, achieving 99.01% of the optimal utility.

Chapter 5 introduces a UAV-assisted WBAN-based FL framework designed for smart healthcare applications, where UAVs collect physiological data from WBANs and collaborate with an MBS for model training. An optimization problem is formulated to maximize the revenue for both WBANs and UAVs through RA, while minimizing interference among WBANs. To solve this, we propose an efficient sub-optimal solution using *stable matching* [30,31] and *graph coloring* techniques to tackle the revenue maximization challenge, considering the resource demands of WBANs. Additionally, interference among WBANs is modeled by transforming the WBAN topology into an interference graph  $G(\mathbb{V}, \mathbb{E})$  (discussed in Chapter 5), where  $\mathbb{V}$  represents the set of nodes indicating WBANs, and  $\mathbb{E}$  represents the set of edges indicating interference, thereby enabling effective interference management. Our simulation and prototype results using real-world data demonstrate the efficacy of our proposed model, achieving 92.8% of the optimal value.

Chapter 6 presents a blockchain-based FL framework to enhance energy efficiency and privacy in collaborative training across multiple WBANs. We formulate an optimization problem that maximizes utility for WBANs and miners, considering energy consumption, WBAN rewards, miner revenue, and FL loss, as an NP-hard. Additionally, we propose a stable WBAN-Miner association algorithm to maximize utility in polynomial time. Our approach integrates QNN to reduce energy consumption and strengthens privacy through DP and Paillier HE. Furthermore, blockchain is integrated with the Proof of Work (PoW) consensus mechanism to enable decentralized, tamper-resistant model weight sharing. Our approach demonstrates significant improvements of

15.1%, 9.03%, and 15.35% over state-of-the-art methods, with efficient communication costs, using real-world data.

Chapter 7 presents a novel incentive mechanism designed to select reliable WBAN users with high-quality health data for differentially private multiple FL models in smart healthcare applications. The incentive mechanism is formulated as an NP-hard optimization problem by incorporating a cost model that considers data collection, computation, communication, and privacy. Additionally, an Auction-Driven Incentive Mechanism (ADFL) is proposed, which selects WBAN users across multiple FL models by integrating critical factors such as local model accuracy, user reputation, and data volume. The proposed mechanism outperforms state-of-the-art approaches, achieving an average utility improvement of 15.9% and 18.08%, as demonstrated through extensive simulations and real-world data analysis.

Finally, Chapter 8 concludes the thesis by summarising the findings and discussing future research directions that can build upon this thesis.

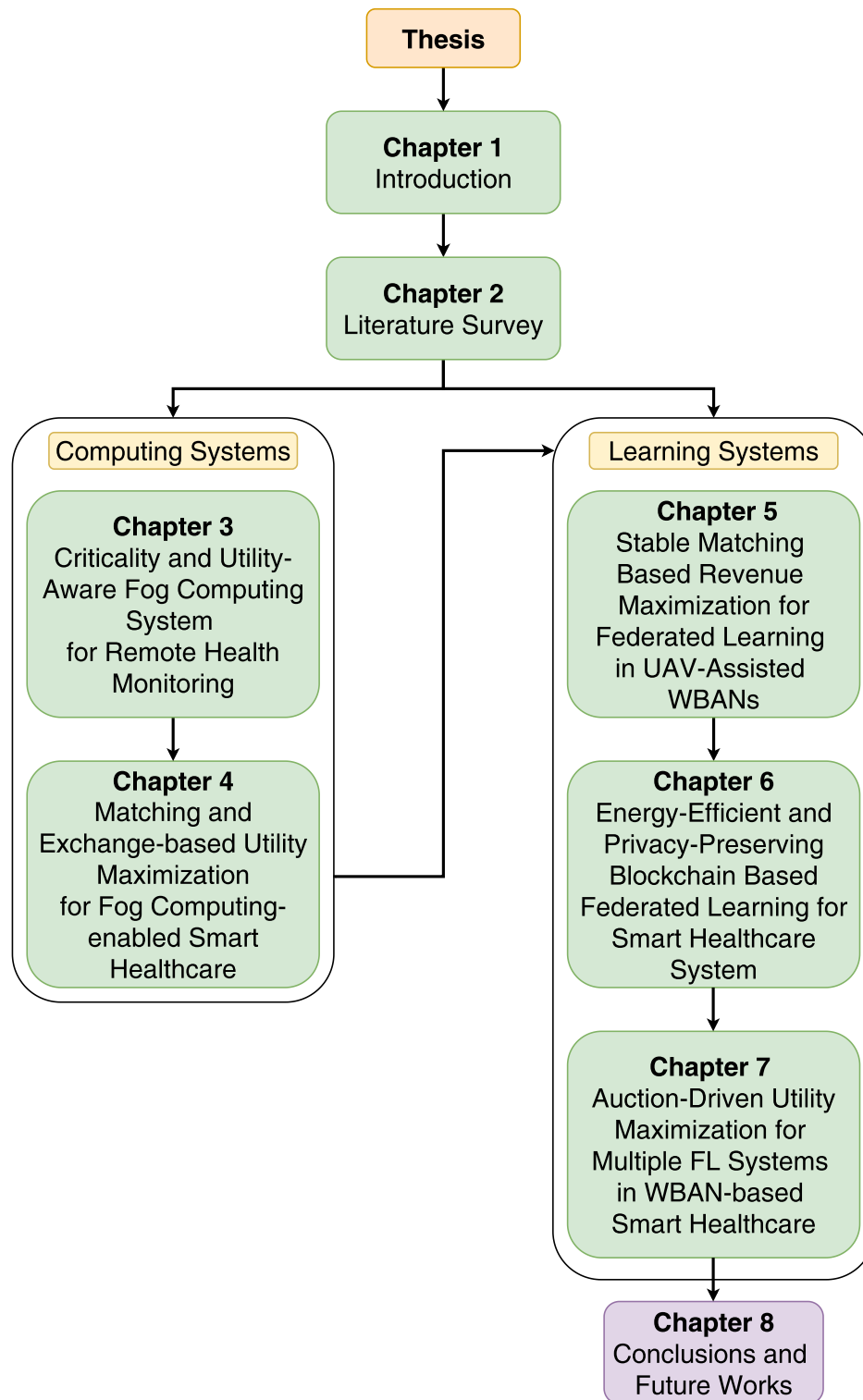


Fig. 1.2. Thesis organization.