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CONTINUOUS IOT-BASED MATERNAL MONITORING: SYSTEM DESIGN, EVALUATION, OPPORTUNITIES, AND CHALLENGES

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ABSTRACT

Maternal care encompasses health care services for pregnant women during pregnancy, childbirth, and the postpartum period. Maternity care providers aim to ensure a healthy pregnancy, safe delivery, and smooth transition to motherhood. Traditional maternal care is offered through regular check-ups by health care professionals.
In recent years, the emergence of Internet-of-Things (IoT)-based systems has transformed the way health care services are provided. These systems offer low-cost ubiquitous monitoring in everyday life settings and can be used for maternal monitoring. However, IoT-based maternal monitoring systems lack a comprehensive approach in maternal care because they are limited by sensing capabilities, specific health problems, and short periods of monitoring. Moreover, the use of IoT-based systems for maternal health monitoring requires addressing critical quality attributes, such as feasibility, energy efficiency, and reliability and validity of the collected physiological parameters. Quality assessment methods also must be integrated with such systems to discard the noisy part of collected parameters and improve the data quality. Furthermore, long-term, continuous IoT-based maternal monitoring by collecting data that was not traditionally available provides new opportunities, including analyzing the trend of physiological parameters during pregnancy and postpartum, as well as detecting maternal health issues.
This thesis presents an IoT-based maternal monitoring system and explores its potential in maternal care. We evaluate the system's feasibility, reliability, and energy efficiency. We also discuss the practical challenges of implementing the system.
Then, we validate the heart rate (HR) and heart rate variability (HRV) parameters that the system collects while the user is asleep and awake. In addition, we propose a deep-learning-based method for quality assessment of HR and HRV parameters to discard unreliable data and improve health decisions. We use the system to collect data from 62 pregnant women during pregnancy and three-months postpartum. Then, the reliable HR and HRV parameters are used to track the trends during pregnancy and postpartum.
Finally, we investigate maternal loneliness as a major mental health problem. We develop two predictive models to detect maternal loneliness during late pregnancy and the postpartum period. The models use the objective health parameters passively collected by the system and achieve high performance (weighted F1 scores > 0.87).

KEYWORDS: maternal health, heart rate variability, remote health monitoring, loneliness, photoplethysmography, quality assessment, Internet of things

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TIIVISTELMÄ

Äitiysterveydenhuollon tavoitteena on varmistaa terve raskaus, turvallinen synnytys ja sujuva siirtyminen äitiyteen. Perinteistä äitiysneuvontaa tarjotaan säännöllisten tarkastuskäyntien avulla terveydenhuollon ammattilaisten toimesta.
Viime vuosina Internet of Things (IoT) -pohjaisten järjestelmien kehittyminen on mahdollistanut terveydenhuoltopalvelujen tarjoamisen entistä monipuolisemmin. Nämä järjestelmät mahdollistavat edullisen ja laaja-alaisen terveydenseurannan ajasta ja paikasta riippumatta. Kuitenkin tällä hetkellä IoT-pohjaiset järjestelmät ovat hyvin vähäisessä määrin käytössä äitiysterveydenhuollossa.
Tämä väitöskirja esittelee IoT-pohjaisen äitiyshuollon seurantajärjestelmän ja tutkii sen tuomia mahdollisuuksia ennenkaikkea äitiysterveyshuollossa. Järjestelmän toteutettavuutta, luotettavuutta ja energiatehokkuutta analysoidaan sekä käsitellään myös järjestelmän käyttöönoton käytännön haasteita. Järjestelmä kerää käyttäjän sydämen sykkeen (HR) ja sydämen sykkeen vaihtelun (HRV), jotka järjestelmä kerää käyttäjän ollessa unessa ja hereillä. Lisäksi esitellään syväoppimiseen perustuvaa menetelmää kerätyn sydämen sykkeen ja sydämen sykkeen vaihtelun laadun arviointiin epäluotettavan ja mahdollisesti virheellisen datan poistamiseksi ja sitä kautta järjestelmän luotettavuuden ja käytettävyyden parantamiseksi. Tässä tutkimuksessa hyödynnettiin dataa joka on kerätty tutkimuksen aikana 62 raskaana olevalta naiselta raskauden aikana sekä kolme kuukautta synnytyksen jälkeen.
Tässä väitöskirjassa tutkitaan myös äitiyden yksinäisyyttä merkittävänä mielenterveysongelmana. Työssä kehitettiin kaksi ennustemallia äitiyden yksinäisyyden havaitsemiseksi myöhäisraskauden ja synnytyksen jälkeisen ajanjakson aikana. Mallit käyttävät järjestelmän passiivisesti keräämiä objektiivisia terveysparametreja ja saavuttavat korkean suorituskyvyn (painotetut F1-pisteet $>$ 0,87).

AVAINSANAT: äitiysterveydenhuolto, sykevälivaihtelu, etäterveyden seuranta, yksinäisyys, laadunarviointi, esineiden internet

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Date December 11, 2023
Fatemeh Sarhaddi

Table of Contents

Abbreviations

AI	Artificial intelligence
ANS	Autonomic nervous system
API	Application Programming Interface
AUC	Area Under the Curve
AVNN	Average of normal to normal interbeat intervals
BMI	Body mass index
CI	Confidence Interval
CNN	Convolutional Neural Networks
ECG	Electrocardiography
GAF	Gramian Angular Field
GCG	Gyrocardiogram
HF	Absolute power in high frequency band
HR	Heart rate
HRV	Heart rate variability
HLM	Hierarchical linear model
IBI	Interbeat interval
IMU	Inertial measurement unit
IoT	Internet of Things
KNN	K-nearest neighbors
LF	Absolute power in low frequency band
LF/HF	Absolute power in low frequency band to absolute power in high frequency band ratio
LSTM	Long Short Term Memory
NNI	Normal interbeat interval
PCG	Phonocardiogram
PNN50	Percentage of successive NN intervals that differ by more than 50 ms
PPG	Photoplethysmography
PRV	Pulse rate variability
RFE	Recursive feature elimination
RMSSD	Root mean square of successive NN interval differences
SCG	Seismocardiogram
SD	Standard deviation
SDNN	Standard deviation of NN intervals

SSL	Secure sockets layer
SVM	Support vector machine
TST	Total sleep time
UCLA	University of California, Los Angeles
WASO	Wake after sleep onset

List of Original Publications

This dissertation is based on the following original publications, which are referred to in the text by their Roman numerals:

I Fatemeh Sarhaddi, Iman Azimi, Sina Labbaf, Hannakaisa Niela-Vilén, Nikil Dutt, Anna Axelin, Pasi Liljeberg, and Amir M. Rahmani. ”Long-term IoT-based Maternal monitoring: system design and evaluation.” Sensors 21, no. 7 (2021): 2281.

II Fatemeh Sarhaddi*, Kianoosh Kazemi*, Iman Azimi, Rui Cao, Hannakaisa Niela-Vilén, Anna Axelin, Pasi Liljeberg, and Amir M. Rahmani. ”A comprehensive accuracy assessment of Samsung smartwatch heart rate and heart rate variability.” PloS one 17, no. 12 (2022): e0268361.

III Emad Kasaeyan Naeini, Fatemeh Sarhaddi, Iman Azimi, Pasi Liljeberg, Nikil Dutt, and Amir M. Rahmani. ”A Deep Learning-based PPG Quality Assessment Approach for Heart Rate and Heart Rate Variability”. ACM Transactions on Computing for Healthcare 4, no. 4 (2023): 1-22.

IV Fatemeh Sarhaddi, Iman Azimi, Anna Axelin, Hannakaisa Niela-Vilen, Pasi Liljeberg, and Amir M. Rahmani. ”Trends in Heart Rate and Heart Rate Variability During Pregnancy and the 3-Month Postpartum Period: Continuous Monitoring in a Free-living Context.” JMIR mHealth and uHealth 10, no. 6 (2022): e33458.

V Fatemeh Sarhaddi, Iman Azimi, Anna Axelin, Hannakaisa Niela-Vilen, Pasi Liljeberg, and Amir M. Rahmani. ”Maternal Social Loneliness Detection Using Passive Sensing Through Continuous Monitoring in Everyday Settings: Longitudinal Study”. JMIR Formative Research 7, no. 1 (2023): e47950.

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*Equal contribution

The following peer-reviewed publications were published during doctoral studies. These publications are not included in this thesis but are closely related.

VI Hannakaisa Niela-Vilén, Jennifer Auxier, Eeva Ekholm, Fatemeh Sarhaddi, Milad Asgari Mehrabadi, Aysan Mahmoudzadeh, Iman Azimi, Pasi Liljeberg, Amir M. Rahmani, and Anna Axelin. ”Pregnant women's daily patterns of well-being before and during the COVID-19 pandemic in Finland: Longitudinal monitoring through smartwatch technology.” PloS one 16, no. 2 (2021): e0246494.

VII Milad Asgari Mehrabadi, Iman Azimi, Fatemeh Sarhaddi, Anna Axelin, Hannakaisa Niela-Vilén, Saana Myllyntausta, Sari Stenholm, Nikil Dutt, Pasi Liljeberg, and Amir M. Rahmani. ”Sleep tracking of a commercially available smart ring and smartwatch against medical-grade actigraphy in everyday settings: instrument validation study.” JMIR mHealth and uHealth 8, no. 11 (2020): e20465.

VIII Rui Cao, Iman Azimi, Fatemeh Sarhaddi, Hannakaisa Niela-Vilen, Anna Axelin, Pasi Liljeberg, and Amir M. Rahmani. ”Accuracy Assessment of Oura Ring Nocturnal Heart Rate and Heart Rate Variability in Comparison With Electrocardiography in Time and Frequency Domains: Comprehensive Analysis.” Journal of Medical Internet Research 24, no. 1 (2022): e27487.

IX Hannakaisa Niela-Vilen, Iman Azimi, Kristin Suorsa, Fatemeh Sarhaddi, Sari Stenholm, Pasi Liljeberg, Amir M. Rahmani, and Anna Axelin. ”Comparison of Oura Smart Ring Against ActiGraph Accelerometer for Measurement of Physical Activity and Sedentary Time in a Free-Living Context.” CIN: Computers, Informatics, Nursing (2022).

X Jennifer Auxier, Kaisu T. Savolainen, Miriam Bender, Amir M. Rahmani, Fatemeh Sarhaddi, Iman Azimi, and Anna M. Axelin. ”Exploring access as a process of adaptation in a self-monitoring perinatal ehealth system: Mixed methods study from a sociomaterial perspective.” JMIR Formative Research 7 (2023): e44385.

XI Hannakaisa Niela-Vilen, Eeva Ekholm, Fatemeh Sarhaddi, Iman Azimi, Amir M. Rahmani, Pasi Liljeberg, Miko Pasanen, and Anna Axelin. ”Comparing prenatal and postpartum stress among women with previous adverse pregnancy outcomes and normal obstetric histories: A longitudinal cohort study.” Sexual & Reproductive Healthcare 35 (2023): 100820.

1 Introduction

Maternity care refers to the health care services provided to women during pregnancy, childbirth, and the postpartum period. This care plays a crucial role in ensuring the health and well-being of both the mother and her fetus. Maternity care providers aim to provide comprehensive and compassionate care to women during this special time to ensure that pregnant women have a healthy pregnancy, a safe delivery, and a smooth transition into motherhood. In addition, health complications during pregnancy, such as hypertension or gestational diabetes, may increase the mother's risk of corresponding health issues in the future [1; 2]. Therefore, maternity care is essential to ensure the best possible pregnancy outcome as well as to promote health at the population level. Conventionally, maternal care is offered through regular monitoring and check-ups by health care professionals.

In recent years, digital health and systems based on the Internet of things (IoT) have transformed the way health care services are provided. IoT-based health monitoring services enable cost-effective, continuous health monitoring everywhere [3]. The monitoring systems can collect real-time data from a user and her or his environment, transmit the data to remote servers, analyze the data, and provide feedback. The effectiveness of IoT-based maternal monitoring systems in improving health outcomes for pregnant women and their fetuses has been shown in several studies [4; 5]. IoT-based maternal-monitoring systems can also provide opportunities for a deeper understanding of physiological changes during pregnancy by continuously collecting data from pregnant women that are not traditionally available. At the same time, such systems enable personalized monitoring and intervention based on the history of collected data by using machine learning and artificial intelligence (AI) techniques.

The current works on IoT-based maternal monitoring are constrained by their narrow focus on specific health problems, limited sensing capabilities, and short-term monitoring during pregnancy [6; 7; 8; 9; 10]. Furthermore, the implementation challenges of long-term IoT-based systems for maternal monitoring have not been explored in research. Moreover, using IoT-based systems for maternal health monitoring necessitates addressing some essential quality attributes, including feasibility and usability, energy efficiency, and reliability and validity of the collected physiological parameters. These attributes are crucial for enhancing the user experience and engagement of users with the system as well as for ensuring the accuracy of the results in health care services [11; 12; 13; 14; 15; 16; 17]. In addition, the effectiveness of using such systems to gain a deeper understanding of normal trends in physiological parameters and to predict or prevent health issues during pregnancy and postpartum should be investigated. However, IoT-based maternal monitoring systems lack continuous data collection during the pregnancy and postpartum periods that can be used to analyze trends and detect health issues.

1.1 IoT-Based Maternal Monitoring Opportunities and Challenges

IoT-based maternal monitoring systems offer many opportunities and present several challenges and requirements. One opportunity these systems offer is investigating physiological trends during pregnancy and postpartum. A pregnant woman's body undergoes physiological changes to prepare for a fetus's development and delivery [18; 19]. These changes affect the mother's health parameters. For example, several studies have shown a decrease in the level of physical activity and an increase in heart rate (HR) as pregnancy proceeds [9; 20; 21]. Sleep quality also decreases from the second to the third trimester [22]. Although some physiological changes are normal during pregnancy, they can also be a sign of disease or disorder. Therefore, it is important to distinguish normal physiological changes during pregnancy from abnormal changes that could be signs of disease or health issues [18]. The early detection of disease or health complications during pregnancy provides the opportunity to perform the proper intervention and help to improve the health and well-being of the pregnant woman and her child. Although several studies have investigated the trends of maternal physiological parameters, they are limited to short-term and episodic data collection [21; 23; 24; 25]. An IoT-based maternal monitoring system that acquires health data continuously during pregnancy and postpartum can offer adequate trends of maternal physiological parameters.

Another opportunity of IoT-based maternal monitoring is detecting mental health issues that usually remain undetected during pregnancy and that affect the mother and baby's future health. Pregnancy increases the risk of mental health issues such as anxiety and depression [26]. In the United Kingdom, mental health issues during pregnancy are one of the major causes of maternal death [27]. However, these issues usually remain undetected because the symptoms are assumed to be due to pregnancy-related changes [28]. Detecting these issues and providing appropriate intervention will reduce the risk of further complications during the perinatal period. The rich continuous data collected by a long-term IoT-based maternal monitoring system can be used to develop predictive models for major health issues such as maternal loneliness.

Although IoT-based systems offer many opportunities for maternal health care, several requirements and challenges must be addressed to use these systems. IoT-based maternal monitoring systems should be feasible for mothers to use despite the physiological changes during pregnancy and postpartum. The system requires reliability and energy efficiency. Moreover, because the system aims to be used for a long time, it should provide other quality attributes (e.g., a good user experience) and motivate users for long-tern use. Considering the lack of long-term, IoT-based maternal monitoring in the literature, it is necessary to design, develop, deploy, and evaluate such a system and explore the challenges.

IoT-based monitoring systems use wearable devices to collect data continuously in everyday life settings. Using wearable devices as a part of an IoT-based system enables collecting and analyzing comprehensive health data and providing personalized health care over an extended duration [11]. Therefore, wearable devices offer a wide range of health care services that are not available in traditional health care [29]. For example, wearable devices can detect health risk indicators such as falls or worsening disease conditions for older people who live alone [30; 29]. However, the devices are prone to noise, especially when used in everyday life activities, which can result in low-quality data and subsequently invalid health parameters [31]. Therefore, wearable devices should be validated before use in health care applications.

In addition, the accuracy of physiological trends and mental health detection offered by IoT-based maternal monitoring systems highly depends on the accuracy of the collected data. Low-quality data may result in false predictions or alarms. Therefore, it is necessary to use quality assessment methods to discard unreliable data and only use reliable data in the analysis.

1.2 Aims and Objectives

The thesis investigates IoT-based maternal monitoring to improve the maternal care provided during pregnancy and postpartum. For this purpose, the first aim of the thesis is to design and develop a continuous IoT-based maternal monitoring system offering low-cost continuous monitoring during the perinatal period. Such a system could improve current maternal health care by providing essential monitoring services that traditionally could not be provided by maternity care. Then, health parameters, including HR and heart rate variability (HRV), collected by the system will be validated to ensure accurate monitoring and decisions. The aim is also to assess the quality of collected HR and HRV parameters to improve the quality of decisions and feedback the system offers. In the next step, the presented system will be used to collect data from pregnant women continuously during pregnancy and postpartum. The data are expected to be used to understand the trends in HR and HRV parameters during pregnancy and postpartum. This understanding enables us to discriminate between normal and abnormal changes, which can be a sign of health complications. Finally, the presented system will be further developed to include predictive models to detect maternal loneliness based on the data the system collects.

To summarize, the main research objectives of the thesis are as follow.

- **Research Objective I:** Present, develop, and evaluate a continuous IoT-based maternal health-monitoring system

- **Research Objective II:** Validate and assess the quality of HR and HRV parameters collected by the developed IoT-based monitoring system

- **Research Objective III:** Deploy the IoT-based system for collecting data from pregnant women during pregnancy and 3 months postpartum

- **Research Objective IV:** Investigate the trends of HR and HRV parameters during pregnancy and the postpartum period

- **Research Objective V:** Develop predictive models to detect maternal loneliness during pregnancy and the postpartum period based on data collected passively by the monitoring system

1.3 Contributions

In summary, the contributions of this thesis are as follow:

- **Develop, implement, and evaluate a continuous maternal monitoring system and analyze the implementation challenges:** The dissertation presents a long-term maternal monitoring system to monitor mothers' objective and subjective health parameters continuously during pregnancy and postpartum. The system provides several monitoring services (e.g., sleep, stress, and physical activity monitoring), resulting in a holistic view of the mothers' health conditions. The system is evaluated considering user engagement, reliability of collected data, and energy efficiency. Then, the challenges and practical issues in implementing such systems are investigated.

- **Investigating the validity of HR and HRV parameters collected by the presented system:** The dissertation investigates the accuracy of HR and HRV parameters collected by the presented IoT-based maternal monitoring system against the corresponding gold standard of electrocardiogram (ECG) signals.

- **Proposing and implementing a deep learning-based PPG quality assessment method based on HR and HRV parameters:** We introduce a deep learning-based photoplethysmogram (PPG) quality assessment method to determine the quality of the PPG signals collected by our presented system based on the desired HR and HRV parameters. The proposed method uses convolutional neural network (CNN) architecture and outperformed the existing PPG quality assessment methods.

- **Continuous long-term monitoring of physiological health parameters of pregnant women in everyday settings:** We used the developed IoT-based maternal monitoring system to collect data continuously from 62 pregnant women during pregnancy and 3 months postpartum.
- **Analyzing the trends of HR and HRV parameters during pregnancy and the postpartum period:** The dissertation noninvasively assessed the trends of HR and HRV parameters during pregnancy and postpartum noninvasively. For this purpose, the continuous data collected by the developed maternal monitoring system were used. Then, reliable HR and HRV parameters were extracted. The hierarchical linear mixed models (HLM) were used to investigate the trends of HR and HRV parameters during the second and third trimesters as well as the postpartum period.
- **Proposing predictive models for maternal loneliness detection using passive sensing:** Two predictive machine-learning models were developed for maternal loneliness detection during late pregnancy and postpartum. The models use the objective data collected passively by our presented IoT-based maternal monitoring system.The results show the promising performance of the presented models. In addition, important physiological parameters that are associated with maternal loneliness are investigated.

1.4 Thesis Organization

This thesis is based on five original publications that were published in international peer-reviewed journals. All five papers resulted from collaborations with other researchers. The thesis is article-based and organized into two main parts. Part 1 consists of eight chapters and provides an overview of the research, and Part 2 contains original publications.

Part 1 aims to provide a big picture of the research published in the original publication. Chapter 1 presents the introduction, research objectives, and contributions. Chapter 2 outlines the background of the thesis. Chapter 3 describes the state-of-the-art IoT-based maternal health-monitoring systems and our presented long-term IoT-based maternal monitoring system. The presented system is used in the following chapters as well. Chapter 4 shows the validity and accuracy of HR and HRV parameters collected by the smartwatch used in our IoT-based maternal monitoring system. This chapter first provides the validation of HR and HRV parameters collected by the smartwatch against an ECG device. Then it introduces a deep learning-based PPG-based quality assessment method to assess the quality of HR and HRV parameters extracted from PPG signals. The PPG signals were collected by smartwatch that used in our presented system in free-living conditions. Chapter 5 presents the data collection from pregnant women using the presented IoT-based system in

Chapter 3. Then, we analyze the changes in nighttime HR and HRV parameters during pregnancy and postpartum. Chapter 6 explains two machine-learning methods developed for detecting maternal loneliness during late pregnancy and postpartum as a major mental health issue. The developed models use passively collected data using the presented IoT-based system. Research conclusions and future directions are presented in Chapter 7. Finally, Chapter 8 presents a summarized overview of the original publications and the author's contributions to each paper.

The second part of this thesis consists of five original publications. The attached original publications support the research aspects presented in the first part of the thesis. Paper I contributes to the content presented in Chapter 3. This paper presents an IoT-based system for long-term remote maternal health monitoring and covers Research Objective I. Paper II and Paper III correspond to the contents of Chapter 4. These papers contribute to Research Objective II. Paper II validates the HR and HRV parameters acquired by the smartwatch used in our presented system, and Paper III introduces a deep learning-based PPG quality assessment method in everyday life settings. Paper IV is in accordance with Chapter 5 and represents the HR and HRV trends during pregnancy and postpartum and contributes to Research Objectives III and IV. Finally, in Paper V, two machine-learning methods were developed to predict loneliness and analyze physiological parameters that are associated with loneliness, which is related to Chapter 6 and Research Objective V. An overview of the thesis organization is illustrated in Figure 1.

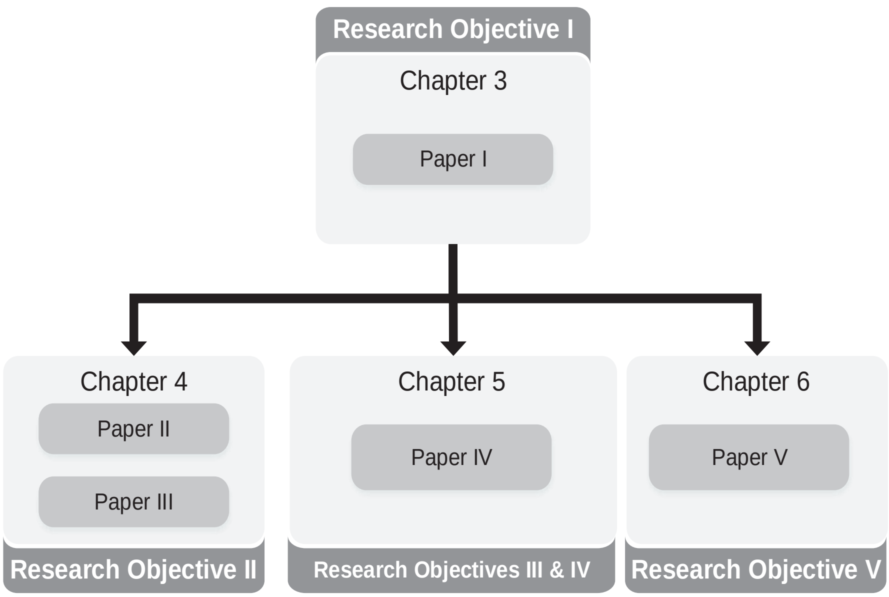


Figure 1. Overview of original publications, chapters, and research objectives of the thesis

2 Preliminaries

This chapter briefly explains the essential concepts that have been used in the following chapters. First, IoT-based health-monitoring systems are described. Then, the chapter outlines the cardiac activity measurement and HRV parameters that are fundamental concepts in the following chapters.

2.1 Internet of Things-based Health-Monitoring Systems

The Internet of Things (IoT) is a network of physical and virtual objects or “things” that interact with each other and a remote cloud server [32]. Each thing or object in an IoT-based system is uniquely identifiable and has self-configuring capabilities, and they can be integrated as an information network.

Advancements in wearable devices and activity trackers facilitate and increase the use of IoT-based systems in health and well-being applications. The paradigm enables ubiquitous monitoring everywhere continuously 24 hours everyday. In this thesis, we presented an IoT-based maternal monitoring system which could continuously monitor physical activity and sleep parameters. The system also collects 12 minutes of PPG signals every second hour to monitor heart activity due to battery-life constraints of the wearable device. The PPG signals could provide an approximation of changes in heart activity during the day.

IoT-based health-monitoring systems conventionally perform four main functionalities: collecting health data using various data sources, transmitting data to a cloud server, analyzing the data, and presenting the analyzed data [33; 34]. The architecture of an IoT-based health-monitoring system based on the mentioned functionalities consists of four layers and is represented in Figure 2:

1. Perception layer: The perception layer collects health data from the user using various types of data sources such as wearable devices, smartphones, portable devices, and background and demographic information.

2. Gateway layer: The gateway layer transmits the data collected in the perception layer to the cloud layer. The gateway can be a router or smartphone providing the transmission functionality or can be a smart gateway [35] and provide more advanced functionalities such as local data analysis, data compression, and security.

3. Cloud layer: The cloud layer receives the data collected via data sources in the perception layer using the gateway layer. The cloud layer enables the secure

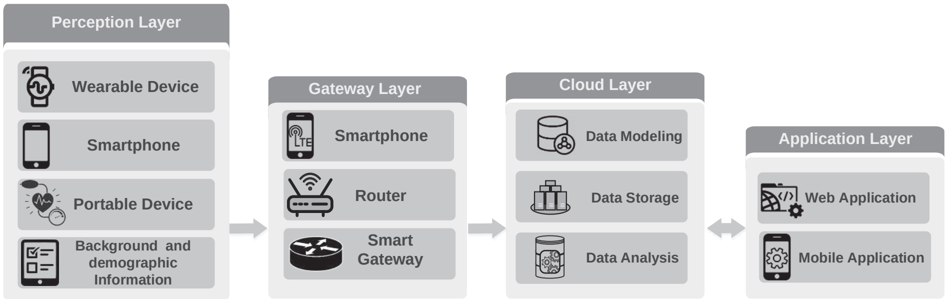


Figure 2. IoT-based health-monitoring architecture [34]

storage of the collected health data. Moreover, the cloud layer provides data analysis functionalities by incorporating AI, machine learning, and deep learning methods. As a result, the cloud layer provides personalized modeling, trend and anomaly detection, and early detection of health issues. Moreover, the cloud layer allows analyzed data to be visualized on the application layer.

4. Application layer: The application layer acts as an interface and facilitates interaction with the IoT-based health monitoring system. This layer usually consists of web and mobile applications to visualize and monitor the collected data and communicate between caregivers and users. The mobile application enables users to visually monitor their health data and gain awareness of their health. In addition, the web application visualizes and models the users' data for caregivers.

2.2 Cardiac Activity Measurement

Cardiac activity can be measured by various bio-signals. Bio-signals refer to signals that can be measured continuously from living organisms such as the human body. Bio-signals represent the activities and nature of the corresponding physiological process and can be in different forms, such as biochemical, electrical, and physical [36]. Accurate measurement of cardiac activity is crucial for assessing cardiovascular health and diagnosing various cardiac conditions. Several bio-signals, including electrocardiogram (ECG), phonocardiogram (PCG), photoplethysmogram (PPG), seismocardiogram (SCG), and gyrocardiogram (GCG), are employed to monitor heart activity and extract related vital sign, contributing to the determination of the health and well-being of individuals [36]. PCG represents a recording of the sound signals generated by the heart [36]. SCG and GCG utilize accelerometers and gyroscopes attached to the chest, typically positioned on top of the heart, to monitor mechanical activity of the heart [37]. In this section, we will provide more detailed explanations of ECG and PPG signals as they are used in subsequent chapters.

2.2.1 Electrocardiogram

ECG is a conventional method for monitoring cardiovascular activity and related health parameters, such as HR and HRV. ECG signals depict the electrical activity of the heart and can be easily recorded by electrodes connected to the skin. This signal is the most commonly used bio-signal and is used widely in clinical settings. Clinical standard ECG measurement uses four electrode attached to the chest and limbs [36]. ECG considered as gold standard for collecting heart-related vital sign, This recognition is primarily attributed to the simplicity and readily identifiable wave-forms present in the ECG signals. Numerous studies have firmly established clinical ECG as a standard procedure.

Additionally, ECG signals can be used to detect cardiovascular diseases and abnormalities because these diseases affect the shape of ECG signals [36]. However, this method cannot be used for long-term health monitoring due to complicated standard ECG setup, which needs four ECG electrodes be attached to the limbs or chest of the user. This may limits the user ability to engage in their daily activity. Furthermore, loose or misplaced electrode connections can compromise the quality of collected ECG signals.

Figure 3 depicts a 1-minutes cardiac template of ECG signals along with the first 5 seconds of the signals. The ECG template maps all the cardiac cycles of the ECG signal to one chart, therefore the abnormalities in the cardiac cycles can be easily identified. The ECG template in Figure 3 shows that the cardiac cycles in a normal ECG signal are aligned and similar. Additionally, in the five-minute signal aslo shown that cardiac cycles have similar waveform. Figure 4 shows the 1-minute template of an ECG sample of atrial fibrillation, along with the first 5 seconds of corresponding ECG signals. As shown in the ECG template in Figure 4, the cardiac cycles are different, and the alteration in the ECG signal are readily apparent. Moreover, the different shapes of cardiac cycles are noticeable in the first five seconds of the corresponding signal.

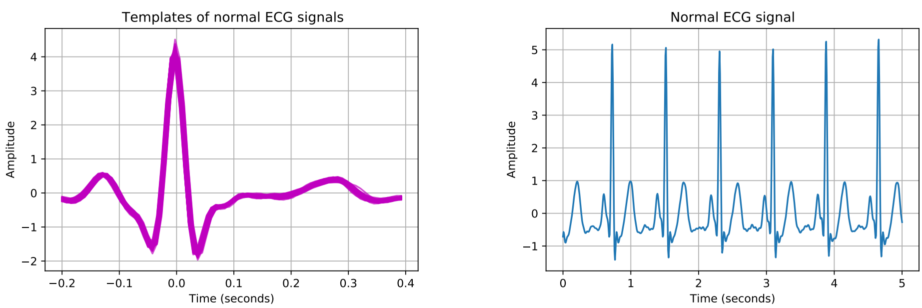


Figure 3. Template of 1-minute normal ECG signal and the first 5 seconds of the signal

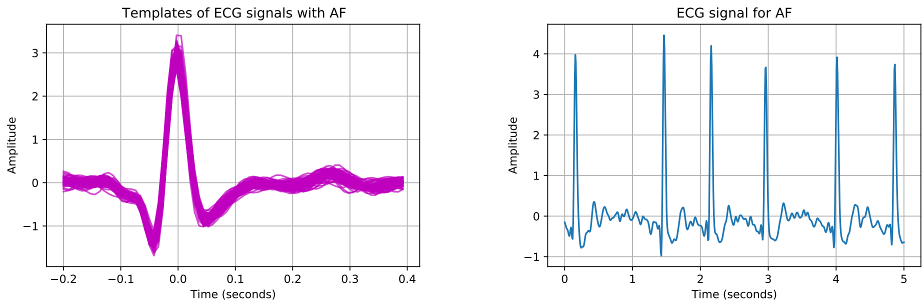


Figure 4. Template of 1-minute ECG signal with Atrial fibrillation and the first 5 seconds of the signal

2.2.2 Photoplethysmogram

Photoplethysmography is an optical method used to monitor heart activity. This method measures the volumetric variation of blood flow using a light emitter and light detector. The method is enabled by emitting light to the skin and measuring the light absorption using a light detector [38; 39]. The PPG sensors can easily be placed on the finger or wrist and are used widely in various wearable devices for HR and HRV monitoring. PPG signals can also be used to extract respiration rate and oxygen saturation.

The PPG method is an easy-to-implement, inexpensive, energy efficient and convenient method that is widely used in both clinical and commercial devices [15]. PPG-based wearable devices can be used in remote health monitoring system and in every day settings. However, PPG method is highly susceptible to motion artifacts and environmental noise, which are inevitable in everyday life setting. For instance, the light sensors might be exposed by environment light sources, or motion artifact affect the signals when users are involved in various daily activities while using the PPG-based wearable devices. A 5-second sample of filtered PPG signals is shown in Figure 5.

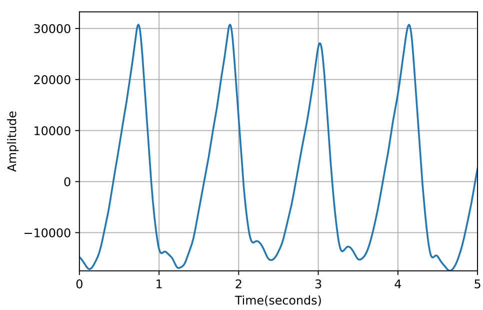


Figure 5. A 5-second sample of filtered PPG signal

Table 1. HRV parameters with definitions [51]

Variable	Units	Description
AVNN	ms	Average of NNIs
RMSSD	ms	The square root of the mean of the sum of the squares of differences between adjacent NNIs
SDNN	ms	Standard deviation of all NNIs
LF	ms^2	Power in the low-frequency range (0.04–0.15 Hz)
HF	ms^2	Power in the high-frequency range (0.15–0.4 Hz)
LF/HF	-	LF to HF ratio

2.3 Heart Rate Variability

HRV shows the variation in the time interval between successive heartbeats and reflects alterations in the regulation of the autonomic nervous system (ANS) [40; 41]. Studies have shown that HRV is associated with stress level, sleep quality, and pain intensity [42; 43; 44; 45; 46], and changes in HRV can be a sign of health issues such as anxiety [47], preeclampsia [48], and hypertension [49].

HRV parameters are extracted based on interbeat intervals (IBIs), defined as the interval between two consecutive heartbeats. IBIs will be processed further to remove abnormal IBIs based on the human HR range, which results in normal interbeat intervals (NNIs). The time-domain HRV parameters show the NNIs variations in the time domain, and the frequency-domain HRV parameters show the NNIs variations in different frequency ranges. Time-domain and frequency-domain HRV parameters used in this dissertation and their definitions are explained in Table 1. Root mean square of the successive differences (RMSSD) reflects the vagal changes. Standard deviation of NNIs (SDNN) during rest is associated with the fluctuations in respiratory sinus arrhythmia modulated by the parasympathetic nervous system. and is an indicator of stress resilience. Power in the low-frequency range (LF) is affected by the activity of both parasympathetic and sympathetic systems, whereas power in the high-frequency range (HF) is mainly affected by the parasympathetic nervous system [40]. LF and HF are correlated with mental stress [42]. LF/HF shows the LF to HF ratio and is associated with psychological stress. Moreover, studies have shown that stressful conditions affect average NNIs (AVNN), RMSSD, HF, and LF/HF [42; 50].

Wearable devices provide opportunities for low-cost continuous monitoring of physiological health parameters, including HR and HRV parameters. The devices mostly implement PPG sensors for HR and HRV monitoring. As described in Section 2.2.2, PPG is a noninvasive optical method that measures changes in blood flow volume. PPG signals are then used to extract pulse rate variability (PRV), which represents the variation of peak-to-peak intervals. PRV is widely used as a substitute for HRV and can be used to extract HRV parameters such as AVNN, SDNN, RMSSD, PNN50, LF, and HF. Many studies have evaluated the agreement between PRV and HRV. Few studies have indicated the difference between PRV and HRV in specific situations such as cold exposure [52; 53]. However, even these studies claim that HRV is the primary determinant of PRV. Moreover, authors in [51] showed that HRV parameters could reliably be estimated by PPG signals with sufficient confidence. Here, we also used HRV for PRV derived from PPG signals.

HRV parameters can be extracted from segments of IBIs with different lengths. Based on the literature, three standards for HRV analysis exist [40; 54; 55]:

- Long-term HRV analysis: This method is the gold standard for clinical HRV analysis and uses 24-hour recordings to extract HRV parameters.
- Short-term HRV analysis: This standard uses 5-minute recordings to extract HRV parameters.
- Ultrashort-term HRV analysis: This method uses less-than-5-minute recordings to extract some of the HRV parameters.

In this thesis, the short-term HRV analysis was used to extract HRV parameters. This standard was selected based on the battery life of the wearable device and collected data in the case studies.

3 IoT-Based Maternal Health Monitoring

In this chapter, we present a long-term IoT-based remote maternal monitoring system. The system continuously monitors maternal stress, sleep, and physical activity, and it can be extended to include other parameters such as diet. The system collects subjective and objective data using various data sources, and it stores and analyzes the data remotely on a cloud server. The data can then be visualized through web and mobile applications. We evaluate the performance of the system in terms of feasibility, reliability, and energy consumption. We also discuss the practical challenges in developing such systems.

3.1 Related Works

Many studies provide remote maternal-health monitoring that aims to improve maternal health. Some studies have used periodic measurements of health parameters such as blood pressure, weight, and blood glucose to investigate specific issues such as hypertension [6] and diabetes [56]. Other studies have used mobile applications with periodic health parameter measurements to predict the risk of health issues such as hypertension [57] and preterm birth [5].

Studies have also used wearable devices to collect health parameters continuously from pregnant women. Lopez et al. [58] used a wristband to monitor HR, sleep, and activity for 3 months. They used the collected data to monitor hypertension. Another study [8] presented a personalized sleep quality assessment method using an IoT-based monitoring system. The system used a wristband to collect HR, sleep, and physical activity. Kumar et al. [4] proposed a general architecture for IoT-based maternal-monitoring systems.

These studies are limited as they only consider specific health issues in a short time and use limited data sources. Thus, a long-term, IoT-based maternal monitoring system is needed to provide continuous monitoring of health parameters and enable a better understanding of normal and abnormal changes during pregnancy. Such a system would improve the well-being of pregnant women by providing a holistic view of their health and identifying the risk factors.

In the following, we first discuss the monitoring services that are essential for maternal monitoring. Next, we introduce our presented IoT-based maternal health system. Then, we evaluate the quality attributes of the system, including feasibility, reliability, and battery life. Finally, we discuss the practical challenges of this system.

3.2 Maternal Health Monitoring Services

This section highlights the importance of extended maternity care services, such as physical activity monitoring, sleep monitoring, and stress monitoring, which could be provided through IoT-based systems for remote maternal health monitoring.

- **Physical activity monitoring:** Physical activity is a key factor in well-being. Physical activity normally decreases during the course of pregnancy [59; 9]. However, a decrease in physical activity during pregnancy increases the risks of obstetric complications [60]. Continuous objective monitoring of physical activity provides accurate and detailed information for both health care providers and pregnant women to improve counseling and to be alert to the risks at an early stage.

- **Sleep monitoring:** Sleep disorders are common during pregnancy, especially during the third trimester [61]. In addition, sleep disorders can increase the risk of gestational hyperglycemia [62], preterm birth [63], and mood disorders [64]. Continuous sleep monitoring will enable a deeper understanding of individual sleep parameters. As a result, health care providers can better help a pregnant woman to have a healthy circadian rhythm, which also results in better weight management [65].

- **Stress monitoring:** Pregnant women can experience more stress compared to nonpregnant women due to pregnancy. For example, physiological changes, pregnancy-related symptoms, and the fetus's health can be sources of stress during pregnancy. A high maternal stress level is associated with a higher risk of depression, hypertensive disorders, and preterm birth, to name a few [66; 67]. Therefore, continuous stress monitoring during pregnancy will provide the possibility to detect high-stress levels early and better enable health care providers to consult with and support highly stressed pregnant women.

3.3 Presented Long-term IoT-Based Maternal Health Monitoring System

In this section, we present our long-term, IoT-based maternal monitoring system. This system continuously collects subjective and objective health data from pregnant women and provides a holistic view of their well-being. Figure 6 indicates an overview of the presented system, which consists of four layers: perception layer, gateway layer, cloud layer, and application layer. The data are collected using various data sources in the perception layer. Then, collected data are transferred to the cloud

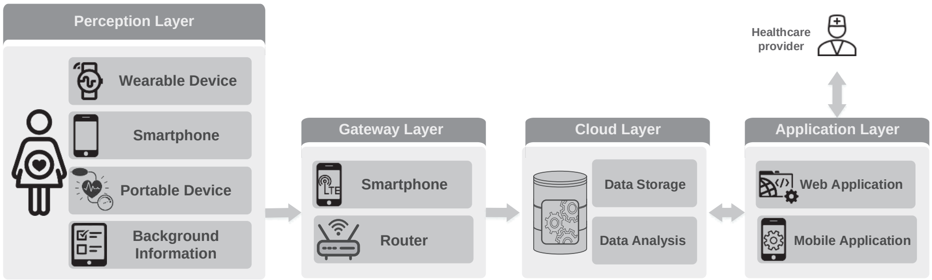


Figure 6. An overview of the presented IoT-based maternal health monitoring system [34]

server using the gateway layer. Next, the data are stored and analyzed within the cloud layer. Finally, the application layer presents the data to the users and provides communication functionalities between users and caregivers and/or researchers. In the following, we briefly describe these four layers in our implemented system.

3.3.1 Perception Layer

The perception layer collects data from various data sources including wearable devices, smartphones, portable devices for periodic monitoring, and background and demographic information. In our system, the data sources consist of a smartwatch, a customized cross-platform mobile application, a blood pressure device, and background information.

Wearable Devices

We used the Samsung Gear Sport smartwatch [68] as a wearable device in the monitoring system. The smartwatch was selected based on its sensors, configurability, and providing access to raw signals. It also has an inertial measurement unit (IMU), acceptable battery life, weight, and internal memory.

The watch has PPG, accelerometer, and gyroscope sensors that can be utilized to extract HR, HRV, physical activity, and sleep parameters. The watch uses the sensors and continuously collects HR, physical activity, and sleep parameters. The smartwatch processes the collected signals and provides step counts, walking steps, running steps, distance, activity duration, and activity intensity per 10 minutes. The watch also provides duration, start and end of the sleep, and intensity of hand movement during sleep. Moreover, HRV parameters as an indicator of stress can be extracted using raw PPG signals.

In addition, the watch runs the Tizen operating system (OS) [69]. Tizen OS is an open-source OS used in various wearable devices [70] and enables the development of customized data collection applications. In the presented maternal monitoring system, we developed several programs for 12 minutes PPG signals collection every second hour and acquire daily activity and sleep data supplied by the watch. The collected data were stored in the smartwatch's internal memory. We developed an application for compressing and sending the data to the cloud server using a Wi-Fi connection. After successfully transferring the data to the server, the application removes the data from the internal watch memory. The smartwatch has sufficient memory to store data for more than a month. We asked the participants to wear the watch continuously and upload the data to the cloud server frequently.

Smartphone

Smartphone can be used to collect self-report and sensor data. In our system, we developed a customized cross-platform mobile application for smartphones to collect self-report data by providing questionnaires on daily, weekly, and specific time and random bases. (See Appendix A: questions provided by the mobile application for more details). The mobile application includes components for users to send health data (e.g., blood pressure) or report technical problems, or for caregivers or researchers to send push notifications, as well as for authentication and authorization. We developed the customized mobile application with Angular 2 [71] and Cordova [72] open-source frameworks.

Portable Devices

Portable devices can be used to measure physiological parameters periodically. In our monitoring system, each participant was provided with an OMRON M3 Intellisense blood pressure device [73] and was asked to measure their blood pressure at least once a week. The device is clinically validated, and even nonexpert users can measure blood pressure accurately due to the 360-degree accuracy feature of the cuff [74]. Moreover, a nurse researcher instructed the participants to use the blood pressure device properly in a face-to-face meeting. The blood pressure values were manually entered into our customized mobile application's blood pressure measurement component and sent to the cloud.

Background Information

Background information (age, previous miscarriage, weight before pregnancy, etc.) can help to assess the risk of pregnancy complications. We collected background information by sending a questionnaire via our mobile application to the participants at the beginning of the study. The questionnaire considers the history of previous pregnancies, diagnosed diseases, risk factors in the current pregnancy, lifestyle before and during the pregnancy, and stress level.

3.3.2 Gateway Layer

Two types of gateway devices (i.e., smartphone and Wi-Fi router) can be used in the monitoring system to transmit data to the cloud layer. Our customized mobile application uses the Internet connectivity of the smartphone to transfer the data to our cloud server. In addition, the smartwatch connects to the Internet through a Wi-Fi router to send the data.

3.3.3 Cloud Layer

The cloud server consists of user management, data management, and data analysis modules. The user management module is responsible for creating and modifying user accounts with different levels of authorization, creating and modifying questionnaires, creating and modifying various groups of users with specified question sets, and scheduling questionnaires and notifications.

The data management module is responsible for receiving, basic validating, and storing the received data. This module uses the functionality of the user management module for authentication upon receiving the data from the smartwatch or the cross-platform mobile application. Then, the data management module checks whether the received data are corrupted. If necessary, the user will be notified to upload the data again. For privacy concerns, no personal data are sent to or stored in the cloud server.

The data analysis module is responsible for preprocessing, analyzing, and modeling the collected data and providing monitoring services. The monitoring services provided by the data analysis module are stress monitoring, sleep monitoring, and physical activity monitoring. This module can also be extended to provide other monitoring services, such as diet monitoring.

Stress monitoring is performed by HR and HRV monitoring using PPG signals collected from the smartwatch (see Section 2.3 for more details). Studies have shown the correlation of several HRV parameters with different types of stress [42; 50]. Based on their results, stress is associated with AVNN, RMSSD, SDNN, LF, HF, and LF/HF HRV parameters [42; 50]. Stress-monitoring services in this system provide monitoring of HR and the aforementioned HRV parameters.

The sleep monitoring service uses the sleep events, hand movements, and physical activity events collected by the watch to extract sleep parameters such as total sleep time, sleep fragmentation, and wake after sleep onset, as described by Mehrabadi et al. [75].

The physical activity monitoring service uses the activity data provided by the watch along with wear-time data to extract physical activity parameters and time spent being sedentary. To provide these monitoring services, the data analysis pipeline used in this module comprised several steps as shown in Figure 7.

- **Preprocessing:** In the preprocessing step, unreliable data are detected and re-

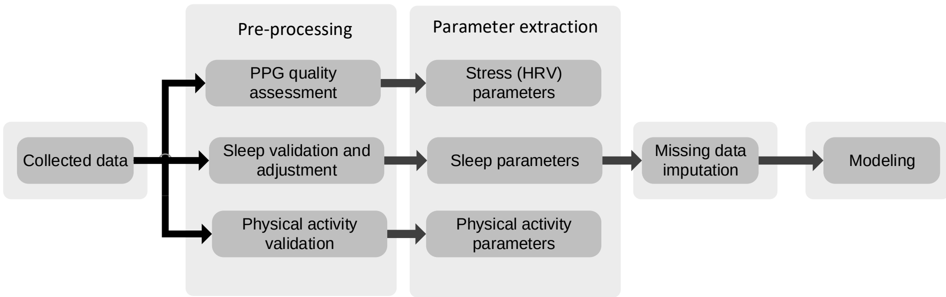


Figure 7. Data analysis pipeline in the presented IoT-based maternal monitoring system [34]

moved from processing. The data are collected in everyday life settings and are prone to noise. Assessing the quality of the collected data improves the accuracy of decisions made based on the data. We used simple rule-based methods for physical activity and sleep data [75] as well as deep-learning-based PPG quality assessment [76] for PPG signals. The PPG quality assessment method is described in detail in Chapter 4.

- **Parameter extraction:** This step uses reliable data from the previous step to extract HR, HRV, sleep, and physical activity parameters.
- **Missing-data imputation:** The proposed missing-data imputation methods by Azimi et al. [77] were used to fill in the missing values in the data.
- **Modeling:** In this step, machine-learning methods were used to detect anomalies, find trends in the data, and create personalized modeling using methods previously proposed by our research group [8; 78].

The server was implemented using Apache 2 [79], the Flask framework [80], and MongoDB [81]. Apache 2 is an efficient, extensible, open-source server that is widely used. Flask is a scalable and flexible open-source framework in Python. In addition, MongoDB is a NoSQL flexible database that we used to store various types of collected data. We also used the Secure Sockets Layer (SSL) Application Programming Interface (API) to enhance the security of communication.

3.3.4 Application Layer

A web application was developed to visualize the data collected from participants. The application provides monitoring functionalities for researchers to follow participants' health parameters. The web application provides various reporting tools (e.g., daily and weekly trends and participants' answers to the questionnaires). As with our mobile application, the web application was implemented in Angular 2 [71]. This approach allows the same component to be used in both applications and decreases the implementation overhead.

3.4 Data collection

The presented IoT-based maternal monitoring system was investigated and evaluated in a longitudinal study on high-risk pregnant women. Pregnant women were asked to wear a smartwatch programmed to continuously collect sleep and physical activity and 12 minutes of PPG signals every other hour. Moreover, participants were asked to install our cross-platform mobile application on their smartphones (Android or iOS). The mobile application provides a questionnaire that includes 2-3 questions daily about the participants' subjective mental and physical parameters. (Daily questions can be found in Appendix A). The mobile application also provides a component for participants to enter their blood pressure measurements and send them to our server. A blood pressure measurement device was also provided for each participant, and they were asked to measure their blood pressure and enter it into the mobile application at least once a week.

Participants and Recruitment: We recruited 32 pregnant women with singleton pregnancies and previous preterm births (gestational weeks 22–36) or late miscarriages (gestational weeks 12–21) through advertisements in social media and maternity clinics. The participants were in early pregnancy (12–15 gestational weeks), were older than 18 years, and were able to understand Finnish. The recruitment happened in January-December 2019 in Southwest Finland.

The eligible pregnant participants attended a face-to-face meeting with the researcher, where the study's objectives were explained, and written consent was obtained. Each participant received a smartwatch and a blood pressure device, along with instructions on proper usage. The researcher also guided participants on installing our custom app on their phones. The participants agreed to participate in the study from gestational weeks 12–15 to 3 months postpartum. Four women withdrew from the study, resulting in a total of 28 participants who successfully completed the study. This study was later extended by recruiting another group of pregnant women with low-risk pregnancies. We used the data from the initially recruited group to evaluate the system.

Research Ethics: This study received ethics approval from the Ethics Committee of the Hospital District of Southwest Finland (Dnro: 1/1801/2018). Written informed consent was obtained from all participants.

3.5 System Evaluation

We evaluated the presented IoT-based maternal monitoring system by implementing the system for recruited high-risk pregnant women. The evaluation considered the feasibility, reliability, and energy consumption of the presented system. We also discuss the practical issues in the development of the system.

3.5.1 Feasibility

We investigated the feasibility of the presented maternal monitoring system in terms of the wear-time of the smartwatch and the use of our customized mobile application during pregnancy and postpartum.

Wearable Device Usage

Figure 8 depicts the average daily wear-time of the smartwatch during pregnancy and postpartum. As shown in Figure 8, the participants used the watches around 18 hours/day in the first weeks after recruitment and the time decreased during the course of pregnancy to around 15.5 hours/day. After the delivery, the average daily wear-time was less than the wear-time during pregnancy. The wear-time during the postpartum period began at 11 hours, then increased after the first weeks, reaching 14.5 hours at the end of the study. In this study, the average wear-time during pregnancy and the postpartum period was 17.01±4.20 hours/day and 13.72±5.71 hours/day, respectively.

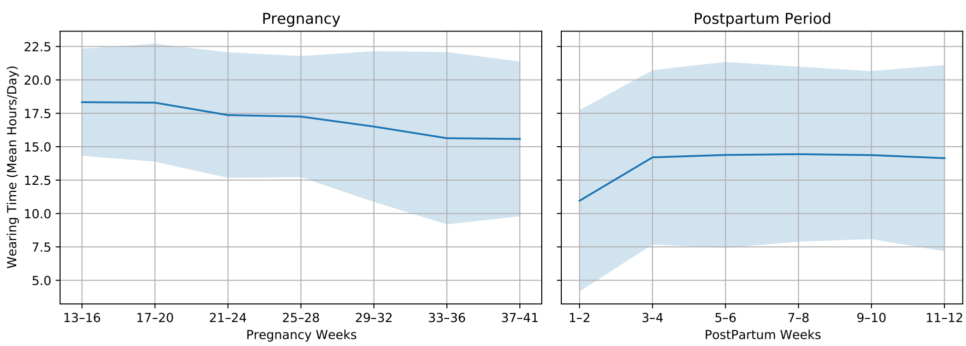


Figure 8. Average wear-time of the 28 high-risk pregnant women during pregnancy and postpartum [34]

It should be noted that several technical and practical issues affected the wear-time during the study, such as hospitalization during pregnancy, preterm births, hospitalization of the newborn baby after delivery, work-related restrictions regarding wearing the device, and technical issues in the server for a few days.

The results show the feasibility of using the wearable device in this system during pregnancy and the postpartum period. Our findings align with [12], showing the average wear-time of 17.3 hours/day during pregnancy and 14.4 hours/day during 1 month postpartum. However, our results are slightly lower compared with this work, which could have resulted from hospitalization and pregnancy complications because our participants had high-risk pregnancies.

Cross-Platform Mobile Application Usage

This section investigates the usage of our cross-platform application in terms of answering daily questions and uploading blood pressure measurements using the application. Figures 9 and 10 show the average responses to daily questions and average weekly blood pressure measurements during the study, respectively. As shown in Figure 9, the question response rate of the questions began at 70% and slightly decreased during the pregnancy. During postpartum, the response rate was less than it was during pregnancy. It began at around 50% after delivery and increased between the second and fourth week postpartum, and then decreased until week 10 and again slightly increased. In total, participants replied to 5493 daily questionnaires. Of the replies, 3879 were during pregnancy and 1614 were after the delivery. The average mobile application usage in terms of the response rate was 67.5% in pregnancy and 57.0% in the postpartum period.

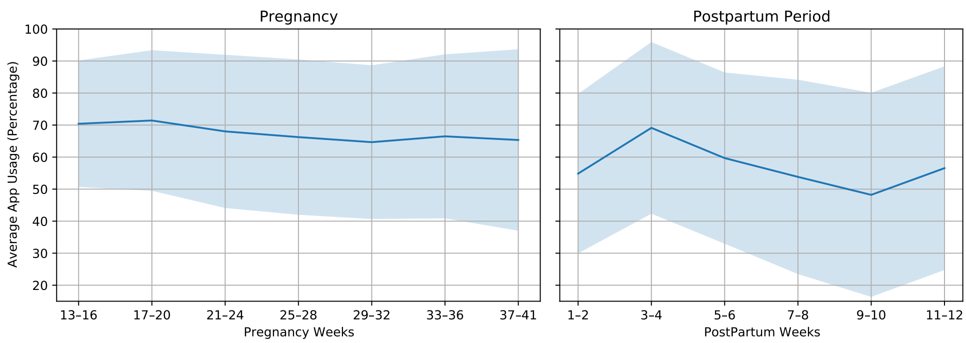


Figure 9. Average mobile application usage (response rate) of the 28 high-risk pregnant women during pregnancy and postpartum [34]

Figure 10 displays the weekly average of blood pressure measurements that were uploaded via the mobile application throughout pregnancy and the postpartum period. We removed one participant as an outlier because she measured her blood pressure daily. Moreover, 10 participants stopped uploading their blood pressure measurement after delivery. The results show that the average weekly blood pressure measurements during pregnancy and postpartum was 0.74 and 0.29, respectively.

To the best of our knowledge, this is the first study to explore the feasibility of mobile application usage in terms of answering daily questions during pregnancy and postpartum. Our results show the feasibility of the mobile application in our system for maternal monitoring during pregnancy and postpartum.

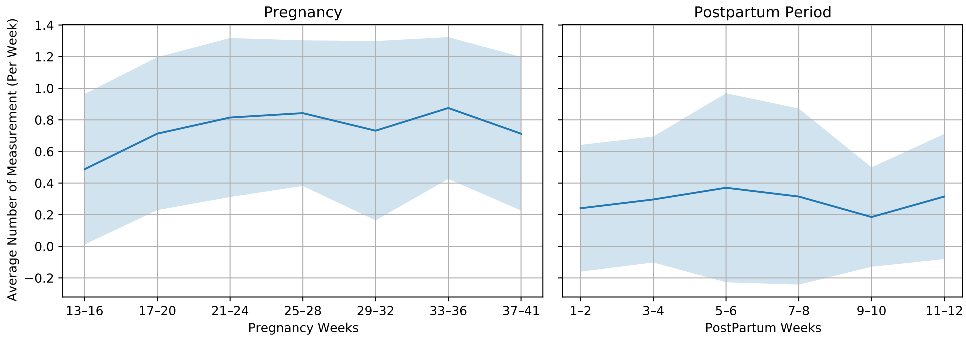


Figure 10. Weekly average blood pressure measurements of 27 high-risk pregnant women during pregnancy and postpartum [34]

3.5.2 Robustness and Reliability of Measurements

Robustness and reliability of measurements are crucial features in remote health monitoring systems. The reliability of the health decisions in these systems is correlated with the reliability of the collected data. Therefore, it is critical to ensure the reliability of collected data in such systems.

In the presented system, PPG signals are collected in everyday life settings to extract HR and HRV parameters. The quality of PPG signals is highly affected by environmental noise and motion artifacts. In this section, we discuss the reliability of HR and HRV parameters by investigating the frequency and duration of collected PPG signals, and we show that our system satisfies the requirements for reliable HR and HRV data collection. The reliability and validity of the collected PPG signals will be discussed in Chapter 4. We also introduced a PPG signal quality assessment method for improving the quality of collected HRV data in Chapter 4.2.4.

Duration of PPG Signal Recording

In this study, the PPG signal was used to extract HR and HRV parameters. As explained in Section 2.3, three standards exist for HR and HRV measurements with different durations of recording (e.g., 24-hour recording, 5-minute recording, and less than 5 minutes recording [40; 54; 55]). A 24-hour recording can result in the most accurate results because it captures changes across an entire day. However, it is inapplicable in long-term health monitoring because wearable devices have limited battery capacity. See the Section 3.5.3 for more details.

Considering battery limitation, we decided to use the short-term HRV measurement standard with 5-minute PPG recordings in our long-term maternal monitoring system. We developed an application for the watch to acquire 12-minute PPG data every second hour. Therefore, after removing the sensor calibration data, we would have two consecutive 5-minute PPG recordings. In this way, we reduced the effect of noisy signals and increased the reliability of extracted HRV parameters.

Sampling Frequency of the PPG Signal

The sampling frequency of the PPG signal is another factor that affects the reliability of HR and HRV parameters. Choi et al. [51] compared the reliability of HR and HRV parameters extracted from PPG signals with sampling frequencies ranging from 5 to 10000 Hz with an ECG signal with 10000 Hz sampling frequency. They showed that desired HRV parameters in this study, including AVNN, RMSSD, SDNN, LF, and HF, could reliably be extracted with a minimum frequency of 20 Hz. Therefore, our setup met the minimum requirement for extracting reliable HRV parameters.

3.5.3 Energy Consumption

The wearable devices used in remote health-monitoring systems have limited battery capacity and must frequently be recharged. The energy consumption of wearable devices is a critical issue in remote health-monitoring systems and can affect the feasibility and usability of such systems. In this section, we investigate the energy consumption of the smartwatch used in our system as one of the feasibility aspects of the system.

PPG sensors in wearable devices and in the smartwatch used in our system have high energy consumption [14; 82]. In the previous section, we discuss the PPG collection duration and sampling frequency of PPG signals. Here, we investigate the time interval between PPG recordings to optimize the energy consumption of the smartwatch.

We performed an experiment on the battery life of the smartwatch with different time intervals between PPG signal recordings. In this experiment, we programmed three smartwatches to collect 12 minutes of PPG signals with 20-Hz frequency at different time intervals (e.g., 15 minutes, 30 minutes, 1 hour, 2 hours, and 4 hours). The watches were on a table and in flight mode to remove the usage bias. The average battery life of the watches is reported in Figure 11. The battery life for 15-minute intervals is about 25 hours and increased to 157 hours for 4-hours intervals. Considering that daily usage of the smartwatch will also decrease the battery life, we decided to have 2-hour intervals between PPG recordings. This interval results in 2 to 3 days of battery life in a normal situation and ensures the feasibility of the smartwatch in long-term monitoring.

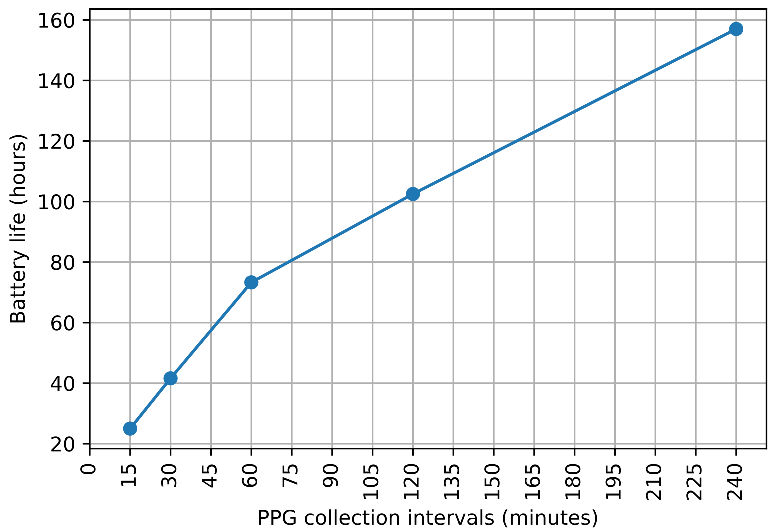


Figure 11. Smartwatch battery life with different intervals of PPG signal collection [34]

3.5.4 Practical Challenges

Long-term remote health monitoring raises several practical challenges, such as long-term engagement of users, maintenance of systems and devices despite evolving technologies, and user experience that we also faced during the course of this study.

To keep users motivated to use an IoT system for a long time, the system should be usable and comfortable in everyday life settings, and the provided monitoring services should be effective [11]. We selected a smartwatch that can be used easily in everyday life activities. We also tried to minimize the effort to use the system by minimizing the interaction needed with the system and selecting a reasonable battery life for the wearable device. We provided technical support through the mobile application to help solve any technical issues our participants faced when using the system. In addition, the monitoring of stress, sleep, and physical activity provided by our system are essential to improve the health and well-being of pregnant women as described in Section 3.2.

Moreover, the IoT-based monitoring system should be easily integrated with the evolving technology in the long term. We used open-source frameworks such as Flask, Angular, and MongoDB and development methodologies such as RESTFul API that improve the maintenance of the system regardless of changing technology. Moreover, backward compatibility in Tizen OS, which runs in the smartwatch, enables our program to run on the watch regardless of updates on the OS. In the future, we will also use other APIs, such as Validic API, to enable us to collect data from various monitoring devices easily.

4 Validation and Quality Assessment of HR and HRV Parameters for Health Monitoring

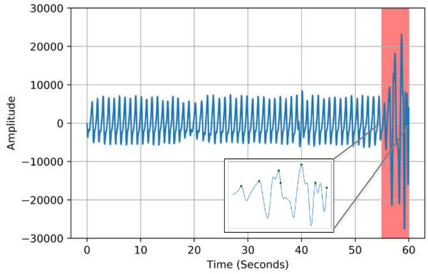
In Chapter 3, we presented a long-term IoT-based maternal monitoring system. We indicated that the HRV collection in the presented system meets the requirements of reliable measurements in terms of frequency and duration. In this chapter, we show the necessity of validation and quality assessment of PPG-based HR and HRV parameters for health-monitoring applications. Then, we will investigate the accuracy of the collected HR and HRV parameters in our monitoring system. Finally, we propose a deep-learning-based PPG quality assessment method to further improve the quality of collected HRV parameters.

4.1 Necessity of Accuracy and Quality Assessment of HR and HRV Parameters Collected by Wearable Devices

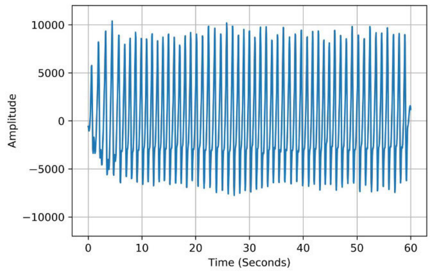
HR and HRV parameters can be continuously collected by wearable devices at a low cost. The devices mostly implement PPG sensors for HR and HRV monitoring. PPG-based wearable devices provide opportunities to collect data in everyday life settings. However, the devices are prone to noise, such as motion artifacts and environmental noise, when people engage in various activities. The noise is unavoidable and negatively affects the PPG-signal quality and, consequently, the reliability of extracted HR and HRV parameters [83; 38]. The unreliable physiological parameters can lead to false predictions or decisions in health care applications, such as loneliness prediction, which is discussed in Chapter 6.

Moreover, the noise affects HR and HRV parameters differently, because the accuracy and reliability of HR and HRV parameters depend on different factors of the signals. For example, RMSSD, which shows the short-term variation in the NNIs, can be affected by small distortion in signals [40]. However, SDNN, which indicates the long-term variation of NNIs, will be unreliable if the noise affects the signal variations [40]. Therefore, a PPG signal can be reliable for extracting some HRV parameters and unreliable for extracting other parameters, as illustrated in Figure 12.

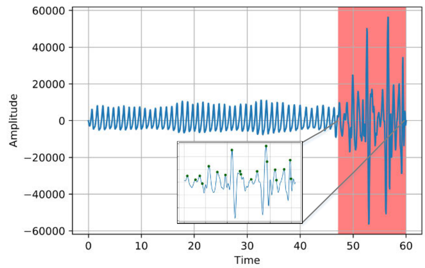
Figure 12 shows three different 1-minute segments of PPG signals that are af-



(a) PPG with reliable HR, AVNN, and SDNN, and unreliable RMSSD



(b) PPG with reliable HR, AVNN, and RMSSD, and unreliable SDNN



(c) PPG with reliable HR and AVNN, and unreliable RMSSD and SDNN

Figure 12. Three 1-minute samples of PPG signals with varying accuracy for HR and HRV parameters [84]

fected by different types of noise. The extracted HR and HRV parameters are shown with their error compared to the ECG baseline. In Figure 12a, only a small part of the signal was affected by the noise, highlighted in red. In this example, HR, AVNN, and SDNN have acceptable errors compared with the ECG baseline. However, the error rate for RMSSD is high because noise affects the short-term variations of the signals. In Figure 12b, the peaks are not distorted, but the noise affected the variation of the NNIs compared to ECG peak-to-peak intervals. In this example, HR, AVNN, and RMSSD can be extracted reliably. However, SDNN, which is correlated with long-term variations of the signal, is unreliable. In Figure 12c, part of the signal is corrupted, and the noise affects the short-term and long-term variation of the signals. Therefore, SDNN and RMSSD extracted from this signal are unreliable, whereas HR and AVNN can be extracted reliably. The above examples were for time-domain HRV parameters, but the situation is the same for frequency-domain parameters.

We must assess the quality of the smartwatch used in our IoT-based maternal monitoring system to ensure the reliability of extracted parameters. Then, quality assessment of the signals is required to distinguish the low- and high-quality segments of PPG signals and discard the unreliable parts of the signals. Moreover, based on the above examples, the validation and quality assessment should be performed separately for HR and each HRV parameter.

4.2 Accuracy Assessment of the Smartwatch HR and HRV Parameters

In this section, we assessed the accuracy of the Samsung Gear Sport smartwatch in terms of HR and HRV parameters. We selected this smartwatch for accuracy assessment because it was utilized in our system developed in Chapter 3. The evaluation was performed against a medical-grade ECG device during 24 hours of data collection in an everyday life setting. The evaluation was performed separately for HR and each HRV parameter during sleep and when awake.

4.2.1 Related Works

Several studies have assessed the HR accuracy extracted by wristbands in different situations in various population groups. Accuracy of HR measurement using multiple wristbands, including Apple Watch [85], Basis Peak [85], Empatica E4 [86], Fitbit Surge [85], Microsoft Band [85], PulseOn [85], Samsung Gear S2 [85], Garmin Forerunner [87], Mio Alpha 2 [85], the Everlast Smartwatch[88], Fitbit Charge HR [89], and Basis Peak [90] have been examined in the previous studies. The studies indicate high accuracy of HR measurement for the PPG-based wristband while participants engaged in low-intensity activities. They also showed that HR accuracy decreased with an increase in the intensity of activity. The studies only assessed the accuracy of HR and were limited to predefined activities in laboratory settings.

Other studies have investigated the accuracy of HRV parameters considering various smartwatches and smart rings. Accuracy of HRV parameters extracted from the Empatica E4 [91; 92], Microsoft Band 2 [93], the Wavelet wristband [94], Apple Watch [95], and Oura ring [31; 96; 97] were evaluated against a medical-grade ECG device. The studies showed that HR and HRV parameters collected by these devices have high accuracy during rest. Moreover, they showed that the accuracy of the HRV parameter was highly decreased by noise and motion artifacts. The studies were performed in laboratory settings (mostly in seated positions) and are limited to less than 1-hour data collection. Thus, assessing the accuracy of the PPG-based smartwatch in everyday settings involving various activities and situations is required. Moreover, the accuracy of different HRV parameters should be evaluated separately because the parameters are affected differently by noise.

Based on the limitation of previous works, the validation of the smartwatch HR and HRV parameters should be performed separately for each parameter and in everyday life settings when participants can be involved in various activities.

4.2.2 Participants and Recruitment

We recruited healthy adults aged 18 to 55 in Southern Finland between July and August 2019. The exclusion criteria included having a previous diagnosis of cardiovascular disease or displaying symptoms of illness during the recruitment, as well as having any restrictions in doing physical activities or wearing wearable devices.

The participants were recruited using snowball sampling. The researcher scheduled a face-to-face meeting with the eligible participants. In the meeting, the study's objectives were explained to the participants. After obtaining written consent from the participants, the wearable devices (a Gear Sport smartwatch [68] and a Shimmer ECG device [98]) and the instructions /were delivered to the participants. The Shimmer device was positioned on the chest, and the smartwatch was worn on the nondominant hand. The researcher helped the participants to use and wear the devices if needed. The participants were asked to wear the devices continuously for 24 hours while carrying out their daily routines. Forty-six participants (23 female and 23 male) were recruited.

The data from 28 participants, including 14 males and 14 females, were used in this assessment. We excluded the data from other participants due to various issues during the data collection, such as missing sleep data, ECG electrodes loosely attached to skin resulting in noisy ECG signals, and insufficient ECG data due to practical issues.

Research Ethics The study was conducted according to the ethical principles based on the Declaration of Helsinki and the Finnish Medical Research Act (No. 488/1999). The study protocol received a favorable statement from the ethics committee (University of Turku, Ethics Committee for Human Sciences, Statement no: 44/2019). The participants were informed about the study, both orally and in writing, before the written informed consent was obtained. Participation was voluntary, and each of the participants had the right to withdraw from the study at any time and without giving any reason. To compensate for the time used for the study, each participant received a 20-euro gift card to a grocery store at the end of the monitoring period when returning the devices.

4.2.3 Data Collection

We collected data using a Samsung Gear Sport smartwatch and a Shimmer3 ECG device as the gold standard. We instructed participants to wear the smartwatch on the wrist of the non-dominant hand. In addition, participants wore the ECG device using a chest strap with four limb electrodes placed on the arms and the legs (see [99] for more details). Moreover, participants filled out self-report questionnaires to log their non-wear, sleep, and awake times.

Samsung Gear Sport Smartwatch: As described in Chapter 3, the Gear Sport smartwatch [68] is an open-source smartwatch that enables customized data collection remotely. For this study, a customized smartwatch application was developed to collect 16 minutes of PPG signals every 30 minutes with a frequency of 20 Hz. The data collection duration was chosen to have a battery life of more than 24 hours. The data were stored in the internal storage of the smartwatch and then sent to our cloud server.

Shimmer ECG Device: We used the Shimmer3 ECG device [98] as a gold standard for the collection of ECG data. The Shimmer is a lightweight device that can be placed on the chest with a strap and utilizes four electrodes connected to the skin for ECG signal collection. We configured the shimmer device to collect ECG, accelerometer, gyroscope, and skin temperature data continuously. The collected data were saved on the device. The Shimmer device has a battery life of more than 24 hours and did not need to be charged to collect our data. We sent the data to our cloud server after data collection. We used Lead II ECG (right arm - left leg) to extract HR and HRV parameters.

4.2.4 Data Analysis

In this case study, as with other case studies in this thesis, we used short-term HRV analysis based on the duration of recordings (see Section 2.3). Therefore, we used 5-minute segments of ECG and PPG signals to extract HR and HRV parameters. The segments were used as an input to our data analysis pipeline. The pipeline consisted of preprocessing, peak detection, abnormal peak removal, feature extraction, and statistical analysis, which are explained in the following. Figure 13 shows the overview of our data analysis pipeline.

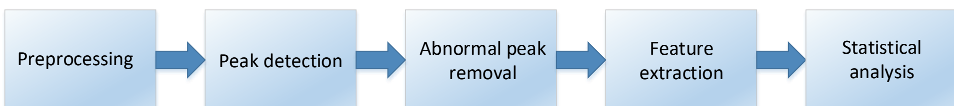


Figure 13. Data analysis pipeline [100]

Preprocessing

Preprocessing consists of synchronization and filtering.

- **Synchronization**: The ECG and PPG signals were collected by different devices. Therefore, it was necessary to synchronized the signals. To find the time difference between ECG and PPG, we used cross-correlation between acceleration signals collected by the Shimmer ECG device and the smartwatch. Then we shifted the ECG signals to synchronize them with the PPG signals.

- **Filtering**: For HR and HRV parameter extraction, only the frequencies in human HR ranges are used. Consequently, other frequencies were eliminated using the Butterworth filter. A 5th-order high-pass Butterworth filter with a cutoff frequency of 0.5 Hz was applied to the PPG signals, while a Butterworth bandpass filter with cutoff frequencies of 0.5–100 Hz was employed for the ECG signals. The choice of cutoff frequencies was determined by the frequency of the PPG and ECG signals.

Peak Detection

The peak detection step involves identifying peaks in both ECG and PPG signals. The following will describe the peak detection methods for PPG and ECG signals separately.

PPG Peak Detection

The PPG peak detection method proposed by Kazemi et al. [101] was used for PPG peak detection. The method uses dilated CNNs and returns a probability of being a peak for each signal point. Then, the peaks are detected as local maximums within the points with a higher probability than a predefined threshold. Figure 14 shows the detected peak in a 30-second window of PPF signals.

ECG Peak Detection

A two-round moving threshold-based ECG peak detection method was used to detect peaks in ECG signals. First, the average of all signal points in an ECG signal window was used to detect peaks. Then, the average of the detected peaks served as a new threshold to update the detected peaks. Moreover, the normal human HR range was used to add undetected peaks. The method was used in [31; 100] and performs well compared with the state-of-the-art methods [31]. Figure 14 shows detected peaks in a 30-second ECG signal window.

Abnormal Peak Removal

The normal HR for humans ranges from 20 to 200 per minute. As a result, NNIs range from 300 ms to 3000 ms. The ranges were used to remove abnormal peaks. Moreover, the average NNIs in a single segment of the signal were used as a threshold, and the NNIs with a variation of more than 20% of the threshold were discarded. If more than half of a signal segment were removed due to abnormal peaks and NNIs, the segment would be removed from the analysis.

Feature Extraction

We used the peak detected in the previous step to extract HR and HRV parameters. The NNIs extracted from detected peaks were used to extract the following time-

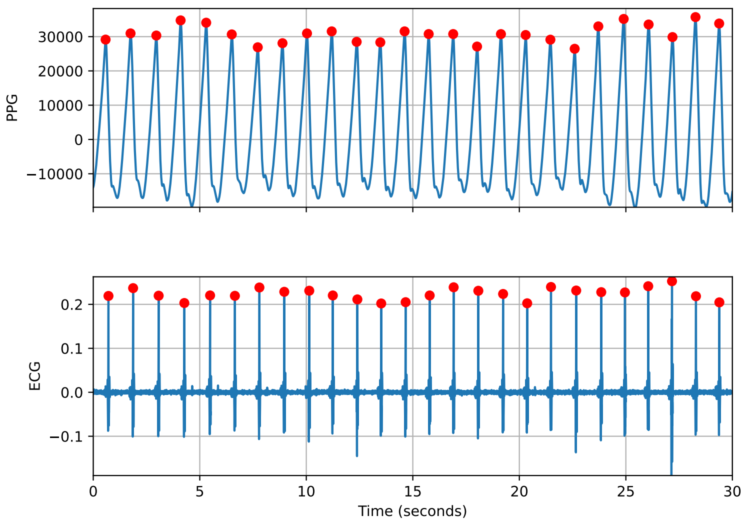


Figure 14. A peak detection sample for a 30-second segment of PPG and ECG signals

domain and frequency-domain parameters: AVNN, RMSSD, SDNN, PNN50, LF, HF, and LF/HF.

Statistical Analysis

We used the Pearson correlation coefficient, linear regression analysis with R-squared value (r^2), and Bland-Altman analysis to validate the parameters extracted from the watch against the ECG device. The statistical analysis was implemented in Python using Scipy [102], sklearn [103], and Statsmodels [104] libraries.

4.2.5 Results and Discussion

We assess the validity of HR and HRV parameters during sleep and while awake. The sleep time was extracted from self-report questionnaires that participants filled in manually.

Table 2 illustrates the Pearson correlation coefficient, 95% confidence interval (CI), mean difference, and r^2 values of the HR and HRV parameters of the smartwatch compared to the ECG gold standard. All p values for Pearson correlation are less than 0.001; therefore, Pearson correlation coefficient values are statistically significant. As shown in Table 2, all values are positively correlated. During sleep, the correlation values for HR, AVNN, SDNN, and pNN50 are high. In addition, RMSSD, LF, and HF have high but slightly lower correlations than previously mentioned parameters. LF/HF values are also moderately correlated. When awake, AVNN values are highly correlated, whereas HR values are moderately correlated.

All other HRV parameters have low positive correlations.

Table 2. Pearson correlation coefficient, 95% CI, mean difference, and r^2 values between the smartwatch and Shimmer3 HR and HRV parameters in 5-minute segments of PPG signals [100]

	Parameters	Pearson Correlation Coefficient	95% Confidence Interval	Mean Difference	r^2
Sleep time	HR	0.941	[-7.53, 6.77]	-0.38	0.882
	AVNN	0.960	[-83.87, 108.59]	12.36 ms	0.909
	RMSSD	0.778	[-68.49, 32.01]	-18.24 ms	0.405
	SDNN	0.802	[-72.66, 28.29]	-22.19 ms	0.246
	PNN50	0.964	[-13.21, 11.58]	-0.81	0.926
	LF	0.784	[-1763.66, 834.77]	-464.45 ms2	0.206
	HF	0.782	[-1188.67, 693.23]	-247.72 ms2	0.462
	LF/HF	0.622	[-2.24, 1.72]	-0.26	0.216
Awake time	HR	0.675	[-43.58 , 24.65]	-9.47	0.293
	AVNN	0.833	[-135.12 , 254.44]	59.66 ms	0.582
	RMSSD	0.251	[-79.59 , 91.89]	6.15 ms	-0.191
	SDNN	0.404	[-76.99 , 61.36]	-7.81 ms	0.099
	PNN50	0.277	[-26.0 , 60.99]	17.5	-1.62
	LF	0.350	[-1727.72 , 1402.18]	-162.77 ms2	0.075
	HF	0.130	[-1215.82 , 1599.31]	191.75 ms2	-0.493
	LF/HF	0.211	[-3.38 , 2.12]	-0.63	-0.453

Figures 15 and 16 depict the regression lines for parameters extracted from PPG collected by the smartwatch compared with ECG during sleep and while awake, respectively. The ideal line is also illustrated in black. As shown in these figures, during sleep, the regression line of HR, AVNN, and PNN50 are close to the ideal line, and when awake, only the fitted line of HR and AVNN follow the ideal line. The fitted lines of other HRV parameters diverge both during sleep and when awake. In addition, the r^2 values, which indicate how well the data fit the regression line, are shown in Table 2. The r^2 values of HR, AVNN, and pNN50 during sleep and r^2 of AVNN when awake are high. HR also has moderate r^2 when participants were awake. However, other parameters have low r^2 values during sleep and while awake.

The Bland-Altman plots during sleep and when awake are shown in Figures 17 and 18, respectively. The mean biases and 95% CIs are given in Table 2. As shown in Table 2, during sleep, the smartwatch's AVNN values have very low mean bias with AVNN extracted from the ECG device. RMSSD, SDNN, pNN50, and LF/HF also show low mean biases, whereas LF and HF have moderate mean biases. During waking hours, RMSSD and SDNN have relatively low mean biases, whereas other parameters show moderate mean biases. In addition, during sleep, HR, RMSSD,

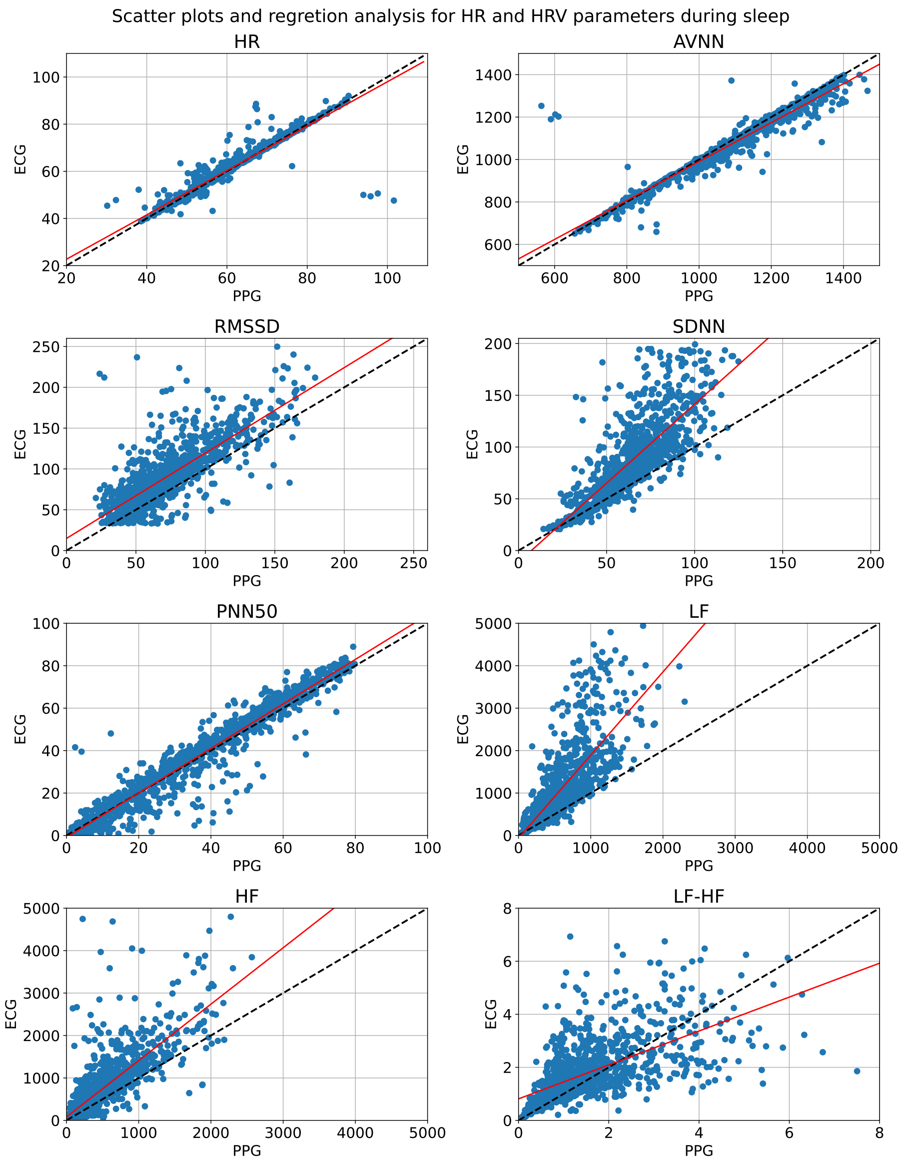


Figure 15. The scatter plots and regression analysis of the HR and HRV parameters collected from the Samsung smartwatch and Shimmer ECG in 5-minute segments during sleep. The regression lines and ideal lines are indicated in red and black, respectively. [100]

SDNN, and pNN50 have narrow CIs, whereas AVNN, LF, HF, and LF/HF have wide CIs. During the awake time, HR and all HRV parameters have wide CIs.

As shown in Figure 17 and Figure 18, the smartwatch underestimates AVNN while overestimating HR and other HRV values during sleep. However, during waking hours, the watch overestimates AVNN, RMSSD, and pNN50 and overestimates

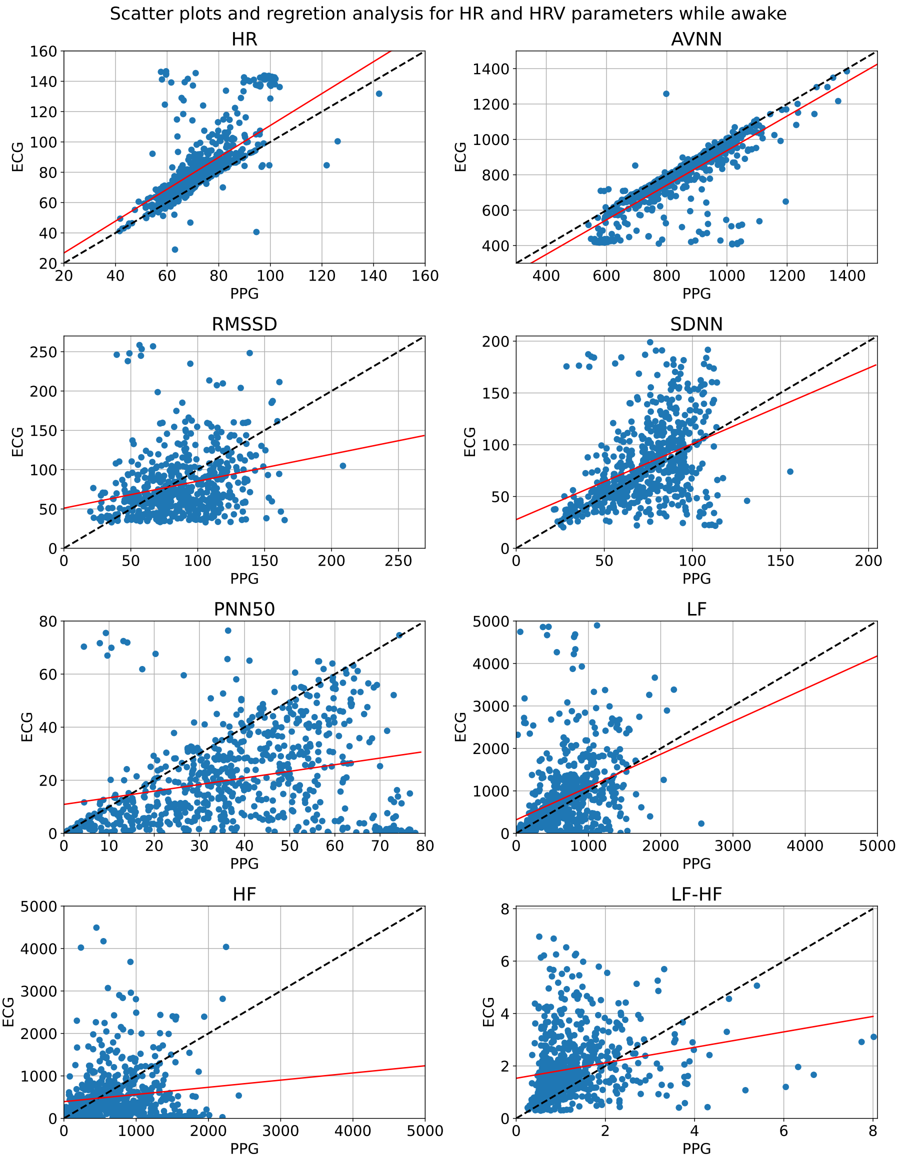


Figure 16. The scatter plots and regression analysis of the HR and HRV parameters collected from the Samsung smartwatch and Shimmer ECG in 5-minute segments when awake. The regression lines and ideal lines are indicated in red and black, respectively. [100]

other parameters (i.e., HR, SDNN, LF, and LF/HF).

The results show that during sleep, the smartwatch has high accuracy regarding HR, AVNN, and pNN50 and acceptable accuracy for RMSSD, SDNN, LF, and HF. However, during waking hours, only AVNN and HR values extracted from the smartwatch have satisfactory accuracy. Therefore, we need to improve the signal

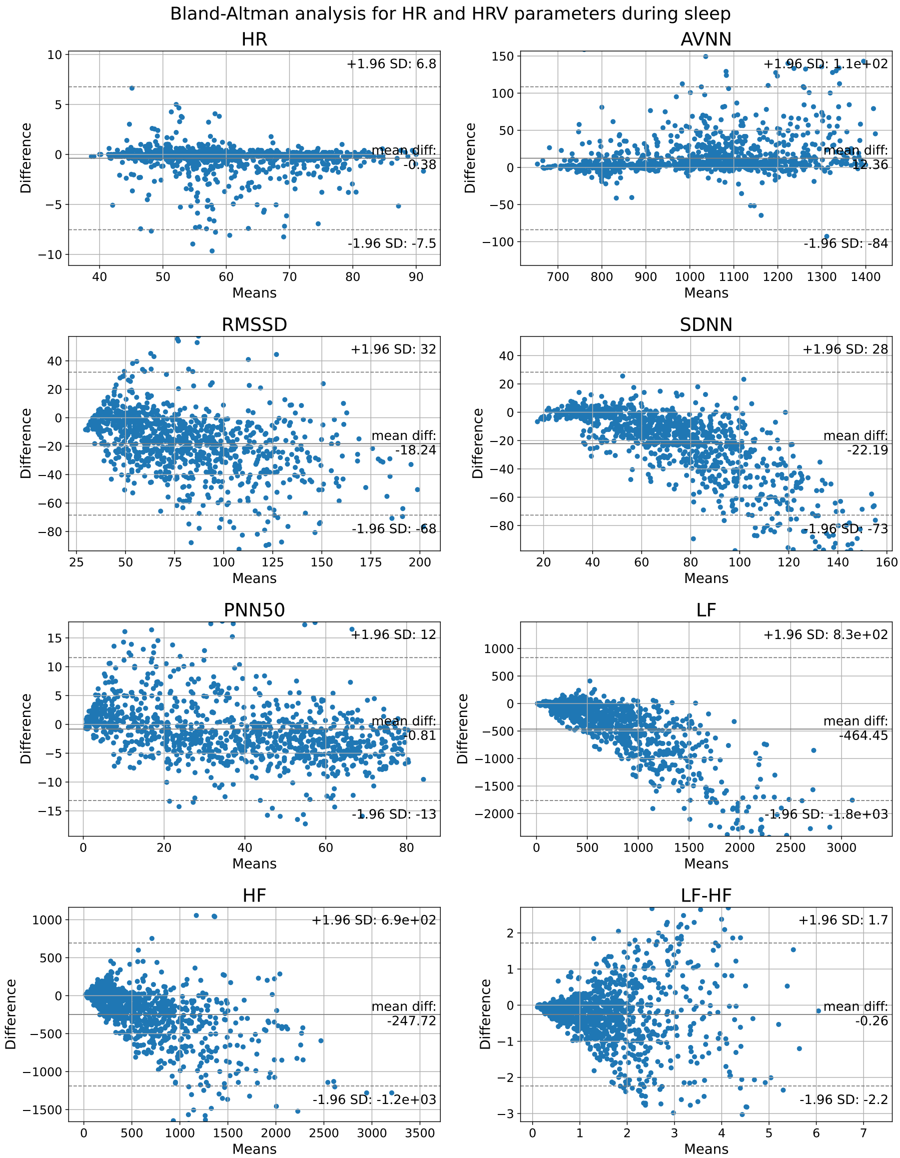


Figure 17. Bland-Altman plots of the HR and HRV parameters in 5-minute segments obtained by the smartwatch and Shimmer3 during sleep [100]

quality by using noise cancellation techniques [105] or quality assessment methods [106; 107] to discard the noisy part of the signals and only use the reliable part of signals to extract HRV parameters accurately. In the following section, we introduce a deep learning-based quality assessment method to distinguish the reliable and unreliable segments of the PPG signals compared with the ECG gold standard, which can be used to improve the accuracy of extracted HR and HRV parameters.

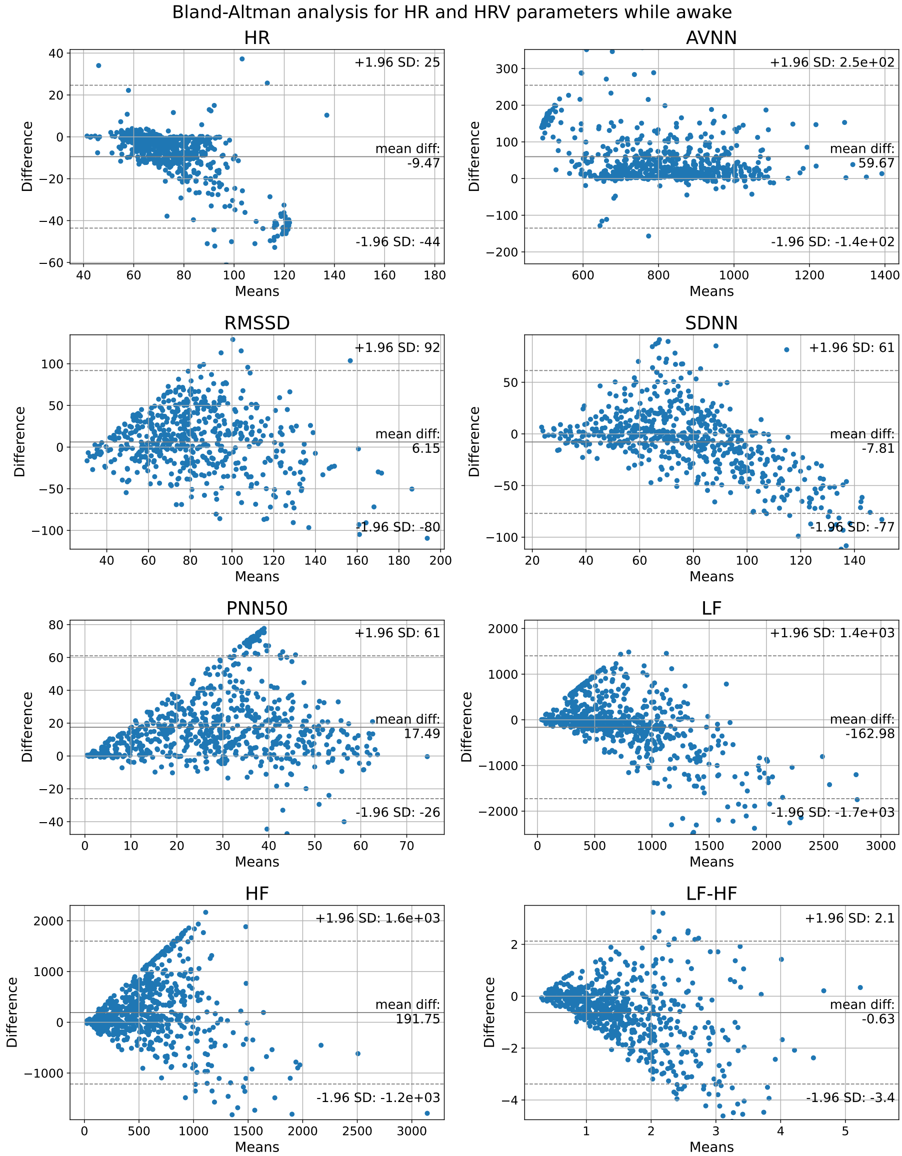


Figure 18. Bland-Altman plots of the HR and HRV parameters in 5-minute segments obtained by smartwatch and Shimmer3 during awake [100]

4.3 A CNN-Based PPG Quality Assessment Approach for HR and HRV Parameters

In this section, we propose CNN-based PPG quality assessment methods based on extracted HR and HRV parameters. One 1-dimensional (1D) CNN and three 2-dimensional (2D) CNN models are proposed for each HRV parameter. The proposed models were evaluated using the data described in the previous section (see Section 4.2.2 and 4.2.3).

In the following, we first briefly explore the previous works in PPG quality assessment methods. Then, we describe the data collection and data analysis. After that, we introduce our proposed deep learning-based PPG quality assessment methods for HR and HRV parameters. The best method was selected for HR and each HRV parameter based on the performance. Finally, we compare the performance of the best proposed methods with the state-of-the-art PPG quality assessment methods. The results show that the proposed methods outperform the other methods for HR and HRV parameters.

4.3.1 Related Works

Various studies have proposed PPG quality assessment methods or PPG quality indicators to distinguish reliable and unreliable segments of PPG signals. Several PPG quality indicators based on the morphology of the signal, including baseline wandering, skewness, and kurtosis, were used to estimate the quality of the PPG signals [106; 108; 109].

Rule-based and template-matching methods have also been proposed to identify low-quality segments of PPG signals [110; 111; 112; 113; 114]. These methods use hierarchical rules or the similarity of the current segment of the signal with template signals based on morphological features and predefined thresholds.

Moreover, several conventional machine-learning methods, including both supervised and unsupervised methods, were used for PPG quality assessment. Several traditional supervised methods such as decision tree [115; 116], random forest [117], support vector machine (SVM) [118; 119; 116], K-nearest neighbors (KNN) [116], and neural network [120] were developed for PPG quality assessment considering the shape, and time and frequency domain parameters of the signals.

In addition, several deep learning-based PPG quality assessment methods have recently been proposed, including real-time PPG quality assessment based on HR value [76], 1D and 2D deep learning-based quality assessment for participants with atrial fibrillation [121], a CNN-based method called DeepBeat [122], 1D CNN-based quality assessment [123], and 2D CNN-based model in [124]. The deep learning-based methods extract features automatically. However, even in these methods, the labeling was performed based on HR and morphological features. In addition, most of the PPG quality assessment methods were evaluated based on the collected data in predefined lab settings with limited noise or with a small number of participants. Table 3 summarizes the PPG quality assessment methods and their features.

	Reference	Features	Method	Annotation	Source code Availability
	Proposed method	Automatic feature extraction	1D CNN/ 2D CNN	Automatic labeling based on HR and HRV parameters	✓
Rule based Methods	Orphanidou et al [110]	Extracted HR and morphological features	Threshold based rules	Manual based on the signal shape	×
	Reddy et al [111]	Predictor Coefficient	Hierarchical decision rules	”	×
	Tyapochkin et al [112]	Statistical parameters of IBIs	Predefined rules	”	×
	Vadrevu et al [125]	Amplitude and time-series features	Hierarchical decision rules	”	×
Supervised methods	Alam et al [117]	Morphological features and HR value	Random forest	Manual based on the signal shape and HR values	×
	Zhang et al [119]	Frequency domain and time series characteristics	SVM	Manual based on the signal shape	×
	Preira et al [118]	Frequency-domain, time-domain, and non-linear features	SVM	”	×
	Preira et al [116]	Frequency-domain, and time-domain features	SVM	”	×
Unsupervised methods	Mahmoudzadeh et al [126]	Statistical features	Elliptical envelope	”	✓
	Roy et al [127]	Entropy and signal complexity features	Self-organizing map	”	×
Deep learning methods	Preira et al [121]	Automatic feature extraction	ResNet18	”	×
	Soto et al [122]	”	Multi-task CNN (pre-training with CDAE)	”	×
	Goh et al [123]	”	1D CNN	”	×
	Roh et al [124]	”	2D CNN	”	×
	Naeini et al [44]	”	1D CNN	Automatic labeling based on HR	×

Table 3. Comparing PPG quality assessment methods [84]

To address previous works' limitations, we propose PPG quality assessment methods for HR and each HRV parameter. Moreover, the methods were evaluated using data collected in everyday life settings. Thus, the model can be better generalized for data in different conditions. In addition, we proposed automatic labeling of the data based on HR and HRV parameters using the gold standard baseline.

4.3.2 Data Collection and Data Analysis

The data described in Sections 4.2.2 and 4.2.3 were used to evaluate the proposed methods. The 210 hours of simultaneous ECG and PPG signals collected from 36 subjects were used to evaluate the proposed method.

We used the same steps as the Section 4.2 for data analysis and extracting HRV parameters (see Section 4.2.4). However, here, different peak detection methods were used, and HR, AVNN, RMSSD, SDNN, and LF/HF HRV parameters were extracted. Then, the extracted parameters from ECG and PPG signals were used for labeling. Here, we first explain the peak detection methods. Then, the automatic labeling will be described.

Peak Detection

We used the deep learning-based method proposed in [128] for ECG peak detection. This method uses Long Short-Term Memory (LSTM) architecture to find the location of the peaks. Then it removes the false peaks by a peak-to-peak distance-based anomaly detection method. This method was selected because it performs better than traditional methods such as Hamilton [129] and Pan-Tompkins [130] (see [128] for more details).

For PPG peak detection, the method Van Gent et al. [131] implemented in the HeartPy package in Python was used. This method uses moving average, adaptive threshold, and outlier detection to detect real peaks in PPG signals. This method also has acceptable accuracy compared with traditional methods [131].

Automatic Labeling

We used the HRV features extracted from each 5-minute segment of PPG signals for labeling. We compared each feature (e.g., HR, AVNN, RMSSD, SDNN, and LF/HF) from one PPG segment with the same feature extracted from the corresponding ECG segment. If the difference is less than a predefined threshold, then the signal is reliable for that HRV parameter; otherwise, it is unreliable with regards to that HRV parameter. The result of this step was five labels. The threshold for each HRV parameter was selected based on the normal range of the parameter as described in [132]. The threshold can be changed according to the acceptable accuracy for the desired application.

4.3.3 Proposed PPG Quality Assessment Approaches

We present 1D and 2D CNN-based deep learning approaches for PPG quality assessments. CNN-based architectures automatically identify the significant features with low-to-zero preprocessing of the input data [133]. CNN also reduces the number of parameters by sharing the parameters between layers, which speeds up the network and training [134].

The architecture of our proposed CNN methods is illustrated in Figure 19. The proposed 1D CNN method comprised two convolution layers, as shown in Figure 19. A batch normalization layer follows each convolutional layer to prevent overfitting of the model. Then, we used a max pooling layer to reduce the dimensionality. Finally, we added a flattened layer, and a sigmoid function provided the classification results. The kernel size used in this model was 1*3, which is common. We used 32 filters in the first and 64 filters in the second convolutional layer. The optimization function was stochastic gradient descent with a learning rate of 0.00001, and the loss function was binary cross entropy.

Moreover, we used pretrained 2D CNN models VGG16 [135], ResNet50 [136], and MobileNetV2 [137], which have shown good performance in similar applications, and we tuned them for our purpose. To make the models work with 2D input (images), we converted PPG signals to images using the Garmin angular field (GAF) method [138]. The GAF preserves the temporal dependencies in PPG signals while transforming them into images. We used the transformed PPG image along with the corresponding label as an input for the models.

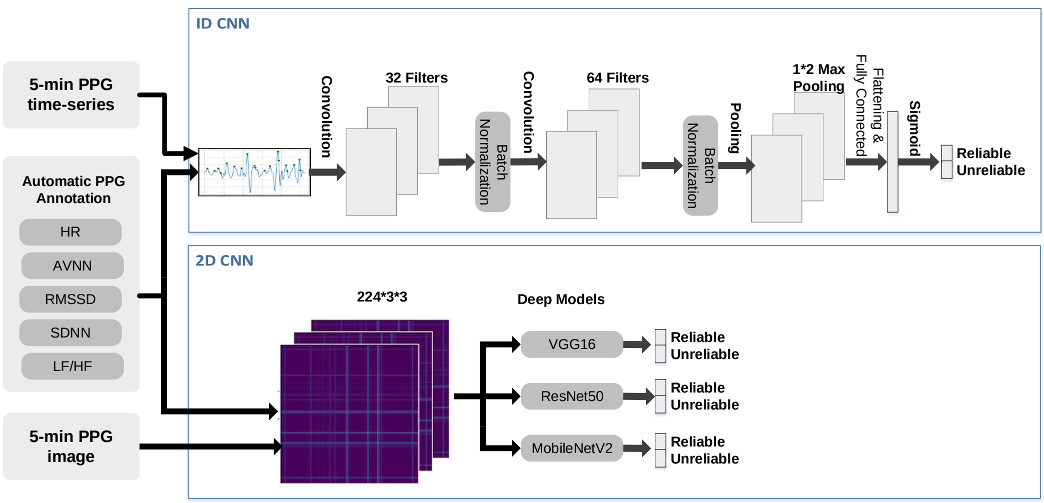


Figure 19. Overview of our CNN-based PPG quality assessment models [84]

4.3.4 Model Implementation and Evaluation

The Keras Sequential API, which implements Tensorflow in Python, was used to implement and train the presented models [139]. We used Adam optimizer and binary cross-entropy as optimizer and loss functions for our models. Moreover, the accuracy, F1 score, and area under the curve (AUC) were used to evaluate the models.

The proposed models were trained separately for HR, AVNN, RMSSD, SDNN, and LF/HF. Each model used the corresponding label generated from our automatic annotation. Therefore, five models were trained for each method.

We first trained and validated the proposed models. Then, the model with the best performance was chosen for comparison with state-of-the-art methods. We used 80%, 20%, and 20% of the collected data for training, validation, and test sets, respectively. The distribution of class label in dataset is shown in table 4.

Table 4. Distribution of class labels for each parameter [84]

parameters	Train+ validation		Test	
	Reliable	Unreliable	Reliable	Unreliable
HR	46175	12413	11544	3104
AVNN	50925	7663	12732	1916
RMSSD	16327	42261	4082	10566
SDNN	25823	32766	6456	8192
LF/HF	42388	16200	10597	4050

Table 5 shows the performance of the proposed models on the validation set. As shown in the table 5, the 1D CNN models outperform 2D CNN models for all HR and HRV parameters. Therefore, we used the 1D models for HR and HRV parameters and compared the 1D models with current methods. LF/HF achieved the highest performance, whereas RMSSD had the lowest performance for all models.

Table 5. Validation Set performance results of different CNN models for various HR-HRV features [84]

Model	1D_CNN			MobileNet			ResNet50			VGG16		
Metric	ACC	F1	AUC	ACC	F1	AUC	ACC	F1	AUC	ACC	F1	AUC
HR	**95.63**	**96.11**	**96.21**	94.58	93.93	94.63	92.49	92.44	93.52	92.38	94.42	94.87
AVNN	**96.71**	**97.68**	**97.71**	95.68	95.95	96.93	90.43	90.22	91.32	93.36	94.29	94.85
RMSSD	**91.42**	**91.48**	**91.69**	89.68	89.44	89.46	86.47	85.81	87.17	85.72	85.09	85.79
SDNN	**96.01**	**96.97**	**97.09**	92.66	93.91	93.66	92.52	92.12	93.66	93.42	93.82	93.99
LF/HF	**97.71**	**97.71**	**97.71**	91.92	91.95	92.93	90.22	90.22	91.31	94.36	94.29	93.99

Table 6. Performance of the proposed and state-of-the-art models on Test sets [84]

Label	**HR**			**AVNN**			**RMSSD**			**SDNN**			**LF/HF**		
Metric	**ACC**	**F1**	**AUC**	**ACC**	**F1**	**AUC**	**ACC**	**F1**	**AUC**	**ACC**	**F1**	**AUC**	**ACC**	**F1**	**AUC**
Rule Based[125]	61.19	77.28	67.80	63.08	72.44	68.35	52.13	59.95	61.81	63.08	75.44	71.35	67.65	76.15	65.70
KNN[118]	87.56	92.20	79.66	92.47	95.71	80.69	**93.70**	88.62	92.01	85.78	83.60	85.40	79.56	86.23	72.38
SVM[118]	78.70	88.08	50.00	86.84	92.95	50.00	89.54	79.52	84.46	78.39	75.84	78.24	72.42	84.00	50.00
DT[118]	78.70	88.08	50.00	86.84	92.95	50.00	89.54	79.52	84.46	78.39	75.84	78.24	72.42	84.00	50.00
Elliptical Envelope[126]	71.54	81.94	57.39	78.89	87.85	53.64	67.35	41.28	59.33	61.76	56.54	61.19	62.54	74.14	53.10
Xception[121]	89.30	90.28	85.80	89.54	90.44	85.35	81.03	70.95	77.81	88.54	90.44	85.35	85.09	88.15	84.70
Proposed Method	**95.64**	**96.12**	**97.71**	**96.71**	**97.68**	**97.71**	91.43	**91.48**	**93.59**	**94.02**	**94.98**	**95.02**	**94.82**	**95.22**	**95.31**

4.3.5 Comparison with the State-of-the-Art Models

The evaluation results showed that the proposed 1D CNN model outperformed other deep learning-based models for HR and all HRV features. Thus, we compared the 1D CNN model with various types of PPG quality assessment methods, including a rule-based method, several supervised machine-learning models, an unsupervised machine-learning model, and a deep learning-based model. For the rule-based method, we selected the hierarchical rule-based model introduced in [125]. For supervised machine-learning methods, we selected SVM, KNN, and decision tree as described in [116]. The elliptical envelope was chosen as an unsupervised learning model [126]. We also selected Xception [121] as a deep learning-based model.

The performance of our 1D method in comparison with the selected state-of-the-art PPG quality assessment method is shown in Table 6. For each HRV parameter, the corresponding label was used in the classification of the PPG signals and evaluation of the performance of the methods. As shown in Table 6, the proposed 1D CNN method, in general, had better performance than the other methods had. KNN had slightly better accuracy for RMSSD than the proposed 1D CNN method had. However, for other performance metrics and for other HRV parameters, the proposed 1D CNN method performed better. Moreover, Xception had better overall performance than the other selected methods had. After Xception, supervised machine-learning methods had good performance. KNN has better performance for AVNN and RMSSD than Xception had. Unsupervised elliptic envelope and rule-based methods had the lowest performance.

5 IoT-Based Maternal Monitoring During Pregnancy and Postpartum: Analyzing the Trends of HR and HRV Parameters

Chapter 3 presented a long-term IoT-based maternal monitoring for remote health monitoring during pregnancy and postpartum. Chapter 4 investigated the accuracy of collected HR and HRV parameters against the ECG gold standard in everyday life settings. Moreover, Chapter 4 provided a quality assessment method to improve the quality of collected HR and HRV parameters by discarding noisy parts of the data.

This chapter uses the presented IoT-based system to monitor physiological parameters during pregnancy and postpartum. Therefore, the system was used to collect data from pregnant women. The data were then used to investigate HR and HRV changes during pregnancy and postpartum. Hence, this chapter aims to provide a better understanding of autonomous nervous system alteration during pregnancy and postpartum. Here, we first describe our data collection using our IoT-based maternal monitoring system, where physiological data of 62 pregnant women were continuously collected during pregnancy and postpartum. Then, using the collected data, we investigate the trends in nighttime HR and HRV during the second and third trimesters and the postpartum period.

5.1 Data Collection

The data were collected by the IoT system introduced in Chapter 3. The participants used a smartwatch and our customized cross-platform mobile application during the study. They also used a blood pressure device to measure their blood pressure once a week. The smartwatch collected PPG signals and sleep and activity parameters. Moreover, the mobile application collected responses to our questionnaires and background information.

In this chapter, we used the nighttime PPG signal collected by the smartwatch from the participants to monitor HRV during pregnancy and postpartum. The PPG signals collected from gestational week 16 until 3 months postpartum were used in this chapter. Moreover, we used background information such as BMI, age, education level, and delivery- and infant-related information collected by the mobile application in our analysis.

5.1.1 Participants and Setup

Two groups of pregnant women (high-risk and low-risk) were recruited in this study. The recruiting was performed in Southwest Finland through advertisements in maternity clinics and on social media. The inclusion criteria were as follow: (a) a singleton pregnancy, (b) ability to understand the Finnish language, (c) possession of an android or iOS smartphone, (d) 12–15 gestational weeks of pregnancy, (e) age 18 years or older, and (f) willingness to use the provided smartwatch and our customized mobile application from recruitment to 3 months postpartum.

The high-risk pregnancy group had histories of preterm births (gestational weeks 22–36) or late miscarriages (gestational weeks 12–21) as described in Section 3.4. The low-risk pregnancy group had no previous miscarriages or preterm births and had histories of full-term births (gestational weeks 37–42).

Interested participants contacted the researcher via email and arranged a face-to-face meeting. In the meeting, the researcher explained the procedures and details of the study. After obtaining written informed consent from the participant, a smartwatch and a blood pressure device was delivered to the participant. Moreover, our mobile application was installed on her smartphone. In the high-risk pregnancy group, 32 pregnant women were recruited from January to December 2019, but four participants withdrew from the study, resulting in 28 participants in this group. In the low-risk pregnancy group, 30 participants were recruited from October 2019 to March 2020.

To investigate the trend of HR and HRV, we used the PPG signals collected from our participants. We combined the data from the low-risk pregnancy group with the high-risk pregnancy group because no significant difference existed between the HRV trends of the two groups. Therefore, the data of 58 pregnant women were included in our analysis.

5.2 HR and HRV Trends During Pregnancy and Postpartum

Studies have shown that HR increases and HRV parameters normally decrease during pregnancy [21; 23; 24; 25]. At the same time, variations in HRV parameters can be a sign of physical or mental health complications during pregnancy. For example, higher LF/HF in early pregnancy compared with a normal pregnancy may indicate hypertension [140]. Pregnant women with pre-eclampsia have lower LF and higher LF/HF than normal pregnant women have [141; 142]. Moreover, women with normal pregnancies have higher time-domain parameters compared with depressed pregnant women [143]. Anxiety or induced stress during pregnancy could also cause a decrease in HF [144]. Moreover, mindful pregnant women who can manage their stress experience less reduction in RMSSD and HF during pregnancy [145]. Therefore, it is necessary to investigate normal HRV variation during pregnancy to distinguish normal changes from complication-related changes in HRV. This may help in the early detection of health issues during pregnancy and, subsequently, the improvement of the mother and fetus's health. It also should be noted that HRV interpretation is challenging because HRV behavior differs between people [40].

Many studies have investigated HRV during pregnancy. Table 7 summarizes works on HRV trends during pregnancy and postpartum. As shown in Table 7, previous works used ECG signals (see Section 2.2.1) to measure HRV. Most of the studies measured HRV once from pregnant women at several pregnancy weeks or during labor, and they have one measurement from nonpregnant women [146; 147; 148; 149; 150]. These studies evaluated HRV changes by comparing HRV from different women. Although these studies provided normal ranges of HRV parameters and their changes during pregnancy, they could not consider individual variation in HRV parameters [40].

Table 7. Summary of research on HR and HRv trends during pregnancy and postpartum

Study	Results	Duration of study and frequency of recording	Number of participants
Voss 2000 [149]	No significant changes in HRV parameters	One recording during the second half of pregnancy (Gestational week 21-40)	27 women with normal pregnancy 14 nonpregnant women
Stein 1999 [151]	HRV declined during pregnancy	One time before pregnancy, and 4 time during pregnancy (week 6, 10, 18, and 34)	8 pregnant 12 nonpregnant women
Baumert 2012 [152]	AVNN: decreased significantly SDNN: no significant changes	Once per month during weeks 20 - 40	32 pregnant women
Garg 2020 [153]	SDNN and HF: decreased significantly LF and LF/HF: increased significantly	Once per trimester (gestational weeks 11-13, 20-22, and 30-32)	66 pregnant women
Walther 2005 [154]	HR and LF/HF: increased HF: decreased	Once every four weeks during the second half of pregnancy	16 pregnant women with chronic hypertension 35 healthy pregnant women
Moertl 2009 [155]	HR: slightly increased Frequency-domain HRV: no significant changes	Once per gestational weeks 10-13, 15-18, 20-22, and >30 (During pregnancy)	20 healthy pregnant woman
Gandhi 2014 [156]	LF, HF, SDNN and RMSSD: decreased significantly HR and LF/HF:increased significantly	During pregnancy Once at 1st trimester (weeks 6-12), and one at 3rd trimester (Weeks 25-36)	30 pregnant women 30 non-pregnant women
Heiskanen 2008 [25]	HR: No significant changes LF and HF: significantly lower during the 3rd trimester compared to postpartum	Once at 3rd trimester and once at postpartum	28 pregnant women

Other studies have few ECG recordings from the same pregnant women ranging from per month to per trimester [25; 154; 155; 152; 153; 156]. These studies used short-term ECG recordings ranging from 10 to 30 minutes while resting in laboratory settings. The studies are limited because they have few short-term ECG recordings

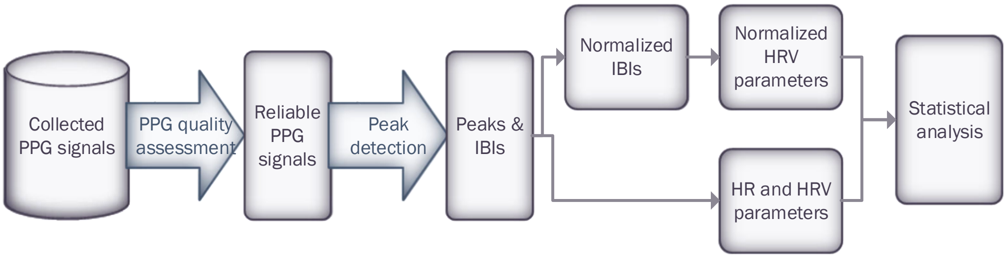


Figure 20. HR and HRV parameters analysis pipeline [157]

from pregnant women that could not accurately reflect the changes during pregnancy. Moreover, the recordings are restricted to predefined positions in laboratory settings. Only Stein et al. [151] performed four 24-hour ECG recordings during pregnancy in everyday life settings. However, this work still lacks continuous HRV measurement. Continuous HRV measurement during pregnancy and the postpartum period provides accurate and reliable information about HRV trends and patterns of HRV changes. Therefore, in this case study, we performed a continuous HRV measurement starting from the second trimester to 3 months postpartum in everyday life settings. To the best of our knowledge, this is the first study that has continuously measured PPG signals from pregnant women to investigate HRV trends. In the following sections, we will explain the method and the results of collecting and analyzing the trend of HRV parameters collected continuously during pregnancy and postpartum.

5.2.1 HR and HRV Parameters Analysis

An overview of the HR and HRV parameters analysis pipeline, which was implemented in our cloud server, is illustrated in Figure 20. As shown in the figure, we first used a PPG quality assessment method to extract reliable signals from the collected data. Then, we used the peak detection method to detect peaks and extract IBIs. We then normalized the extracted IBIs. In the following step, we used IBIs and normalized IBI to extract HR and HRV and normalized HRV parameters. Finally, we used statistical analysis (i.e., HLM models) to investigate the trend of HR and HRV and normalized HRV parameters during pregnancy and the postpartum period.

Reliable Signal Extraction

As mentioned earlier, PPG is a convenient, noninvasive optical method to measure HR and HRV parameters. However, PPG is prone to noise such as ambient light or motion artifacts when participants engage in their physical activity. The inevitable noise affects the quality of the signals negatively [106]. The low-quality PPG signals could result in inaccurate extracted parameters (e.g., HRV parameters [106]). Therefore, we employed a PPG quality assessment method to identify and discard unreliable segments of PPG signals. For this purpose, an SVM classifier was utilized to differentiate between reliable and unreliable signals. The classifier was trained using morphological features extracted from PPG signals, including skewness, kurtosis, approximate entropy, Shannon entropy, and spectral entropy, as described in [126]. Subsequently, we applied this SVM classifier to detect and discard unreliable 5-minute segments from the collected PPG signals.

Peak Detection and IBI Extraction

In this step, we first enhanced the reliable PPG signals by filtering the noise that was outside the human HR range. Therefore, we used a bandpass filter with 0.7 Hz and 3.5 Hz cut-off frequencies. Then, we used a moving average-based peak detection method as described in [158]. The method included an adaptive threshold based on the morphology and amplitude of PPG signals. After detecting the peaks, the IBIs were calculated as the interval between two consecutive peaks. In the error detection phase, too-large or too-small IBIs compared to the average IBIs of the segments were discarded. The method was implemented in the HeartPy library in Python [159].

Parameter Normalization

Changes in HRV parameters are caused by variation in HR or alteration in average HR [160]. Therefore, we must remove the effect of normal HR increase during pregnancy [151; 21] on HRV parameters to investigate the trend of HR variation during pregnancy. For this purpose, we computed normalized IBIs by dividing the IBIs by the average IBIs in each 5-minute window of reliable signals [161].

HR and HRV Extraction

We used short-term HRV analysis to extract HR, AVNN, RMSSD, SDNN, LF, HF, and LF/HF from IBIs as described in Section 2.3. The HRV parameters were chosen because a previous study [51] showed that they can be reliably extracted at the frequency at which we collected PPG signals (e.g., 20 Hz). Moreover, we extracted nRMSSD, nSDNN, nLF, nHF, and nLF/nHF, which represent normalized RMSSD, normalized SDNN, normalized LF, normalized HF, and normalized LF to normalized HF ratio from normalized IBIs. Table 8 shows the normalized HRV parameters and their definitions.

Table 8. Normalized HRV parameters definitions [157]

	Parameters	Unit	Description
Time-domain	nSDNN	ms	Standard deviation of normalized IBIs
	nRMSSD	ms	Square root of the mean of the sum of the squares of differences between adjacent normalized IBIs
Frequency-domain	nLF	ms2	Power in low-frequency range from normalized IBIs (0.04- 0.15 Hz)
	nHF	ms2	Power in high-frequency range from normalized IBIs (0.15- 0.4 Hz)
	nLF/nHF	-	Ratio of nLF to nHF

Statistical Analysis

We used the HLM model to investigate the HR and HRV trends during pregnancy and the postpartum period. The HLM model is a multilevel statistical analysis method that is used widely in longitudinal analysis. The model can analyze the trends in between- and within-person variances while considering the correlation of data in measurements from each individual [162].

We investigated the HR and HRV trends in three time periods; that is, the second trimester (16–28 weeks of gestation), the third trimester (29–40 weeks of gestation), and the postpartum period (12 weeks after delivery). Then, we compared the trends in each period with other periods. In our analysis, we used days as the independent variable and added age, education level, and BMI before pregnancy as controlling factors.

We included the second trimester and the postpartum data from all participants in our analysis. However, we removed seven participants who had preterm births from the third trimester data. Therefore, the data of 51 participants were included in the third trimester analysis. The data were analyzed using the statsmodels library in Python [104].

5.2.2 Results and Discussion

Figures 21 and 22 represent the weekly mean of HR, time-domain, and frequency-domain HRV parameters averaged from all participants during pregnancy and the 3-month postpartum period. In addition, trends (slope), and average initial value (intercept) of HR and HRV parameters are shown in Table 9 and Table 10.

As indicated in Table 9 and Table 10, during the second trimester, HR increased significantly, whereas the AVNN, SDNN, nSDNN, RMSSD, nRMSSD LF, HF, and nHF decreased significantly. In addition, nLF/nHF increased significantly during the second trimester. During the third trimester, HR decreased significantly, whereas AVNN, SDNN, nSDNN, RMSSD, and HF increased significantly.

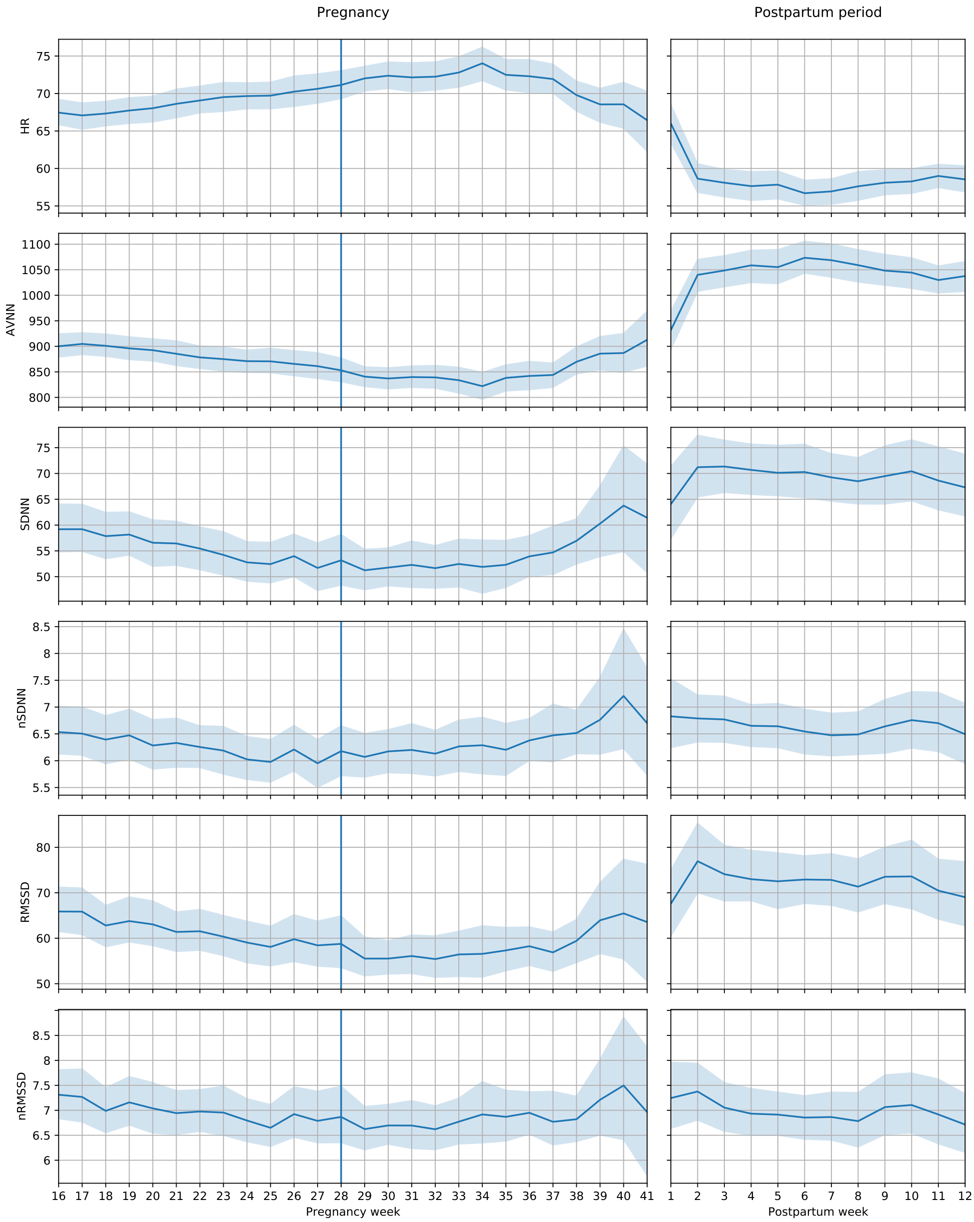


Figure 21. Weekly mean and 95% CI of HR and time-domain HRV parameters during pregnancy and the postpartum period. (The vertical line separates the second and third trimesters) [157]

During pregnancy, beginning from gestational week 16, HLM showed that HR increased significantly, whereas HRV parameters AVNN, SDNN, RMSSD, LF, and HF decreased significantly. However, analysis shows that starting from gestational week 35, HR began to decrease, and the mentioned HRV parameters started to in-

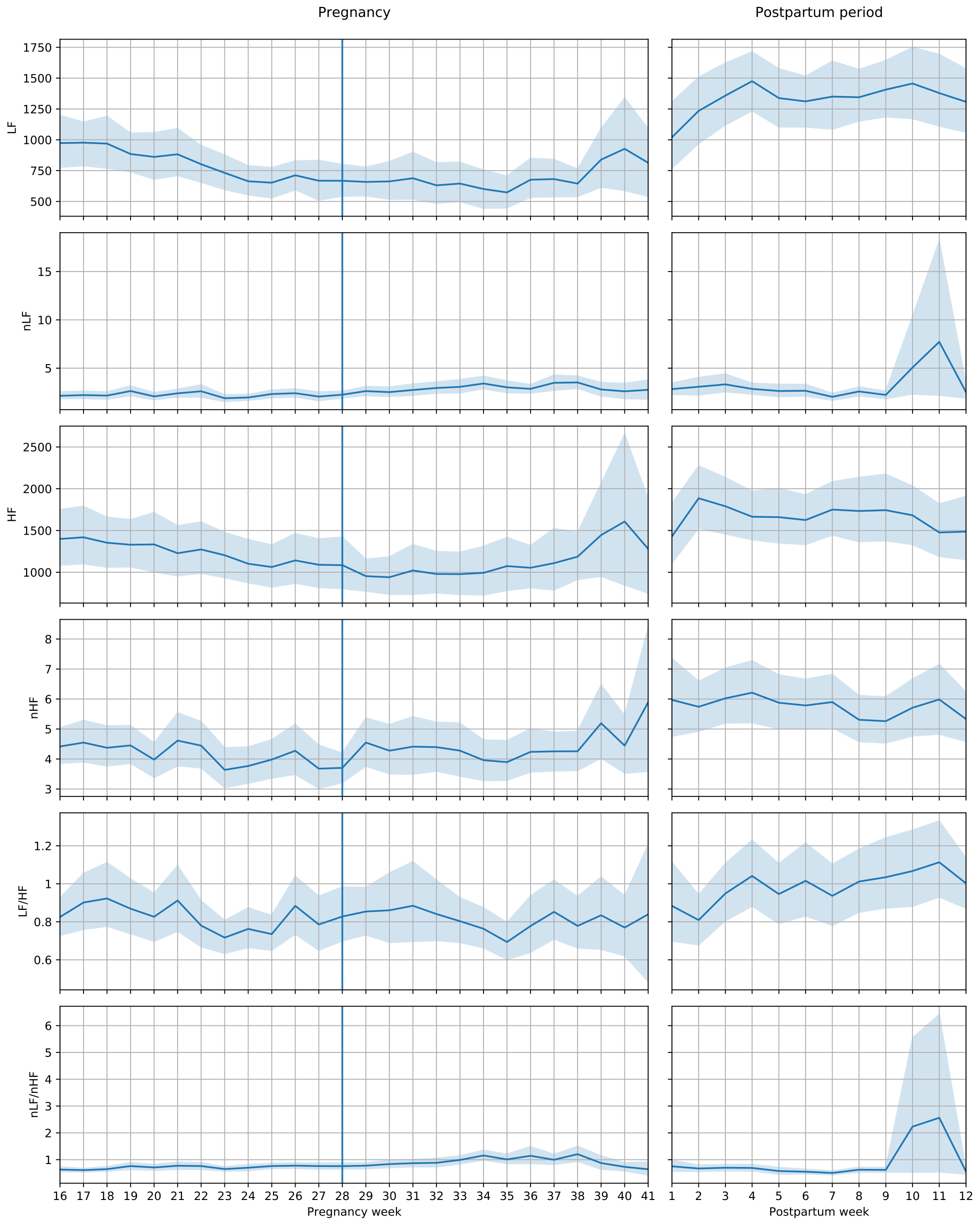


Figure 22. Weekly mean and 95% CI of frequency-domain HRV parameters during pregnancy and the postpartum period. (The vertical line separates the second and third trimesters) [157]

crease. However, HR and HRV parameters did not reach their initial values (i.e., the value at pregnancy week 16). In the postpartum period, most parameters were stable except nRMSSD, which decreased slightly, and LF/HF, which increased slightly. Previous works have also shown an increase in HR during pregnancy [21; 154] and

Table 9. Trends of HR and time-domain HRV parameters during the second trimester, the third trimester, and the postpartum period [157]

		HR	AVNN	SDNN	nSDNN	RMSSD	nRMSSD
Second trimester	Intercept (P-value)	62.736 (P<.001)	916.443 (P<.001)	84.023 (P<.001)	9.079 (P<.001)	89.293 (P<.001)	9.986 (P<.001)
	Slope (P-value)	0.045 (P<.001)	-0.585 (P<.001)	-0.082 (P<.001)	-0.006 (P<.001)	-0.103 (P<.001)	-0.007 (P<.001)
Third trimester	Intercept (P-value)	81.324 (P<.001)	708.181 (P<.001)	69.787 (P<.001)	9.237 (P<.001)	70.275 (P<.001)	8.366 (P<.001)
	Slope (P-value)	-0.025 (0.006)	0.345 (0.002)	0.084 (P<.001)	0.007 (P<.001)	0.071 (P<.001)	0.006 (0.971)
Postpartum period	Intercept (P-value)	47.237 (P<.001)	1216.255 (P<.001)	115.321 (P<.001)	9.481 (P<.001)	135.233 (P<.001)	11.620 (P<.001)
	Slope (P-value)	-0.009 (0.366)	0.130 (0.464)	0.001 (0.954)	-0.001 (0.689)	-0.037 (0.115)	-0.004 (0.012)

a decrease in HRV parameters during the course of pregnancy [23; 24; 25].

Table 10. Trends of frequency-domain HRV parameters during the second trimester, the third trimester, and the postpartum period [157]

		LF	nLF	HF	nHF	LF/HF	nLF/nHF
Second trimester	Intercept (P-value)	1045.893 (P<.001)	2.422 (P<.001)	2990.343 (P<.001)	4.727 (P<.001)	-0.248 (P<.001)	0.565 (0.002)
	Slope (P-value)	-3.109 (P<.001)	0.001 (0.718)	-4.224 (P<.001)	-0.007 (0.003)	-0.061 (0.103)	0.001 (0.007)
Third trimester	Intercept (P-value)	1008.979 (0.026)	4.248 (0.001)	1743.362 (0.010)	6.166 (0.001)	0.67 (0.839)	0.995 (0.003)
	Slope (P-value)	0.424 (0.443)	0.006 (0.093)	2.767 (0.007)	0.004 (0.209)	-0.097 (0.113)	0.001 (0.276)
Postpartum period	Intercept (P-value)	2124.653 (0.002)	2.486 (0.087)	4969.652 (P<.001)	6.670 (0.001)	-0.397 (0.269)	0.416 (0.022)
	Slope (P-value)	2.415 (0.053)	-0.005 (0.402)	-0.682 (0.626)	-0.001 (0.769)	0.234 (0.004)	-0.002 (0.050)

Association Between BMI, Age, and Education with HRV During Pregnancy and Postpartum

We also investigated the association between BMI before pregnancy, age, and education level with the HRV trends during pregnancy and the postpartum periods. We added these factors as independent variables in our HLM models. Our models indicated that BMI before pregnancy is not significantly associated with changes in HRV during pregnancy and the postpartum period. Moreover, the results showed that age is negatively associated with nSDNN, nRMSSD, and HF in the second trimester. However, in the third trimester and in the postpartum period, age is positively associated with SDNN, nSDNN, RMSSD, nRMSSD, HF, and LF/HF. Studies have also illustrated that HRV normally decreases when people age [40].

Our results showed a positive correlation between education level and SDNN, nSDNN, RMSSD, nRMSSD, and HF during the third trimester. However, education level is not significantly associated with HRV parameters during the second trimester or the postpartum period. Lower HRV levels are associated with higher stress levels [42], and these results may indicate lower stress levels in pregnant women with higher education levels. Cardwell [163] showed that low education level is a predictor of higher stress during pregnancy. Other studies have also shown that people with higher education levels experience lower stress levels compared with less educated people in the same stressful situation [164].

6 Maternal Loneliness Detection Based on Passive Data Sensing Using Our IoT-Based Maternal Monitoring System

In this chapter, we focus on loneliness as an important mental health issue during pregnancy. We develop two predictive models for detecting maternal loneliness using data collected passively by the IoT-based system introduced in Chapter 3. We used the data collected in Chapter 5 from pregnant women during pregnancy and postpartum to train and test the developed model.

6.1 Maternal Loneliness

Loneliness is a negative subjective feeling related to the perception of being alone or isolated or having deficient meaningful relationships [165]. Social loneliness and emotional loneliness are two kinds of loneliness. Social loneliness refers to the lack of desired network or social relationships, and emotional loneliness refers to the lack of intimate and close relationships [166; 167]. Loneliness is a global health issue that considerable parts of the populations in many countries face [168], and it is increasing, especially in the era of social isolation due to the COVID-19 pandemic [169; 170; 171; 172].

Several studies in the literature have investigated the health-related effects of loneliness in different population-based groups. Studies have indicated that loneliness is associated with psychiatric and physiological disorders such as depression [173], anxiety [173], alcohol abuse [174], Alzheimer's disease and cognitive impairment [175], sleep problems [176], hypertension [177], autoimmune disorders [175], obesity [178], and an increased rate of physiological deterioration. Loneliness during adolescence is associated with a worse health condition and is worse in females compared with males [179]. Loneliness can also increase the risk of mortality [180].

Loneliness during pregnancy and the postpartum period is also correlated with various health problems for both the mother and her child. Many studies in different countries showed that maternal loneliness during pregnancy is associated with depression [181; 182; 183; 184; 185; 172]. Other studies have shown the correlation between loneliness and postpartum depression [186; 187]. Moreover, several studies during the COVID-19 pandemic showed the correlation of maternal loneliness with anxiety [188], cognitive distortion [183], psychological distress [189], and increase of perceived stress [181]. Maternal loneliness also has adverse effects on newborn babies, such as increasing the risk of respiratory tract infection [190]. Hence, the early detection of maternal loneliness helps to improve the health and well-being of the mother and her child by preventing the associated health issues through intervention.

Conventionally, loneliness was investigated by self-reported questionnaires [172; 182; 181; 183] and interviews [191]. The subjective standard questionnaires or interviews examined the association between loneliness and health problems such as depression, anxiety, lack of social support, cognitive distortion, and stress. However, these methods are not able to predict loneliness in individuals.

In addition, few studies have taken advantage of the rapid growth of IoT-based systems and wearable devices and used passive sensing for loneliness prediction [192; 193]. Wu et al. [193], investigated the association of momentary loneliness with location and Bluetooth data collected from college students. In another study, Doryab et al. [192] used sleep, activity, location, screen time, call logs, and Bluetooth information collected by activity trackers and smartphones of college students for loneliness prediction. These studies were also restricted because they only considered college students on a campus.

To the best of our knowledge, no study in the literature has predicted maternal loneliness based on objective data collected passively. This case study presents two machine-learning models to predict maternal loneliness using passively collected data. Using such models can help to improve the well-being of the mother and her child with low cost and minimal engagement from mothers. We used a smartwatch to collect objective physiological parameters (HR, HRV, physical activity, and sleep) passively because previous studies have shown the association of these parameters with loneliness [194; 195; 196; 197]. We developed decision tree and gradient boosting models to predict maternal loneliness using the passively collected data. Finally, we investigated the importance of physiological health parameters in each model.

6.2 Setup and dataset Preparation

In this section, we first briefly explain our participants and data collection. Then, we describe our data analysis pipeline, which was used to extract features and create datasets for this study.

6.2.1 Participants

For this study, we used the data collected from pregnant participants described in Section 5.1.1. As mentioned, 62 pregnant women were recruited in total. However, we only included participants in our loneliness prediction case study if they had an acceptable amount of missing data, resulting in 31 participants in this study.

6.2.2 Data Collection

We collected data using the IoT-based maternal monitoring system introduced in Chapter 3. As mentioned in Chapter 3 and Chapter 5, we used a smartwatch and a cross-platform mobile application for data collection. The smartwatch continuously collected HR, HRV, sleep, and physical activity data during pregnancy and 3 months postpartum. In addition, we used the University of California, Los Angeles (UCLA) standard questionnaire to evaluate loneliness. The 12-item Revised UCLA questionnaire was provided to our participants using our customized mobile application. The revised UCLA questionnaire includes six questions regarding social loneliness and six questions regarding emotional loneliness [198]. Participants responded to this questionnaire at week 36 during pregnancy and at 12 weeks after delivery. The background information was also collected by our mobile application.

6.2.3 Data Analysis

We used the data collected by the smartwatch to generate seven datasets. Each data record in our datasets contained the data from 7 days before and the day of responding to the UCLA questionnaire. Seven days was chosen because the UCLA instrument examines a person's feelings during the prior week. We only considered valid days in our analysis, defined as having sleep data and having worn the smartwatch for at least 10 hours while awake. Moreover, data records with less than 4 valid days were discarded due to missing data. Our analysis of the data records comprised the following steps:

1. Feature extraction
2. Labeling
3. dataset generation
4. Missing data imputation
5. Machine-learning models development
6. Important features investigation

Figure 23 summarizes these steps. We describe these steps in the following subsections.

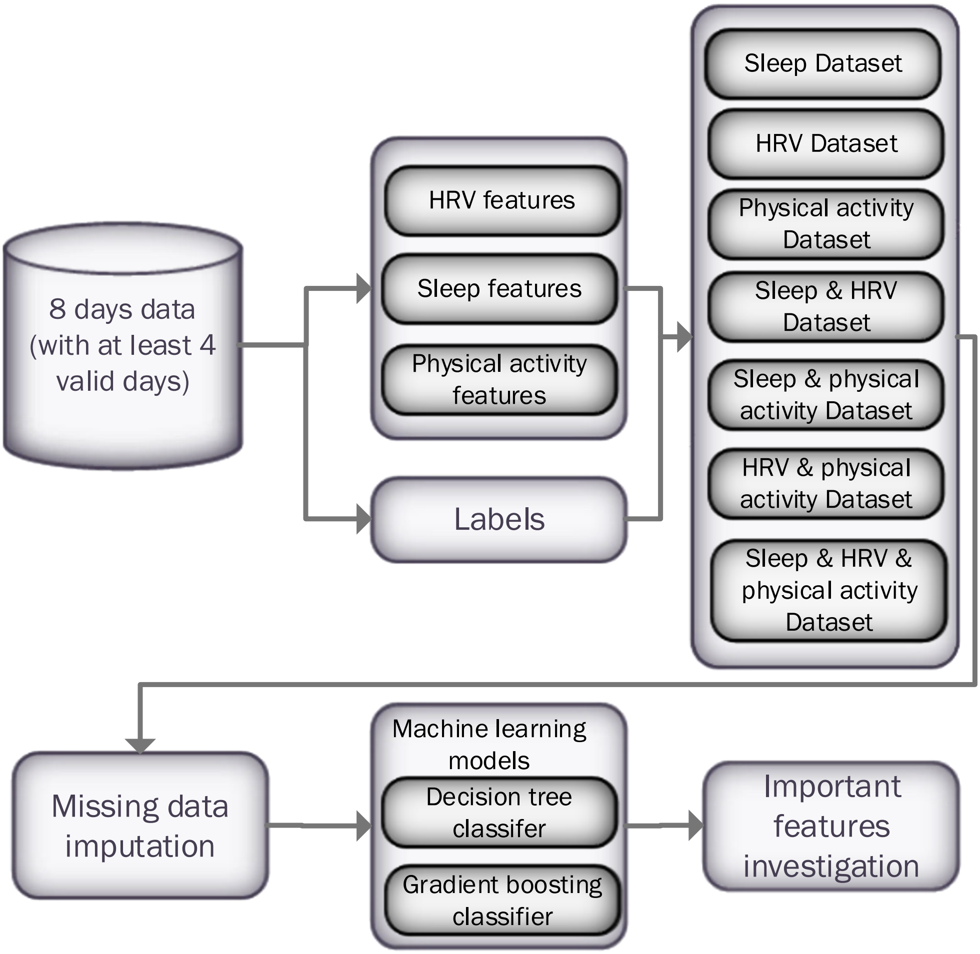


Figure 23. Data analysis pipeline [199]

6.2.4 Feature Extraction

We used the data collected by the smartwatch to extract resting HR and HRV, sleep, and physical activity features. Here, we briefly explain the extracted features:

HR and HRV Features

We used the same pipeline described in Section 5.2.1 to extract HR and HRV parameters. We used resting HR at night and corresponding HRV parameters (i.e., AVNN, SDNN, RMSSD, LF, HF, and LF/HF) for our analysis.

Sleep Features

We extracted total sleep time (TST), wake after sleep onset (WASO), sleep fragmentation, the average intensity of hand movement during sleep, a sleep quality indicator, and a sufficient sleep parameter using the collected data from the watch. We defined the sleep quality indicator as being awake for less than 20 minutes during the night sleep and the sufficient sleep parameter as having TST between 7 and 8.5 hours during the night [200]. Other sleep parameters were defined and calculated as described in [75].

Physical Activity Features

The smartwatch continuously collected physical activity parameters, including step counts, walking steps, running steps, distance, activity duration, and activity intensity per 10 minutes. We accumulated the data to extract daily values. We also extracted statistical parameters (i.e., mean, minimum, median, maximum, SD, interquartile range, range, skewness, kurtosis, and root mean square) from the distribution of hourly step counts and hourly activity duration. We defined a sufficient activity indicator that indicates more than 7000 step counts during the day. Moreover, we calculated sedentary time by subtracting active time from time spent awake.

The summary of extracted features in this study is illustrated in Table 11.

Table 11. Summery of extracted features [199]

HR and HRV features	Sleep features	Physical activity features
HR	TST	Step counts
AVNN	Sleep fragmentation	Walking steps
RMSSD	WASO	Running steps
SDNN	Average hand movement	Distance
LF	Sleep quality indicator	Activity duration
HF	Sufficient sleep parameter	Activity intensity
LF/HF		Sedentary time
		Sufficient activity indicator
		Statistical features from distribution of daily steps
		Statistical features from distribution of daily activity duration

6.2.5 Labeling

UCLA questionnaire scores were used as labels. The questionnaire has social and emotional scores ranging from 0 to 24. The emotional scores were ignored because we had a few participants with emotional loneliness, and only social scores were used. UCLA social score $\geq$ 12 is considered loneliness, and UCLA social score $<$ 12 non-loneliness [198].

6.2.6 datasets

The extracted data from each data record, along with the corresponding label, were used to generate seven datasets. The datasets include different combinations of sleep, HRV, and physical activity features, which result in the sleep dataset, HRV dataset, physical activity dataset, sleep and HRV dataset, sleep and physical activity dataset, HRV and physical activity dataset, and sleep, HRV, and physical activity dataset. The datasets were used for training and testing the developed machine-learning classifiers.

6.2.7 Missing Data Imputation

The data record in our datasets has at least four valid days. Therefore, the data record may have missing data. We used the average value of the missing features within the data record to fill in the missing values.

6.3 Predictive Machine-Learning Models

Several machine-learning models have been developed for maternal loneliness prediction. The decision tree and gradient boosting models were chosen for prediction because they have better performance than other models. We briefly explain the decision tree and gradient boosting models in the following.

6.3.1 Decision Tree

The decision tree classifier is a supervised model that stands out because of its simplicity and intelligibility. This model is a robust model well suited for complex data [201; 202]. The model has a tree-like structure, including internal nodes and leaves. Internal nodes represent a feature, and a split rule based on that feature and leaves show the class label. The features in internal nodes are selected using the Gini index, which shows the purity of classification.

6.3.2 Gradient Boosting

The gradient boosting method is a machine-learning method that performs well on complex data with high cardinality. The model provides speedy and accurate prediction and usually outperforms other conventional machine-learning models [203]. Gradient boosting is an ensemble of weak prediction models that tries to build several models sequentially, and the added models in each step eliminate the error of previous models [203]. This model can find nonlinear relationships. Moreover, it performs well in loneliness prediction studies [192].

6.4 Model Evaluation

We first employed the recursive feature elimination (RFE) method on physical activity features to remove the least important feature and prevent overfitting. Then, we used the leave-one-participant-out cross-validation method to evaluate the developed methods and report the average performance. The predictive models, RFE method, training, testing, and evaluation were implemented in Python using the scikit-learn library [204]. The predictive models were evaluated based on the following measures:

- Precision: percentage of predicted samples that actually belonged to a class
- Recall: percentage of correctly predicted samples per class
- F1 score: harmonic mean of precision and recall per class
- Weighted F1 score: weighted average of F1 scores
- Sensitivity: percentage of lonely participants correctly detected
- Specificity: percentage of non-lonely participants correctly detected

6.5 Results and Discussion

This section evaluates the performance of machine-learning models for maternal loneliness prediction. Then, the important features of each model are discussed.

6.5.1 Performance of Maternal Loneliness Prediction

The performance of decision tree and gradient boosting classifiers based on precision, recall, F1 score, weighted F1 score, sensitivity, and specificity are summarized in Table 12. Moreover, Figure 24 represents the performance of models in terms of F1 scores.

For the decision tree model, the best performance was reached in the physical activity dataset, HRV and physical activity dataset, physical activity and sleep features dataset, and all features dataset. The results showed that physical activity features are the most important features for loneliness prediction in decision tree models. In

Table 12. Per class precision, recall and F1 score, weighted F1 score, sensitivity, and specificity performance measures for the decision tree and gradient boosting models [199]

Model	Dataset	Precision		Recall		F1 score		Weighted F1 score	Sensitivity	Specificity
		Non-lonely	Loneliness	Non-lonely	Loneliness	Non-lonely	Loneliness			
Decision Tree	Sleep	0.778	0.619	0.636	0.765	0.7	0.684	0.693	0.765	0.636
	HRV	0.6	0.528	0.614	0.514	0.607	0.521	0.567	0.513	0.614
	PA	0 .905	0.833	0.864	0.882	0.884	0.857	0.872	0.882	0.864
	Sleep & HRV	0.7	0.579	0.636	0.647	0.667	0.611	0.642	0.647	0.636
	Sleep & PA	0 .905	0.833	0.864	0.882	0.884	0.857	0.872	0.882	0.864
	HRV & PA	0.864	0.824	0.864	0.824	0.864	0.824	0.846	0.824	0.864
	All	0.864	0.824	0.864	0.824	0.864	0.824	0.846	0.824	0.864
Gradient Boosting	Sleep	0.611	0.476	0.5	0.588	0.55	0.526	0.540	0.588	0.5
	HRV	0.553	0.471	0.591	0.432	0.571	0.451	0.516	0.432	0.591
	PA	0.87	0.875	0.909	0.824	0.889	0.848	0.871	0.823	0.909
	Sleep & HRV	0.667	0.524	0.545	0.647	0.6	0.579	0.591	0.647	0.545
	Sleep & PA	0.833	0.867	0.909	0.765	0.87	0.812	0.845	0.765	0.909
	HRV & PA	0.909	0.882	0.909	0.882	0.909	0.882	0.897	0.882	0.909
	All	0.87	0.875	0.909	0.824	0.889	0.848	0.871	0.823	0.909

addition, the high specificity of the decision tree on the datasets with high performance indicate that the model can identify non-lonely individual with high accuracy. Moreover, the high sensitivity of the decision tree for physical activity or all features datasets demonstrates that the decision tree performs well in accurately detecting individuals experiencing loneliness.

Similar to the decision tree, the gradient boosting model performed best on the datasets containing physical activity features. The highest performance of the model was achieved on the physical activity and HRV dataset. For gradient boosting, adding physical activity features to the dataset improved the results. Adding HRV features also resulted in improvement, though less than with physical activity. However, adding sleep features to physical activity features resulted in a decrease of performance. Consequently, this model highlights the importance of physical activity and HRV features for detecting maternal loneliness. In addition, the gradient boosting model can identify lonely individuals with an accuracy higher than 88% for HRV and physical activity features, while the accuracy of the model for identifying non-lonely individuals is more than 90% for all the datasets containing physical activity features. As you can see in Table 12, sleep features can have a negative impact on the accuracy of detecting individuals experiencing loneliness, while having no effect on detecting non-lonly individual.

The developed predictive models performed well in maternal loneliness prediction. The gradient boosting and decision tree models achieved weighted F1 scores of 0.897 and 0.872, respectively. Additionally, both gradient boosting and decision tree achieved the same sensitivity; therefore, both model had the same performance in detecting participants experiencing loneliness. However, the gradient boosting model achieved higher specificity, indicating its better performance in correctly detecting non-lonely individuals. The results showed the feasibility and possibility of passive sensing for maternal loneliness prediction.

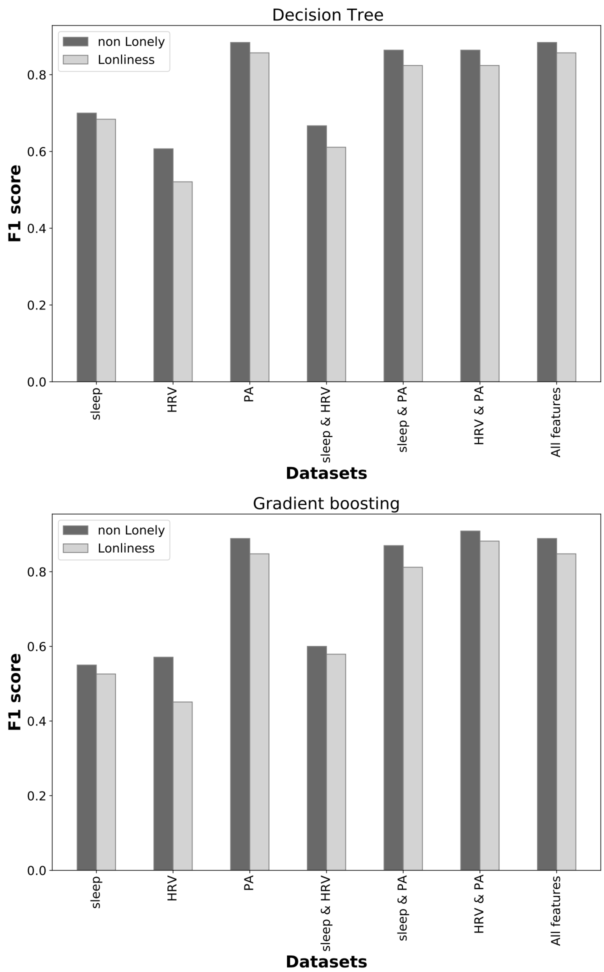


Figure 24. Performance evaluation (F1 score) of decision tree and gradient boosting for different datasets [199]

As mentioned, a few have works used passive sensing with wearable devices to predict loneliness in college students. Wu et al. [193] collected self-report questions regarding loneliness along with location and Bluetooth data. However, our models achieved better performance and used standard loneliness measures as labels. Doryab et al. [192] also used activity tracker and smartphone data and presented machine-learning models for loneliness prediction in college students. They achieved an accuracy of 80.2%. Our models for maternal loneliness prediction achieved higher performance. In addition, their model needed sensitive information such as phone numbers of close friends, whereas our models only used physiological parameters collected by a smartwatch.

6.5.2 Important Features in Maternal Loneliness

In this section, the important features of loneliness detection in each predictive model are discussed. For this purpose, the most important features in the datasets that have weighted F1 scores ≥ 0.8 were investigated. Therefore, the datasets containing physical activity features (four datasets) were considered for both models.

For the decision tree model, the most important features were the intensity of activity and kurtosis of hourly steps per day. Other effective but less important features include SDNN, LF, LF/HF, statistical features of hourly activity duration. For the gradient boosting model, same as the decision tree, the most important features were also the intensity of activity and kurtosis of the step count. Moreover, statistical parameters of hourly step count and activity duration also contribute in loneliness detection.

To summarize, the results show that the intensity and pattern of daily physical activity during the day are the most important features of loneliness. Moreover, resting HR and HRV parameters are also correlated with loneliness. The results indicate that more intensive physical activity is correlated with a lower level of loneliness. In contrast, less intensive activity, when most of the activity happens in the morning or early evening, along with low resting HRV, can be a sign of loneliness.

The finding of the negative association between physical activity and maternal loneliness is very important for maternal health. It is known that physical activity decrease while pregnancy proceeds due to physiological changes in the body [9]. Therefore, maternal care providers should be aware that lower physical activity could also be a sign of maternal loneliness and be alert to other signs of loneliness.

In addition, Studies on college students have also shown the same results regarding the negative correlation of loneliness with the duration of the activity, total step counts, and activity duration in the evening [138; 192; 205]. Moreover, Ben-Zeev et al. [206] reported that loneliness was not related to sleep duration, which is in accordance with our results.

It is important to note that, considering the typical decrease in physical activity during pregnancy, in order to generalize our models for the entire pregnancy or other demographic groups, the models should also incorporate data from different population groups. This is crucial, as the threshold for activity levels may vary among different population groups.

7 Conclusion

IoT-based health monitoring systems provide new opportunities in health care services by providing low-cost continuous health monitoring all times in everyday settings. However, using such systems in practice raises many challenges. In this research, we presented and evaluated an IoT-based system for maternal health monitoring during pregnancy and postpartum. We also investigated and discussed the requirements and challenges of deploying such maternal monitoring systems. Then, we validated the HR and HRV parameters collected by the presented system. In addition, we proposed a deep learning-based quality assessment method to assess the quality of HR and HRV parameters collected with our system.

We used our system to conduct a study on pregnant women and collected continuous data from 62 women during pregnancy and 3 months postpartum. The collected data were used to analyze the changes in HR and HRV parameters comprehensively during pregnancy and postpartum. Finally, we used the collected data to develop predictive machine-learning models for maternal loneliness as a major mental health problem during pregnancy and postpartum.

To achieve Research Objective I (i.e., present, develop, and evaluate a continuous IoT-based maternal health monitoring system), Chapter 3 presents a long-term IoT-based maternal monitoring system. The system was evaluated against both system-level and user-level requirements, including reliability, feasibility, usability, and energy efficiency. The practical challenges of developing the system were also discussed in detail.

Research Objective II (i.e., validate and assess the quality of HR and HRV parameters collected by the developed IoT-based monitoring system) was achieved in Chapter 4. In Chapter 4, we first validated the accuracy of the smartwatch, which was used in our monitoring system, against a clinical-level ECG gold standard. The validation was in terms of HR and HRV parameters and was performed during sleep and waking hours. The results revealed the need for a PPG quality assessment method, especially during waking hours, because the accuracy of most parameters was not acceptable during waking hours. We then introduced a deep-learning-based quality assessment method for HR and HRV parameters. Four CNN-based models for HR, RMSSD, SDNN, and LF/HF were proposed. The models demonstrated superior performance compared to existing state-of-the-art models on the data set collected from 46 participants in everyday settings.

Research Objective III (i.e., deploying the presented IoT-based system to collect data from pregnant women during pregnancy and 3 months postpartum) was realized in Chapter 5. In this chapter, we described our data collection from 62 pregnant women. We collected data from two groups of pregnant women (i.e., high-risk and low-risk groups). The high-risk group had a history of miscarriage or preterm birth, whereas the low-risk group had a history of full-term birth. Our system continuously collected the objective and subjective data from the participants for 9 months.

Research Objective IV (i.e., investigate the trends of HR and HRV parameters during pregnancy and the postpartum period) was addressed in Chapter 5. In this chapter, we employed the data collected during pregnancy and postpartum, which was described in Research Objective II. We analyzed the trends of minimum HR and corresponding HRV and normalized HRV parameters at nighttime using the hierarchical linear model. With this model, we analyzed the trend of parameters during the second and third trimesters and the postpartum period. We then compared the trend of changes in different trimesters and with the postpartum period. The effect of age, BMI, and education level on the trend of HR and HRV parameters was also investigated.

Research Objective V (i.e., develop predictive models to detect maternal loneliness during pregnancy and the postpartum period based on data collected passively by the developed monitoring system) was accomplished in Chapter 6. In this chapter, we proposed two predictive models to detect maternal loneliness. The physiological data collected passively through the IoT-based maternal monitoring system developed in the thesis, along with loneliness scores, were used to train and test the models. The results showed the high performance of the developed models in maternal loneliness detection. Moreover, the results indicated that intensity of activity, activity in the evening, and resting HR and HRV are important features in predicting loneliness.

In this thesis, we have contributed toward the above Research Objectives. However, there are still open directions to be explored. The IoT-based maternal monitoring system can collect a large amount of previously unavailable data. The data can be used to predict mental and physiological health issues, including depression and hypertension. Moreover, our current system lacks intervention functionalities. The system should be extended to provide appropriate notifications, interventions, and alarms in case of risk conditions. Furthermore, the system should be further developed to include other monitoring services, for example, diet, weight, and mobile usage, and connect with other wearable and mobile applications that are currently available.

Moreover, the accuracy validation of HR and HRV parameters was performed using data from healthy nonpregnant adults in a 24-hour data collection. In the future, we should consider validating the data with pregnant women experiencing various health conditions. During pregnancy, changes in body weight, hormonal levels, and the growing fetus can influence sleep patterns and body movements, potentially resulting in different motion artifacts. These variations may impact HR and HRV parameters and need further investigation. Additionally, the proposed CNN-based PPG quality assessment method was based on the same data as the accuracy validation. This method can also be extended, providing data from different population groups with various health conditions. Moreover, other HRV parameters should be considered, including frequency domain and nonlinear HRV parameters.

We analyzed the nighttime trends of HR and HRV parameters during the second and third trimesters and the postpartum period. Analyzing daytime HR and HRV trends is an open direction in this research. Moreover, as suggested in [151; 147], HRV changes occur mostly during the first trimester. In the future, we will analyze the trends of HR and HRV parameters during the first trimester and compare them to other trimesters and the postpartum period.

We presented machine learning models for maternal loneliness detection. However, our data set was small, and we only considered data at two-time points during late pregnancy and postpartum. In the future, we should use data during the whole pregnancy with a greater number of participants to generalize our models. Moreover, participants with different health conditions should be considered.

8 Overview of Original Publications

This chapter presents a brief overview of original publications and the author's role in each publication.

8.1 Long-Term IoT-Based Maternal Monitoring: System Design and Evaluation

In this paper, we present a long-term IoT-based maternal health monitoring system. This system enables remote and continuous health monitoring of pregnant women during pregnancy and the postpartum period. The system provides several monitoring services, including stress, physical activity, and sleep, by collecting objective and subjective physiological health data. The data are collected using wearable devices and smartphones and transferred to our cloud server to be stored and analyzed. We leveraged several machine learning-based methods to enhance the data analysis, such as anomaly detection, personalized modeling, and quality assessment methods. The presented system was implemented and used by pregnant women from the second trimester to 3 months postpartum. The paper extensively investigates and discusses the challenges of such a long-term maternal monitoring system.

Author's contribution

The author is the first author of this publication. She had a significant role in designing, developing, implementing, and deploying the maternal monitoring system. She had a major role in collecting and analyzing the system's usage data. She also contributed to drafting the manuscript.

8.2 A comprehensive accuracy assessment of Samsung smartwatch heart rate and heart rate variability

In this paper, we investigated the accuracy of the HR and HRV parameters extracted from PPG signals collected by the Samsung smartwatch in free-live settings. We utilized short-term HRV analysis to assess the validity of HR, AVNN, RMSSD, SDNN, pNN50, LF, HF, and LF/HF extracted from the collected PPG-signal in comparison with a medical-grade ECG monitor during sleep time and awake time. We used the 24-hour continuous data from 28 participants in home-based monitoring for evaluation. The accuracy of HR and HRV parameters obtained from the Samsung smartwatch was investigated using the linear regression method, the Pearson correlation coefficient, and the Bland–Altman plot.

Author's contribution

The author is the joint first author of this publication. She has contributed to the design of the study. She had a major role in the setup and data collection. She also contributed to the data analysis. She had a significant role in drafting the manuscript.

8.3 A Deep Learning-based PPG Quality Assessment Approach for Heart Rate and Heart Rate Variability

In this paper, we propose a deep learning-based quality assessment for PPG signals based on the HR and HRV parameters. We first indicated that conventional PPG quality assessment methods could be improved by considering the desired HRV parameters. The quality of each extracted HRV parameter is affected by different signal features. Therefore, we proposed different CNN-based models for each HRV parameter. We evaluated the proposed method for HR, RMSSD, SDNN, and LF/HF parameters compared with the state-of-the-art PPG-quality assessment methods. The evaluation was performed using the simultaneous PPG and ECG data collected in everyday life settings. Moreover, we presented an automated annotation method for labeling PPG segments as reliable/unreliable based on the ECG baseline. The proposed quality assessment models are implemented as an open-source portable model in Python and are available for others to use in their studies.

Author's contribution

The author is the second author of this publication. She had a major role in data collection and data analysis. She contributed to the study setup, model development, literature review, and manuscript drafting.

8.4 Trends in Heart Rate and Heart Rate Variability During Pregnancy and the 3-Month Postpartum Period: Continuous Monitoring in a Free-living Context

In this paper, we investigate the trends of HR and HRV during pregnancy and the postpartum period. We collected PPG signals from 58 pregnant women using the

IoT-based maternal monitoring system presented in the first paper. The PPG signals were acquired continuously during the second trimester, the third trimester, and three months in the postpartum period in everyday life settings. We analyzed the minimum HR and HRV parameters corresponding to min HR at night. We also investigate the trends of normalized HRV parameters based on average HR. This normalization enabled us to remove the impact of normal HR changes during pregnancy on HRV trends. We utilized hierarchical linear modeling to investigate the trend of desired parameters considering in-person and between-person differences. Moreover, we investigate the effect of age, BMI before pregnancy, and education level on HRV trends.

Author's contribution

The author is the first author of this publication. She played a significant role in the design of the study. She was the main contributor to the design, development, and deployment of the long-term maternal monitoring system utilized for data collection in this paper. Moreover, she had a significant role in data analysis and investigating the parameters' trends. She contributed to drafting the manuscript.

8.5 Maternal Social Loneliness Detection Using Passive Sensing Through Continuous Monitoring in Everyday Settings: Longitudinal Study

In this paper, we developed two machine learning models to predict maternal social loneliness using passive sensing. We used physiological data, i.e., HR, HRV, physical activity, and sleep, collected passively by a smartwatch during pregnancy and postpartum. We also collected the UCLA loneliness questionnaire in gestational weeks 36 and 12 weeks after delivery, which was used to classify participants as lonely or non-lonely. We utilized eight days of collected physiological data from the smartwatch and the corresponding response to the UCLA questionnaire from 31 pregnant women. We leveraged these data for training and testing the decision tree and gradient boosting models for loneliness prediction. These two models achieved high F1 scores. Moreover, the results show that activity pattern, intensity of activity, and resting nighttime HR and HRV parameters are important features of the models to predict loneliness. This paper demonstrated the feasibility of maternal loneliness prediction based on objective data and passive sensing. Therefore, it provides opportunities for maternal well-being improvement through early detection of loneliness.

Author's contribution

The author is the first author of this publication. She was the major contributor to the study design. She also has a significant role in developing machine learning models and data analysis. Moreover, she contributed to the design, development, and deployment of the long-term maternal monitoring system used for data collection in this paper. She contributed to drafting the manuscript.

Appendix A: questions provided by the mobile application

This appendix includes daily questions that were asked through our cross-platform mobile application throughout pregnancy and postpartum. The questions were based on the pregnancy week and day. The questions for day 7 for all pregnancy and postpartum weeks are the same and are shown in Table 13 along with the answers. Questions for other days of the week are yes/no questions and are determined based on the specific pregnancy day and week, as shown in Table 14. Participants received two or three questions available for that day.

Table 13. Day 7 questions

Questions		Answers	
Finnish	English translation	Finnish	English Translation
Millaiseksi arvioisit stressitasosi viimeisen viikon aikana?	How would you rate your stress level during the last week?	0 (Ei lainkaan stressiä) – 100 (pahin mahdollinen stressi)	0 (No stress at all) - 100 (Worst possible stress)
Millaiseksi arvioisit liikunnan määräsi viimeisen viikon aikana?	How would you rate your exercises level during the last week?	0 (Ei lainkaan) – 100 (Erittäin paljon)	0 (Not at all)- 100 (Very much)
Millaiseksi arvioisit unen laatusi viimeisen viikon aikana?	How would you assess the quality of your sleep over the past week?	0 (Erittäin huono) – 100 (Erittäin hyvä)	0 (Very poor) - 100 (Very good)

Table 14

	Question in Finnish	Question in English	Weeks
DAY1	Onko sinulla raskauteen liittyviä huolia?	Do you have concerns related to pregnancy?	gwk 12 to the delivery
DAY4	Onko raskautesi sujunut odotustesi mukaisesti?	Has your pregnancy progressed as you expected?	gwk 12 to the delivery
DAY1	Onko sinulla ollut tänään pahoinvointia?	Have you experienced nausea today?	gwks 12-15
DAY2	Oletko oksentanut tänään?	Have you vomited today?	gwk 12–15
DAY3	Onko sinulla ollut tänään turvotusta?	Have you experienced swelling today?	gwks 12 and 14
DAY3	Onko sinulla ollut tänään kipuja lantion alueella?	Have you had pain in the pelvic area today?	gwks 13 and 15
DAY4	Onko sinulla ollut tänään närästystä?	Have you had heartburn today?	gwks 12 and 14
DAY4	Onko sinulla vauvaan liittyviä huolia?	Do you have concerns related to the baby?	gwks 13 and 15
DAY5	Onko sinulla ollut tänään suonenvetoja?	Have you had cramps today?	gwks 12 and 14
DAY5	Onko sinulla ollut tänään selkäkipuja?	Have you had back pain today?	gwks 13 and 15
DAY6	Oletko tänään onnellinen?	Are you happy today?	gwks 12 and 14
DAY6	Oletko tänään tuntenut itsesi masentuneeksi tai alakuloiseksi?	Have you felt depressed or downhearted today?	gwks 13 and 15
DAY1	Onko sinulla ollut tänään turvotusta?	Have you experienced swelling today?	gwk 16 to the delivery
DAY1	Oletko tänään onnellinen?	Are you happy today?	gwk 16 to the delivery
DAY2	Onko sinulla suonikohjuja?	Do you have varicose veins?	gwk 16 to the delivery
DAY2	Oletko tänään tuntenut itsesi masentuneeksi tai alakuloiseksi?	Have you felt depressed or downhearted today?	gwk 16 to the delivery
DAY3	Onko sinulla ollut tänään närästystä?	Have you had heartburn today?	gwk 16 to the delivery
DAY3	Pelottaako synnytys sinua?	Are you afraid of childbirth?	gwk 16 to the delivery
DAY4	Onko sinulla ollut tänään suonenvetoja?	Have you had cramps today?	gwk 16 to the delivery
DAY4	Onko sinulla vauvaan liittyviä huolia?	Do you have concerns related to the baby?	gwk 16 to the delivery
DAY5	Onko sinulla ollut tänään selkäkipuja?	Have you had back pain today?	gwk 16 to the delivery
DAY5	Onko sinulla ollut tänään supistuksia?	Have you had contractions today?	gwk 16 to the delivery
DAY6	Onko sinulla ollut tänään kipuja lantion alueella?	Have you had pain in the pelvic area today?	gwk 16 to the delivery
DAY6	Oletko tuntenut tänään vauvan liikkeitä?	Have you felt the baby's movements today?	gwk 16 to the delivery
DAY1	Onko sinulla vauvaan liittyviä huolia?	Do you have concerns related to the baby?	Postpartum weeks 1-12
DAY1	Onko sinulla ollut tänään kipuja?	Have you had pain today?	Postpartum weeks 1-12
DAY2	Oletko tänään onnellinen?	Are you happy today?	Postpartum weeks 1-12
DAY2	Oletko tuntenut itsesi virkeäksi tänään?	Have you felt energetic today?	Postpartum weeks 1-12
DAY2	Onko sinulla ollut tänään supistuksia?	Have you had contractions today?	Postpartum weeks 1-4
DAY3	Oletko liikkunut tänään ulkona?	Have you been outdoors today?	Postpartum weeks 1-12
DAY3	Oletko imettänyt tänään?	Have you breastfed today?	Postpartum weeks 1-12
DAY4	Onko sinulla itseesi liittyviä huolia?	Do you have concerns related to yourself?	Postpartum weeks 1-12
DAY4	Onko sinulla ollut tänään jälkivuotoa?	Have you had postpartum bleeding today?	Postpartum weeks 1-4
DAY4	Koetko palautuneesi synnytyksestä?	Do you feel that you have recovered from childbirth?	Postpartum weeks 5-12
DAY5	Oletko tavannut tänään muita aikuisia puolisosi lisäksi?	Have you met other adults today besides your spouse?	Postpartum weeks 1-12
DAY5	Onko sinulla ollut tänään mielialan vaihteluja?	Have you experienced mood swings today?	Postpartum weeks 1-12
DAY6	Oletko tänään tuntenut itsesi masentuneeksi tai alakuloiseksi?	Have you felt depressed or downhearted today?	Postpartum weeks 1-12
DAY6	Onko vauvasi ollut tänään kovin itkuinen?	Has your baby been very fussy today?	Postpartum weeks 1-12

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