Early detection of patient deterioration at home using smart medical sensors

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Peter L. Reichertz Institut für Medizinische Informatik (PLRI)
der Technischen Universität Braunschweig
und der Medizinischen Hochschule Hannover

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Julian Sharif Lobbes
4343013
geboren in Hannover

Erstgutachter: **Prof. Dr. med. Dr.-Ing. Michael Marschollek** (PLRI)

Zweitgutachter: **Prof. Dr. Thomas M. Deserno** (PLRI)

Summary

This research investigated the feasibility of Remote Warning Score Monitoring (RWSM) for outpatients using commercially available smart medical devices. A system, named Medwings, was designed, implemented, and evaluated. A usability study was carried out and found that consumer-grade smart devices can be used to facilitate remote patient monitoring integrated with Early Warning Scores (EWS). While the system was largely successful in demonstrating the practicability of RWSM, it also identified several operational challenges. The Medwings system shows potential for improving patient quality of life and optimizing healthcare resources. Despite its current limitations, Medwings opens the door for future research and development, given the fast-evolving market for advanced smart medical devices. The study fills a critical knowledge gap and sets the stage for further advancements in the field of remote patient monitoring with early warning scores.

Table of contents

1 Introduction

1.1 Background

Clinical deterioration is a critical concern in healthcare, particularly for vulnerable populations such as the elderly and chronically ill patients. It refers to a decline in a patient's health status and may lead to adverse outcomes, including hospitalization, longer stays in intensive care units, and increased healthcare costs. The Early Warning Score (EWS) has been widely adopted internationally for preemptive detection of deteriorating patients[1]. A large body of scientific evidence validates the effectiveness of EWSs in assessing severity of illness, and in predicting adverse clinical events, such as severe deterioration, likelihood of intensive care unit (ICU) admission and mortality, both in hospital wards[2, 3, 4, 5, 6, 7, 8] and in ambulatory care [9, 10, 11].

Two commonly used clinical scores are the National Early Warning Score 2 (NEWS2) and the Modified Early Warning Score (MEWS)[10]. Both are calculated by capturing various vital parameters from the patient at a specific point in time, followed by numerical aggregation of the captured data according to the score being used[2, 12]. For MEWS, each measured physiological parameter is assigned an individual score based on which range it lies in. The ranges for scoring each parameter, as proposed by Subbe et al. in 2001[2], are shown in Table 1. The individual scores are then added together to produce the final MEWS. A MEWS value of 5 or above indicates an elevated risk of death, and likelihood of ICU admission[2].

Individual Score	+3	+2	+1	+0	+1	+2	+3
Systolic Blood Pressure [mmHg]	< 70	$71 - 80$	$81 - 100$	$101 - 199$	—	≥ 200	—
Heart Rate [bpm]	—	< 40	$41 - 50$	$51 - 100$	$101 - 110$	$111 - 129$	≥ 130
Respiratory Rate [bpm]	—	< 9	—	$9 - 14$	$15 - 20$	$21 - 29$	≥ 30
Temperature [°C]	—	< 35	—	$35 - 38.4$	—	≥ 38.5	—
AVPU	—	—	—	alert	reacting to voice	reacting to pain	unresponsive

Table 1: MEWS calculation ranges as proposed by Subbe et al. in 2001[2]

Traditionally, doctors and nursing staff perform collection and evaluation of the data manually, often inputting data into EWS-calculators by hand. However, low scoring frequency and increased proclivity for errors are downsides of manual EWS calculation[13].

Remote patient monitoring (RPM) can improve deterioration detection[14] by greatly reducing the amount of human interaction required to take measurements and perform EWS calculations. A number of studies have explored RPM combined with automated EWS calculation in hospitals[13, 15, 16, 17]. With hospitals facing overwhelming patient load during the SARS-CoV-2 pandemic, interest in exploring RPM surged to new heights, and NEWS2 emerged as an effective tool for predicting severe infection outcomes[15, 18, 19, 20] while reducing person-to-person contact during patient monitoring.

1.2 Review of existing literature

In order to examine the current state of scientific knowledge about the use of wearable devices for automated EWS monitoring of patients at home, a comprehensive review of the existing literature was conducted. By systematically examining and synthesizing the current body of knowledge, this review identified a variety of approaches for utilizing smart medical devices in post-discharge patient care, as well as existing limitations and challenges in future research in this rapidly evolving field.

1.2.1 Search strategy

A systematic search strategy was implemented on the Scopus database, aimed to encompass a broad spectrum of literature relevant to the use of smart medical devices for automated early warning score monitoring of outpatients. The search focused on topics related to the research area, encompassing the examination of EWSs, hospital admission, care escalation, and medical emergencies in combination with IT automation, medical wearables and Internet of Things (IoT). The Scopus database was chosen for its extensive coverage of scholarly literature across multiple disciplines.

For the search strategy, the following inclusion and exclusion criteria were employed to select relevant articles:

Inclusion criteria:

- Articles focusing on the utilization of medical wearable devices for remote patient monitoring
- *OR* articles addressing the automated calculation of early warning scores
- *OR* articles discussing the application of early warning scores outside of medical care facilities

Exclusion criteria:

- Non-English language articles
- Publications for which full-text access was not available
- Duplicate articles
- Articles unrelated to the “Medicine”, “Medical Informatics” or “Computer Science” subject areas

The following Scopus query was used to identify relevant literature:

```
TITLE−ABS−KEY(("patient" OR "clinical" OR "medical")
   AND ("deterioration" OR "instability" OR
   "decompensation" OR "admission" OR "hospitalization"
   OR "escalation" OR "triage" OR "emergency")) OR
   ("early warning" OR "early warning score" OR
   "warning" OR "score∗" OR "EWS") AND
   TITLE−ABS−KEY("system" OR "automat∗" OR "smart∗" OR
   "wearable∗" OR "internet of thing∗" OR "iot" OR
   "digital" OR "sensor∗" OR "signal" OR "intelligen∗"
   OR "predict∗" OR "monitor∗" OR "sreen∗" OR "remote"
   OR "it" OR "comput∗" OR "mobile" OR "5G" OR
   "network" (("vital∗" OR "bio∗") AND ("marker∗" OR
   "sign∗" OR "monitor∗"))) AND TITLE−ABS−KEY("home" OR
   "domestic" OR "community" OR "remote" OR "longterm"
   OR "nursing" OR "rehabilitation" OR
   "out∗of∗hospital" OR "telemedicine" OR "ehealth" OR
   "mhealth")
```

1.2.2 Results

An initial query on Scopus yielded a total of $N_0 = 1997$ records. After removing $n_d = 952$ duplicates, the titles and abstracts of $N_s = 1045$ records were screened. Of these, $n_i = 963$ items did not meet the inclusion criteria, leaving $N_a = 82$ articles to be assessed for eligibility in full text. Finally, after a thorough evaluation, $N = 45$ articles were included in the literature review, providing insight into the current state of research on the use of smart medical devices for automated early warning score monitoring in patients transitioning from ambulant or hospital care. Figure 1 shows the screening process. The complete list of reviewed literature is shown in Tables 2, 3 and 4.

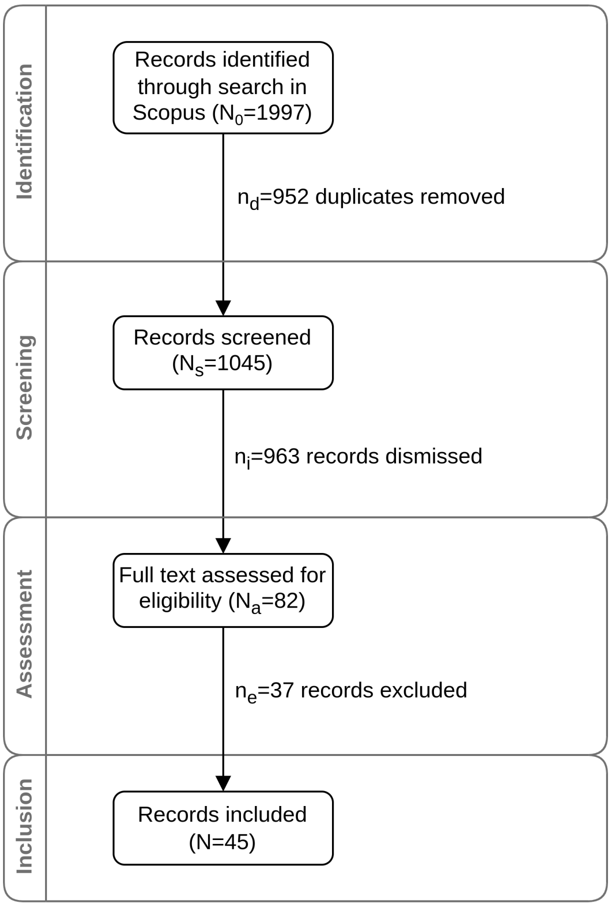


Figure 1: PRISMA flowchart showing screening and assessment of identified literature

1.2.3 Discussion

While the application of EWSs in ambulant care facilities and hospitals has been thoroughly investigated, very little research has been done to assess their practicability for remote monitoring of at-risk patients at home. Furthermore, it was observed that previous research on the use of IoT-devices for this purpose was largely conducted in laboratory settings, limiting the generalizability of the results. Some studies have examined monitoring vital signs of at-home-patients for abnormalities, however in most of them, no automated EWS calculations were made[23, 26, 31, 54, 42, 25, 45, 50]. In 2015, Anzanpour et al. developed a monitoring system which collects vitals data and calculates an EWS, however due to limited or nonexistent availability of wireless sensors for all relevant vital signs, the work was limited to using a laboratory prototype and required manual interaction in transferring vitals data[21]. Sahu et al. documented their development of an EWS-supported digital early warning system using the PM6750[48], an experimental vitals data monitoring device capable of taking continuous mea-

Number	Title	Author(s), Year
1	Internet of things enabled in-home health monitoring system using early warning score[21]	Anzanpour 2015
2	Context-Aware Early Warning System for In-Home Healthcare Using Internet-of-Things[22]	Anzanpour 2016
3	An IoT based system for remote patient monitoring[23]	Archip 2016
4	Wireless sensor network-based smart room system for healthcare monitoring[24]	Arnil 2011
5	Design and Development of IOT Based Multi-Parameter Patient Monitoring System[25]	Athira 2020
6	Medical warning system based on Internet of Things using fog computing[26]	Azimi 2016
7	Self-aware early warning score system for IoT-based personalized healthcare[27]	Azimi 2017
8	Review on IoT based Healthcare systems[28]	Krishna 2022
9	Effectiveness of Early Warning Scores for Early Severity Assessment in Outpatient Emergency Care: A Systematic Review[10]	Burgos-Esteban 2022
10	A QRS Detection and R Point Recognition Method for Wearable Single-Lead ECG Devices[29]	Chen 2017
11	Adopting the Internet of Things technologies in health care systems[30]	Chiuchisan 2014
12	An Efficient Wireless Health Monitoring System[31]	Chowdary 2018
13	DeepSigns: A predictive model based on Deep Learning for the early detection of patient health deterioration[32]	da Silva 2021
14	Use of ultra-low cost fitness trackers as clinical monitors in low resource emergency departments[33]	Dagan 2020
15	A data fusion algorithm for clinically relevant anomaly detection in remote health monitoring[34]	de Mello Dantas 2020
16	Patient attitudes towards remote continuous vital signs monitoring on general surgery wards: An interview study[1]	Downey 2018
17	Developing a real-time detection tool and an early warning score using a continuous wearable multi-parameter monitor[13]	Eisenkraft 2023
18	An IoT-Based Healthcare Platform for Patients in ICU Beds During the COVID-19 Outbreak[15]	Filho 2021

Table 2: List of reviewed articles *(Part 1 of 3)*

surements in a laboratory setting[57]. However, the methodology they used to calculate the EWS in real-time with laboratory data is both inconsistent and weak.

Recent studies indicate a growing trend towards investigating automated

Number	Title	Author(s), Year
19	Patient Monitoring System Based on Internet of Things[35]	Gomez 2016
20	Continuous monitoring is superior to manual measurements in detecting vital sign deviations in patients with COVID-19[36]	Gronbaek 2023
21	Secure and lightweight privacy preserving Internet of things integration for remote patient monitoring[37]	Imtyaz 2022
22	Remote Continuous Health Monitoring System for Patients[38]	Jagadish 2018
23	Cost utility analysis of continuous and intermittent versus intermittent vital signs monitoring in patients admitted to surgical wards[39]	Javanbakht 2020
24	Wearable sensors to improve detection of patient deterioration[40]	Joshi 2019
25	Intelligent Healthcare[41]	Kale 2021
26	A Hospital Healthcare Monitoring System Using Internet of Things Technologies[17]	Karvounis 2021
27	All-day mobile healthcare monitoring system based on heterogeneous stretchable sensors for medical emergency[42]	Lee 2020
28	Analysis of the early warning score to detect critical or high-risk patients in the prehospital setting[43]	Martin-Rodriguez 2019
29	An IoT-based framework for early identification and monitoring of COVID-19 cases[19]	Otoom 2020
30	A conceptual IoT-based early-warning architecture for remote monitoring of COVID-19 patients in wards and at home[11]	Paganelli 2022
31	Personalized Mobile Health for Elderly Home Care: A Systematic Review of Benefits and Challenges[44]	Pahlevanynejad 2023
32	CuraBand: Health Monitoring and Warning System[45]	Phaltankar 2021
33	Internet of Things in Healthcare, A Literature Review[46]	Quraishi 2021
34	Vital Sign Monitoring System for Healthcare Through IoT Based Personal Service Application[47]	Sahu 2022
35	Internet-of-Things-Enabled Early Warning Score System for Patient Monitoring[48]	Sahu 2022
36	Cloud-Based Remote Patient Monitoring System with Abnormality Detection and Alert Notification[49]	Sahu 2022

Table 3: List of reviewed articles *(Part 2 of 3)*

Number	Title	Author(s), Year
37	Remote patient monitoring using artificial intelligence: Current state, applications, and challenges[14]	Shaik 2023
38	Prototype development of continuous remote monitoring of ICU patients at home[50]	Thippeswamy 2021
39	IoT based Smart Healthcare Monitoring Systems: A Review[51]	Tiwari 2021
40	Observational study on wearable biosensors and machine learning-based remote monitoring of COVID-19 patients[16]	Un 2021
41	Adaptive threshold-based alarm strategies for continuous vital signs monitoring[52]	van Rossum 2022
42	A retrospective comparison of the Modified Early Warning Score (MEWS) and machine learning approach[53]	Wu 2021
43	IoT based Real Time Health Monitoring[54]	Yeri 2020
44	Vital Signs Prediction and Early Warning Score Calculation Based on Continuous Monitoring of Hospitalised Patients Using Wearable Technology[55]	Youssef Ali Amer 2020
45	Features of electronic Early Warning systems which impact clinical decision making[56]	Zarabzadeh 2012

Table 4: List of reviewed articles *(Part 3 of 3)*

EWS calculations in real-world scenarios[1, 17, 28, 33]. Notably, the availability of comprehensive, mobile vital signs monitoring equipment has seen a significant increase, especially in the wake of the SARS-CoV-2 pandemic[11, 15, 19, 36]. This surge in accessibility has paved the way for more extensive remote monitoring of outpatients. Moreover, there is a growing interest in incorporating machine learning algorithms to enhance the predictive capabilities of deterioration detection[16, 32, 34]. This demonstrates the evolving landscape of remote patient monitoring, aiming to improve clinical outcomes and alleviate the burden on hospital wards.

Despite the wealth of literature reviewed, no existing empirical studies evaluating the use of early warning scores for patients at home were identified. This highlights a crucial research gap and prompts the need for further investigation in this area, potentially warranting the development of an EWS specialized for use outside of medical care facilities.

1.2.4 Conclusions

Based on the conducted literature review, some key implications can be drawn. The improved availability of smart sensors and the demonstrated effectiveness of EWSs in predicting deterioration in direct medical care settings warrant research into their utilization at home. Monitoring EWSs remotely may make it possible to identify signs of deterioration early for patients dismissed from hospital. It could also hold the potential for significant resource savings, due to the relatively low cost of modern smart medical sensors and a reduction in workload for medical staff, compared to traditional on-site monitoring. However, it is important to acknowledge the lack of research in this area, which calls for a feasibility study in this specific context. While such a study would need to address challenges such as the frequency of measurements required and the absence of immediate diagnosis from qualified medical staff, it would contribute significantly to the existing body of knowledge and help advance the field of automated early warning score monitoring in home-based care.

1.3 Motivation

Installing and operating traditional continuous monitoring systems, like the vital sign monitors used in medical facilities, demands specialized equipment and technical expertise. Furthermore, these systems are cumbersome for patients, as they involve connecting patient and sensor device with numerous electrodes and cables, restricting patient mobility to the bed area, and physically tying the monitoring equipment to a single location. Conversely, battery-powered, wireless vitals monitoring devices, such as wearable armbands or smartwatches, can combine several biometric sensors into one device, allowing for a much higher degree of patient mobility, faster deployment and better scalability[16]. Therefore, utilizing such devices for RPM is a suitable approach.

With the current availability of wearable, networked biosensors and the validated effectiveness of EWSs in medical facilities, combining both aspects presents an important and interesting research opportunity which could help reduce mortality and improve clinical outcomes for patients at risk of deterioration, both in their homes and on the go.

1.4 State of the problem

The rapid advancements in wearable, networked biosensors have expanded the horizons of RPM. Still, their integration with EWSs remains underexplored, especially for outpatients or those outside of traditional medical care settings. While EWSs have proven effective in hospitals and ambulant care facilities, the practicality of implementing them remotely, under real-life conditions, leveraging state-of-the-art smart medical devices, remains uncertain.

Existing research on RPM predominantly focuses on the technology's capability for vital signs monitoring, often sidelining the integration and automated calculation of EWSs. This results in a knowledge gap concerning the effectiveness, feasibility, and design challenges of a system which combines both concepts. Moreover, there is a lack of available software implementing such a system, while being usable by patients at home or during their daily routines.

1.5 Research goals

The objective of this research is to explore Remote Warning Score Monitoring (RWSM): remote monitoring of patients dismissed from direct medical care using automated EWS assessments.

Specifically, the following questions are asked:

- Can an RWSM system, feasible for everyday use, be implemented using smart medical devices commercially available today?
- What are the technical and operational challenges of implementing such a system?
- Can existing, validated EWSs be utilized in RWSM?

1.6 Tasks

The research questions stated above were pursued by designing, implementing and deploying an RWSM system which utilizes a clinically validated EWS, followed by a feasibility study examining its everyday use, and a subsequent evaluation of the study.

A detailed outline of each step taken to carry out this investigation is shown here:

1. **EWS selection:** identification of an EWS which is:
    - widely recognized
    - clinically validated
    - applicable for adult patient evaluation
    - capable of assessing the overall risk of patient deterioration

- not limited to specific patient populations

2. **Device selection:** procurement of smart medical devices that:
   - are commercially available and have clinical approval for medical use
   - offer user-friendly, non-intrusive measurement procedures, suitable for the patient to use at home and on the go
   - allow secure and automated retrieval of the vitals data needed to calculate the chosen EWS via an Application Programming Interface (API)
3. **System design and implementation:** development of a software application facilitating RWSM using the selected medical devices, ensuring:
   - regular vitals data capture from patients
   - accurate calculation of the chosen EWS based on captured data
4. **Real-world usability trial:** conduction of a trial, wherein a test subject utilizes the implemented system in real-world conditions, collecting data useful for system evaluation.
5. **Evaluation:** methodical review of the implemented RWSM system:
   - Analysis of the effectiveness of the system in regularly gathering vitals data and EWS samples
   - Investigation of failure points when sample retrieval or EWS assessments were unsuccessful
   - Collation of the subject's feedback on user experience
6. **Feasibility and challenge discussion:** reflection on the entire research process to:
   - draw conclusions on the feasibility of RWSM using modern smart medical sensors
   - discuss application of the chosen EWS for RWSM
   - highlight the identified technical and operational challenges

By completing these tasks, the research provided a comprehensive understanding of the practicality and potential pitfalls of RWSM in everyday settings, using current technology.

2 Medwings

The initial step in conceptualizing an RWSM system was to choose an appropriate EWS to use for patient health evaluation. Three widely used EWSs were evaluated as potential candidates: the Pediatric Early Warning Score (PEWS)[58], NEWS2[12] and MEWS[2]. All three are established as being effective in predicting clinical deterioration. PEWS was excluded due to its application being limited to pediatric patients. The choice between MEWS and NEWS2 was made by considering the input parameters to each score's calculation: compared to MEWS, NEWS2 takes into account whether a patient is currently suffering from hypercapnic respiratory failure, and whether or not the patient is currently being ventilated using supplemental oxygen. These parameters are generally not applicable to patients dismissed from medical care, hence MEWS was chosen as the early warning score for the envisioned RWSM system.

To calculate the MEWS, the following vital parameters must be recorded and processed:

- Heart Rate
- Blood Pressure (systolic)
- Body Temperature
- Respiratory Rate
- AVPU Score (AVPU)

To develop an RWSM system capable of gathering these vital signs and making them accessible remotely, wirelessly networked vitals measurement devices were used. The process of selecting the right smart sensors presented a series of challenges. A significant portion of the available medical sensors on the market were either not accessible to the general public, or are not distributed in the geographic area where the research was carried out. While considering devices that met the procurement criteria outlined earlier, a large number of products had to be excluded, as they would have constrained patient mobility to the confines of their home or bedside. Several promising devices were identified, but dismissed due to still being in active development and having not yet received clinical approval.

Among a few options on the final shortlist, Withings emerged as the most feasible choice for several reasons. Notably, they were the only manufacturer who offers a publicly accessible API, allowing for automated retrieval of vitals data. Consequently, three Withings devices were selected for the study. The *Withings Scanwatch*[59], shown in Figure 2a is a smartwatch capable of measuring a user's Electrocardiogram (ECG) and Blood Oxygen Saturation (SPO_2) among other things. A *Withings BPM Core*[60], displayed in Figure 2b, was also procured. It is a digital blood pressure meter capable of recording blood pressure and heart rate. The third and last device used was a *Withings Thermo*[61], a contactless digital thermometer used to measure body temperature. A picture of a Withings Thermo can be seen in Figure 2c.

(a) Scanwatch **(b)** BPM Core **(c)** Thermo

Figure 2: Withings smart medical devices *(image sources: Withings Scanwatch[59], Withings BPM Core[60], Withings Thermo[61])*

All three devices are capable of synchronizing vitals data with the Withings Cloud over the internet, as they connect to the user's phone using a mobile application provided by Withings.

The chosen selection of devices allows measurements and programmatic access to the vital parameters required to determine a MEWS, with some caveats: the AVPU score cannot be measured remotely, as it necessitates a clinical assessment from medical staff. Additionally, the inclusion of the Withings Scanwatch came with a notable limitation: although the device possesses the capability to measure a patient's respiration rate, this functionality is restricted to nocturnal measurements, taken while the user is asleep.

To address these issues, a decision was made to forgo the traditional respiration rate measurement, as well as the AVPU parameter in the MEWS calculation. Instead, a custom *respiration score* was introduced, shown in Table 5, which represents any shortness of breath reported by the patient. To ensure the clinical soundness of these modifications, expert consultations were sought from an anesthesiologist and a pediatrician, each with over 30 years of practical experience in intensive care medicine. The pediatrician affirmed that due to the difficulty of accurately measuring respiration rate in practice, an audiovisual inspection of breathing, as well as patient-reported symptoms of shortness of breath, are often utilized as reliable substitutes. Following the expert consultation, the patient's SPO_2 level was used to replace the respiration rate in combination with the described respiration score. The anesthesiologist affirmed that the AVPU score is inherently unsuited for automated electronic measurement, as it requires a human evaluation of the patient's level of consciousness. Given that a patient with a compromised level of consciousness would be unable to interact with the Medwings system, under expert guidance the decision was made to omit the AVPU score entirely.

Condition	**Score**
Patient is *not* suffering from shortness of breath	0
Patient is experiencing *some* shortness of breath	1
Patient is suffering from *severe* shortness of breath	2

Table 5: Scoring table for Medwings' custom respiration score

2.1 Requirements

Following the selection of an EWS and suitable medical sensors, a comprehensive RWSM application was conceptualized, dubbed as the *Mobile Early Deterioration Warning System (Medwings)*. Prior to its development, several key software requirements for the application were determined.

2.1.1 Functional Requirements

User Authentication: Medwings must provide a robust user authentication and authorization system to ensure confidentiality of sensitive patient data, while preventing unauthorized access to restricted information.

Portability: Patients must be able to access Medwings from their mobile phone. Enabling access from other types of end user devices is also desirable.

Data Collection: The application must be capable of collecting and storing vital sign readings from all three Withings smart medical sensors without the need to transfer data manually. Additionally, it must be able to determine the custom respiration score introduced earlier, by prompting patients on whether they are experiencing shortness of breath.

Measurement prompts: To facilitate a regular MEWS assessment schedule, the application must regularly prompt patients to take vital sign readings.

MEWS Calculation: When sufficient vital signs for a patient are collected, Medwings must automatically compute and store the MEWS.

Data Synchronization: Vitals data, MEWS measurements and any associated metadata should be synchronized and accessible on each of the patient's end devices. Captured data should be stored by the system for later analysis.

Data Visualization Patients should be able to view a history of their recorded vitals and MEWS values.

2.1.2 Non-functional Requirements

Usability: Medwings should be intuitive and user-friendly, requiring minimal technical expertise from end-users. The User Interface (UI) should be adaptive for display on both mobile displays and larger monitors. If measurements fail or errors occur, clear error messages should be displayed to the user.

Availability: The system should be available for patients to use at all times, and from any location, with minimal downtime.

Data Validity: Vitals records retrieved from the smart sensor devices must be converted and displayed correctly. Calculated MEWS values must be correct and take into account all relevant vital parameters:

- systolic blood pressure
- heart rate
- body temperature
- SPO_2
- respiration score

To ensure the medical validity of a MEWS assessment, when a set of vitals measurements is used to calculate a MEWS, the time of measurement for any two measurements in the set must not be further apart than ten minutes.

Security: All personal and medical data must be handled in a secure manner, both during storage and in transit. When transmitting data between Medwings and Withings, or between a user's end device and Medwings, communication confidentiality and integrity must be ensured. The identity of both communication partners must be cryptographically verifiable.

2.2 Design and Implementation

Medwings was designed as a web-based application, accessible through a web browser. Opting for this format offers several advantages: the primary benefit is its inherent cross-platform compatibility, enabling usage on a wide range of devices such as mobile phones and personal computers.

Adhering to the classic client-server paradigm, the Medwings design prioritizes centralized data storage and processing. This architecture was found to be beneficial for simplifying data synchronization, facilitating secure authentication, and ensuring high system availability.

Django, a high-level Python web framework, was employed to develop both the frontend and backend components of the Medwings application. Some of the primary motivations for selecting Django were its out-of-the-box user authentication and session management capabilities. Such features substantially expedited the development process, freeing up time and resources to focus on the more unique functionalities of the Medwings web application. Furthermore, Django's integrated Object-Relational Mapping (ORM) system greatly simplified the creation, management, and querying of the application's database. This was pivotal given the essential role of the database in storing vitals data.

While web applications offer many advantages, one limitation is their increased design complexity required to support push notifications directly on the patient's mobile phone. To simplify this aspect of the design, a separate push notification microservice was deployed on premise and integrated with Medwings. Considering the time constraints under which the application was developed, this approach proved to be an effective compromise.

2.2.1 Architecture

The overall system environment is shown in Figure 3, depicting the following workflow:

1. A patient receives a notification on their mobile phone, prompting them to take vitals measurements.

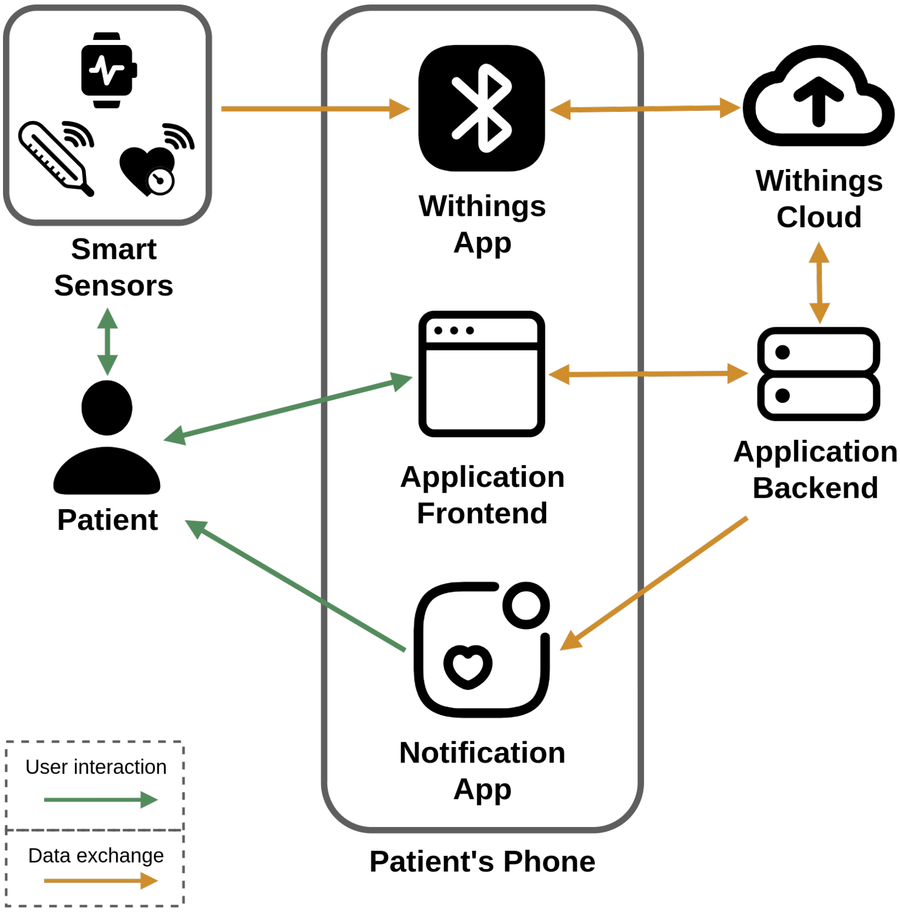


Figure 3: System diagram showing data flow and user interactions between components in the Medwings environment.

2. Upon opening the notification, they are redirected to the Medwings website. Here, they are prompted to self-assess their respiration score by answering a short questionnaire, followed by a prompt to take one measurement on each Withings device.

3. When a measurement is completed, each device transmits the data via Bluetooth to the Withings mobile app, installed on the user's phone. The mobile app now sends the data to the Withings Cloud for storage.

4. A backend process on the Medwings server awaits the arrival of all recorded measurements from the Withings Cloud, storing them upon reception. Once all required vitals measurements have been retrieved, the MEWS is calculated, stored and displayed to the patient.

Throughout the day, measurement prompt notifications are dispatched to the patient at regular intervals.

2.2.2 Modules

To separate the different functional aspects of Medwings according to responsibility, its application code is split into the following five modules:

- `core`
- `withings`
- `gotify`
- `authentication`
- `medwings`

Each module defines classes representing backend logic, database schemata and user interface elements pertaining to its specific function. Implementation details are encapsulated within these classes, while public interfaces are exposed to external program code to provide each module's core functionality.

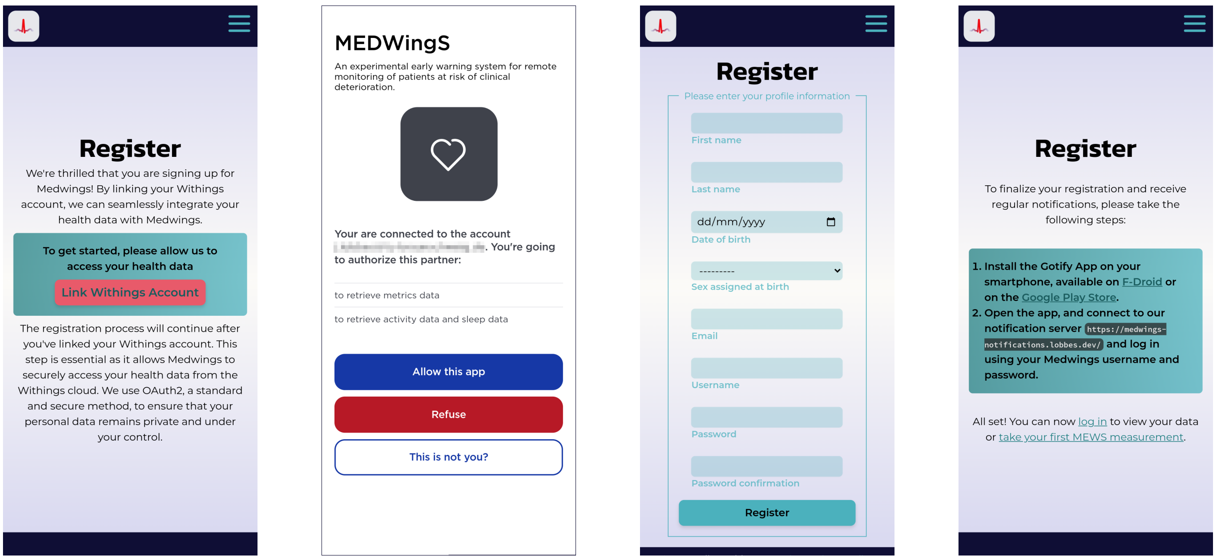
The `core` module forms the backbone of the application. It encompasses configuration settings, handling of secrets such as private encryption keys or API tokens, and functionalities shared across multiple other modules. This includes backend utility functions and shared UI components for the frontend.

Medwings interfaces with the Withings Cloud through the `withings` module. Responsibilities include retrieving vitals data through authenticated requests to the Withings Cloud API, which implements the OAuth 2.0 Authorization Framework. As per its specification, "In OAuth, the client requests access to resources controlled by the resource owner and hosted by the resource server... Instead of using the resource owner's credentials to access protected resources, the client obtains an access token... The client uses the access token to access the protected resources hosted by the resource server. "[62] While this process is largely transparent for the resource owner — the patient in this case — the communication between Medwings as the resource client and Withings as the resource server is complex, and is therefore abstracted by the module. Aside from OAuth 2.0, `withings` also encapsulates fetching, parsing, and storing vitals data retrieved from Withings.

Medwings implements a standalone user authentication system, which is provided by the `authentication` module. Patients must register with a username and password to be able to use the application. The registration occurs in three stages:

1. The patient grants Medwings the permission to retrieve their health data from Withings in an OAuth2 authorization flow. This process is shown in Figures 4a and 4b.
2. A registration form, displayed in Figure 4c, is shown, prompting the user to choose a username and password, and to enter relevant personal information.
3. The user is shown a confirmation that the account was created successfully, and is asked to download the Gotify app, described below, and log in using their Medwings credentials. Figure 4d shows this final step.

Following registration, the supplied information and numerous authentication tokens are saved in the Medwings database. The patient can now log in to the Medwings website and begin using the system to take vitals and MEWS measurements.



(a) User signup initialization **(b)** Withings OAuth 2.0 grant **(c)** User details prompt **(d)** Registration finalization

Figure 4: Medwings user registration process

Managing a user in Medwings requires the respective user's state to be mirrored by two other services, Withings and Gotify. The `authentication` module ensures that user accounts across all three services are kept in sync. Particularly during user creation, user accounts must be linked to Withings, created on the Gotify server and finally saved to the Medwings database. Various integrity checks, such as when the user aborts the registration process midway, are put in place to prevent diverging user states across the three services.

The `medwings` module, pivotal to the core functionality of Medwings, defines the data model used to represent and store the various vital signs handled by the application. Furthermore, it provides interfaces to access the data, as well as the algorithm used to calculate the MEWS, which is listed in Algorithm 1.

Input: $blood\_pressure\_systolic$, $body\_temperature$, $heart\_rate$, $spo2$, $respiration\_score$
Output: $mews$

$mews \leftarrow 0$

if $blood\_pressure\_systolic \leq 70$ **then**
    $mews \leftarrow mews + 3$
else if $blood\_pressure\_systolic \leq 80$ **then**
    $mews \leftarrow mews + 2$
...
```
// systolic blood pressure, body temperature
// and heart rate as per Table 1
```

if $respiration\_score = 1$ **then**
    $mews \leftarrow mews + 1$
else if $respiration\_score = 2$ **then**
    $mews \leftarrow mews + 2$

if $spo2 \leq 90$ **then**
    $mews \leftarrow mews + 2$
else if $spo2 < 95$ **then**
    $mews \leftarrow mews + 1$

return $mews$

Algorithm 1: Medwings MEWS calculation

A MEWS calculation should represent the patient's overall physiological state at – ideally – a discrete point in time. Naturally, there is a delay from when a measurement is taken with a device until it can be retrieved from the API. The transmission delays are mentioned in the Withings public API documentation: "Delays are typically less than two minutes, but it can be longer."[63]. However, in some cases, the measurements taken on a device do not get pushed to the Withings Cloud until much later. While the cause for these longer than normal delays and missing data points is unknown and outside of the control of Medwings, these edge cases had to be taken into account. The time it takes a patient to take measurements using all three devices must also be accounted for. Therefore, Medwings enforces a maximum allowed time difference of ten minutes between measurements of the different vitals records used to calculate the MEWS. If a set of vitals measurements is, across all records in the set, spaced further apart than ten minutes, no MEWS record is calculated, and the user is shown an error message.

Vitals records kept in the Medwings database must be synchronized with all records available on the Withings cloud. Regularly recurring, as well as on-demand data synchronization hooks are used by the `medwings` module to keep the Medwings database up to date, while database constraints ensure validity of imported data and prevent duplication of existing records.

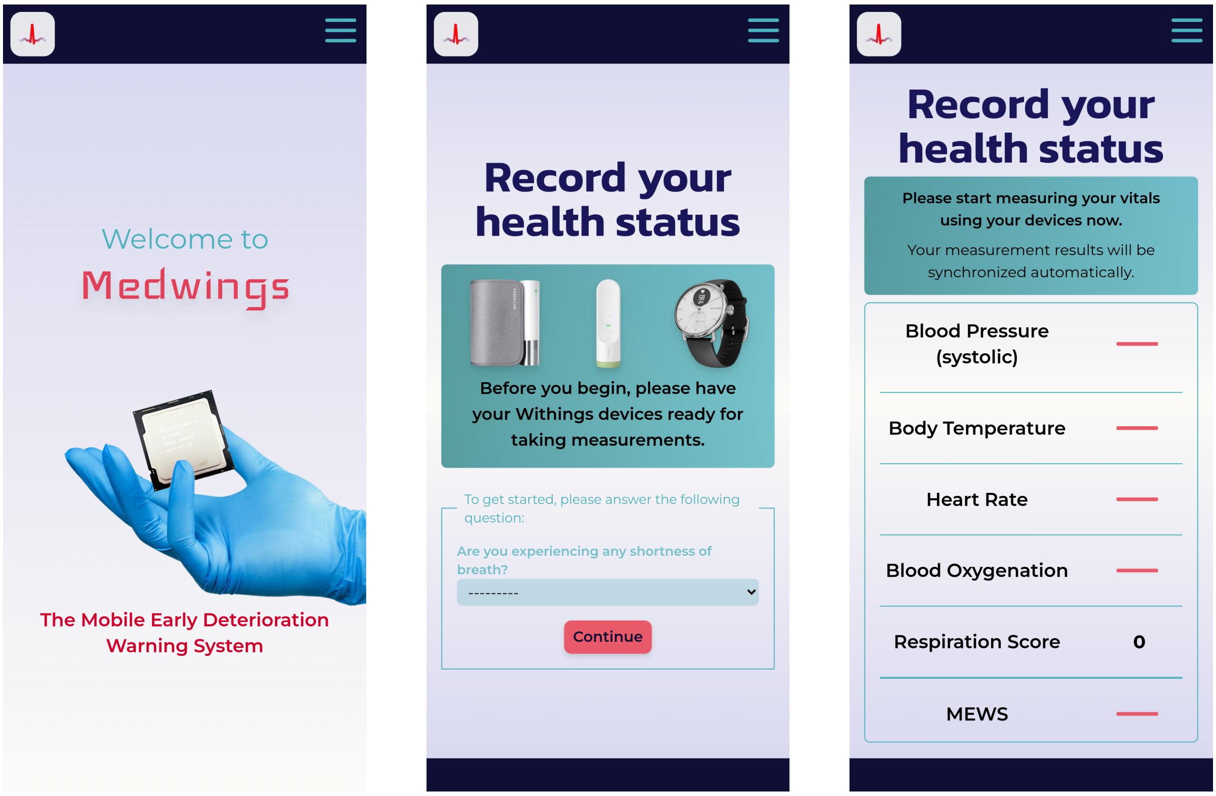
In order to send push notifications to mobile devices, Medwings leverages *Gotify* – a dedicated notification microservice[64]. Gotify is composed of a web server component, and a mobile app acting as the client software. The server exposes its own API, which allows external applications like Medwings to dispatch push notifications programmatically. It uses an independent database for client authentication. The `gotify` module ensures synchronization between the user databases of Gotify and Medwings. In addition, the module provides interfaces to send customized push notifications to specific patients.

2.2.3 User Interface

The Medwings UI was developed with specific design goals in mind to ensure an efficient and intuitive user experience. Figure 5 provides some impressions of what a user sees when using the application.

Aiming for a clutter-free and fast user experience, simplicity served as the guiding principle to enhance usability. A focus was put on developing accessibility-friendly UI components, ensuring that the system is usable by visually impaired individuals.

Security was a top priority in the frontend implementation to protect users and the system from common vulnerabilities. Overall, the use of JavaScript was kept to a minimum to reduce the attack surface. Various security mea-



(a) Medwings home page

(b) Starting a measurement

(c) Waiting for synchronization

Figure 5: Medwings UI screenshots

sures were carefully put in place to reduce the attack surface of the website:

- User input and form field sanitization, alongside strong server-side validation to prevent cross-site scripting (XSS) and SQL injection attacks
- To counteract cross-site request forgery (CSRF) attacks, CSRF tokens were implemented on all forms
- To minimize the risk of supply chain and third-party XSS attacks, no external JavaScript dependencies are used by Medwings

Considering that mobile devices are the primary platform for Medwings, the UI was designed to be fully responsive. It adapts seamlessly to different screen sizes, whether accessed through mobile phones, tablets, or devices with a larger form factor. Fast load times were a crucial design goal to ensure usability under various network conditions.

Navigational elements and the overall layout follow conventional patterns. Animations are sparingly used to visually indicate in-progress system states, such as when waiting for data retrieval from the Withings Cloud.

2.2.4 Datamodel

A relational database was used to store application data, whereby each Medwings module defines the database schema for the underlying data it is responsible for handling. Module interdependencies correlate closely with the foreign key references in the data model. A holistic representation of the Medwings data model is shown in Figure 6.

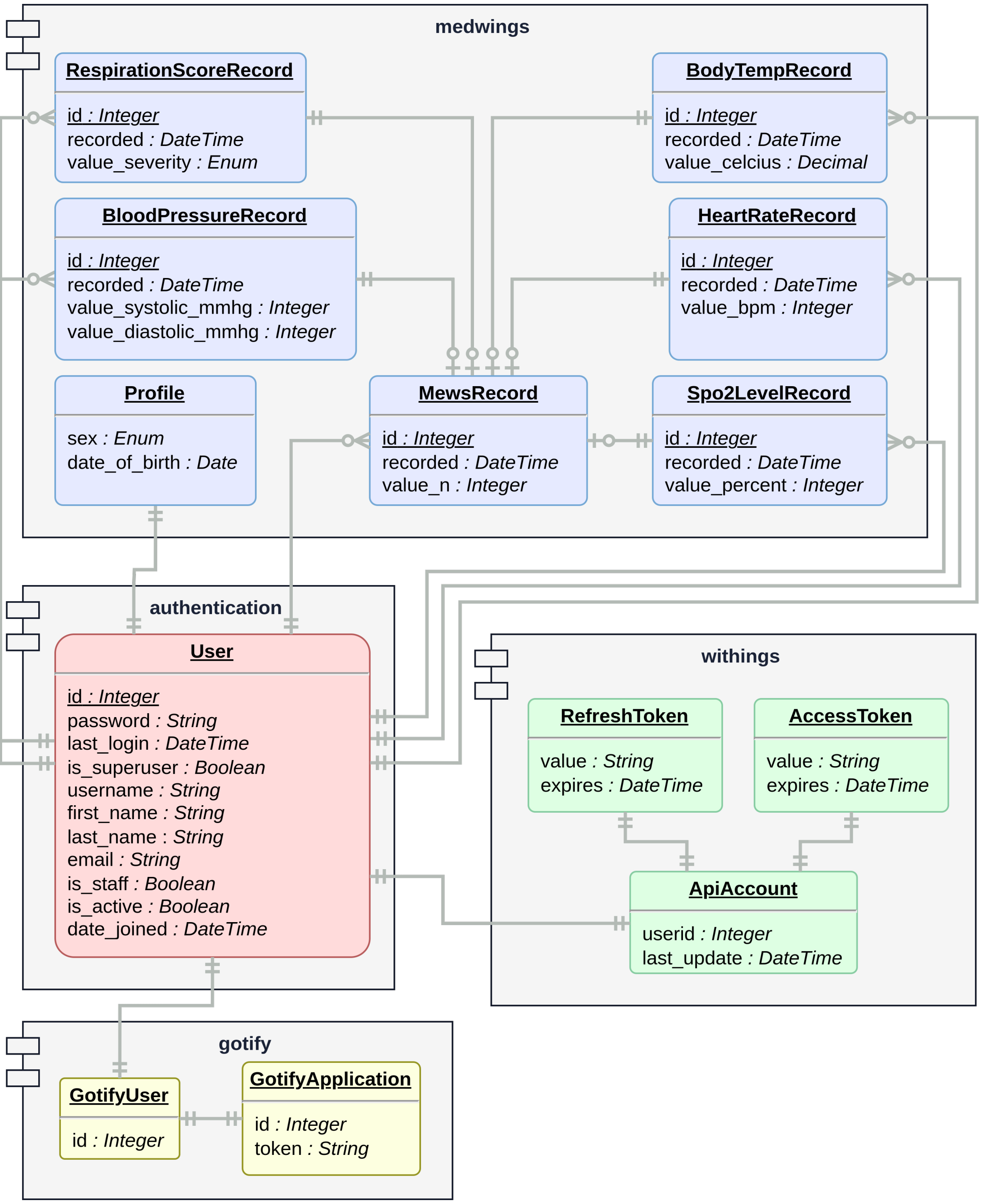


Figure 6: Entity-Relationship diagram (Crow's Foot notation) showing the data model of the Medwings database.

At its heart lies the `User` entity: it forms the nexus to which all vitals data and user information is linked. Withings API tokens are stored in the `RefreshToken` and `AccessToken` entities, while the `GotifyUser` and the `GotifyAccount` entities retain the Gotify API credentials. The numerous vital signs, as well as the MEWS record which can potentially be calculated based on them, are also represented. The `Profile` table stores additional medically relevant patient information as supplied during user registration.

2.2.5 Deployment

To use the smart devices to take measurements, patient users must first install the Withings mobile app on their phone, and use it to create a Withings user account. Following registration, each device must be linked to the app and configured via Bluetooth. Some basic configuration is required in order to enable specific device features, such as measurement of SPO_2 on the Scanwatch. Users are guided through the process by the app's Graphical User Interface (GUI).

Being a web application, no installation is necessary to access the Medwings interface, patients simply visit the website in a web browser. Patients do need to create a Medwings account on the website however, followed by installation and configuration of the Gotify mobile app, as described in the registration process in Section 2.2.2.

The centralized server components, including the Gotify server, a task scheduler used to schedule sending notifications and the Medwings application code itself are deployed on a publicly accessible web server using a Docker container environment.

3 System test and trial

Following the development and deployment of the application, Medwings underwent a performance and usability study. Over the course of one week, a male test subject aged 29, impersonated a patient by using the application several times a day.

Each day, five notifications were dispatched. Starting at 10 AM, one notification was sent every three hours. When prompted by a notification, the subject was asked to visit the Medwings website and begin the measurement process. Following a notification, the measurements were carried out in the following order:

1. The subject responds to a Medwings prompt to assess their respiration score.
2. Using the Scanwatch, the subject starts an SPO_2 measurement and awaits its completion.
3. A blood pressure and heart rate check is initiated on the BPM core, and the subject waits for the results.
4. The subject takes a body temperature reading via the Thermo and waits for it to complete
5. Finally, the subject allows time for Medwings to aggregate all the data and display the MEWS.

Throughout this process, Medwings would continuously attempt to retrieve the vital sign readings from the Withings Cloud, and calculate the MEWS once all required readings are available. If not all readings could be retrieved within the ten minute timeout, Medwings displayed an error message and aborted the MEWS measurement process.

3.1 Methodology

For each vital sign measurement, as well as for each MEWS calculation, Medwings stored the measurement results alongside the time of measurement.

For each received notification, the test subject manually kept track of which environment the system was used in. A distinction was made between the following environments:

- At home: The subject was located at home, and their end device had access to a low latency broadband internet connection
- On the go: The subject was away from home, and their end device had access to a high latency mobile internet connection

The end device used by the subject to connect to Medwings was their phone throughout the trial. In addition, the subject reflected on noteworthy experiences regarding use of the system after the trial was completed.

The occurrence of measurement failures was anticipated, and manually recorded. Measurement failures were categorized into eight distinct classes, as listed in Table 6.

The Scanwatch and BPM Core are equipped with accellerometers[59, 60].

Device	Failure Class	Description
Scanwatch	S_1	Device aborted measurement
	S_2	Measurement synchronization failure
BPM Core	B_1	Device aborted measurement
	B_2	Measurement synchronization failure
Thermo	T_1	Device aborted measurement
	T_2	Measurement synchronization failure
—	P_1	Patient did not take any measurements
	P_2	MEWS calculation timed out

Table 6: Classification of measurement failures during the usability trial

If erratic movement is detected, the devices abort the measurement to avoid misinterpretation of sensor readings. Similarly, upon failure to process captured sensor data into a plausible result, a measurement may be aborted by the device[65, 66, 67]. The measurement failure classes S_1, B_1 and T_1 were used to record these kinds of failure for the Scanwatch, BPM Core and Thermo respectively. Following an S_1, B_1 or T_1 failure, the subject repeatedly carried out measurements using the affected device until a valid reading could be obtained. Subsequent failures caused by the device aborting measurements were also recorded. The count of “device aborted measurement”-failures of each device was compared to the total number of measurement attempts using that device.

As explained in Section 2.2.2, following a successful reading, a device may fail to push the measurement data to the Withings Cloud within the ten minute validity range for a MEWS calculation imposed by Medwings. Depending on whether the Scanwatch, BPM Core or Thermo failed to synchronize its data within the allowed time, an S_2, B_2 or T_2 failure was recorded respectively. The number of measurement synchronization failures which occurred was compared to the number of successfully synchronized measurements for each device. Following an S_2, B_2 or T_2 failure, the measurement process was not repeated until the next notification.

For each notification to which the subject responded, the duration between when the notification was dispatched and when the patient took the first vitals measurement was recorded. Additionally, the average time taken to complete all three vitals measurements was noted. If the subject did not visit the Medwings website or carry out any vitals measurements despite being prompted by a notification, a P_1 failure was noted. Finally, if the patient failed to carry out all three required vitals measurements within the ten minute time limit, a P_2 failure was recorded.

Preceding each MEWS measurement, metrics quantifying the quality of the connection between the subject's end device and other devices across the internet were measured. This was done by sampling and averaging the data transmission rates, both uplink and downlink, as well as the connection round trip times from the end device to a distant reference server, the location of which was kept constant throughout the trial. The collected connection metrics were compared with the occurrence of measurement synchronization failures.

3.2 Results

The trial period encompassed seven days, on each of which five notifications were dispatched to the patient. Thus, an overall of $N = 35$ system interactions were recorded. The patient was at home during 26 of these, and on the go in all other cases.

Seven P_1 measurement failures occurred, wherein the patient did not react to a received notification by taking measurements. Out of these, five occurred while the patient was on the go and, notably, four P_1 failures were consecutive, stemming from a period of 24 hours during which the patient did not have access to the smart devices. No P_2 measurement failures occurred during the trial. The patient reported feeling reluctant about taking measurements using the devices in public spaces, compared to the privacy of their home.

In total, vitals were measured using all three devices in 28 cases. However, in 11 cases, at least one device failed to synchronize its measurements with the Withings Cloud within the ten minute timeout. Throughout the trial, 17 MEWS calculations were recorded successfully. Figure 7 visualizes the overall measurement and failure counts.

Out of 84 successful individual vitals measurements across all devices throughout the trial, 18% took longer than permitted by Medwings to synchronize with the Withings Cloud. Particularly while on the go, synchronization was prone to taking too long: 25% of measurements resulted in synchronization failure, compared to 11% at home. Especially the BPM Core and Thermo devices suffered from slow synchronization times: in a total of 15 synchronization timeouts, $n_{B_2} = 7$ were caused by the blood pressure meter, and $n_{T_2} = 7$ by the thermometer.

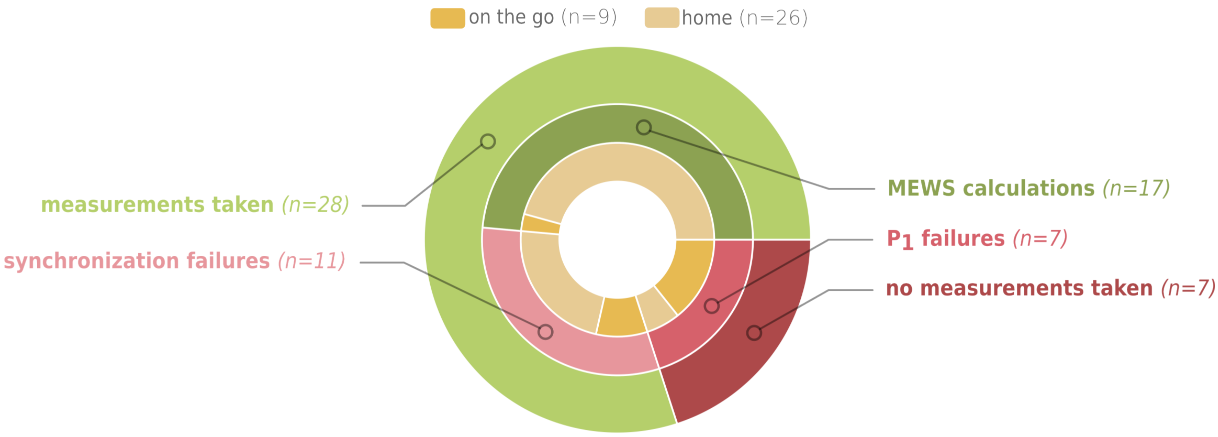


Figure 7: Measurement and measurement failure statistics at home and on the go.

The likelihood of each device aborting a measurement due to inconclusive sensor data was examined and is visualized in Figure 8. For the BPM Core, 15% of attempted measurements had to be repeated ($n_{B_1} = 5$). For the Scanwatch, over 34% of readings ($n_{S_1} = 15$) were inconclusive and had to be repeated. The Withings Thermo did not abort any measurements ($n_{T_1} = 0$).

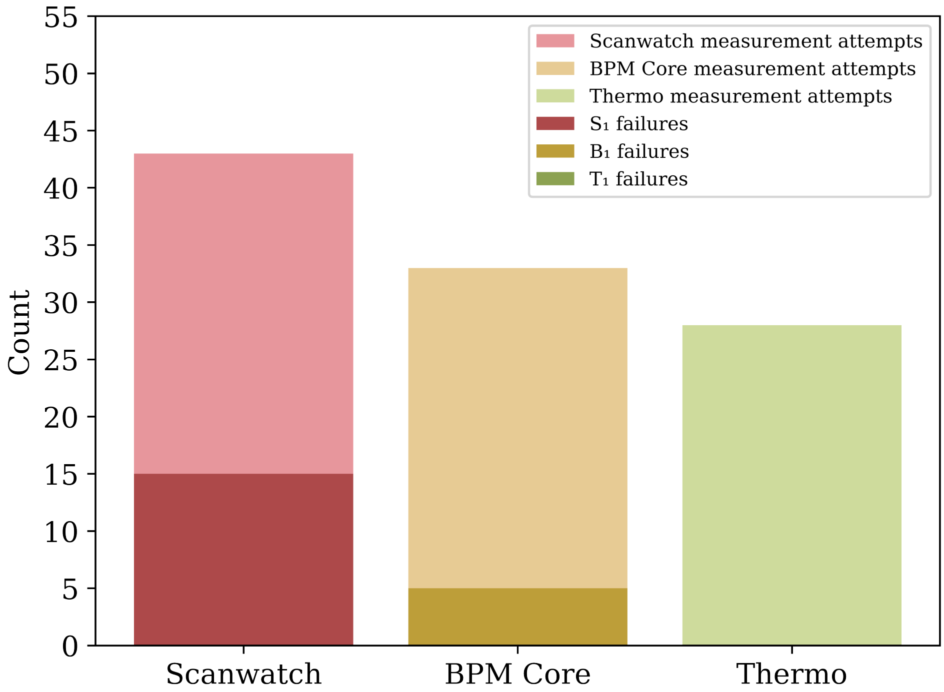


Figure 8: Number of measurement attempts and aborted measurements for each smart device.

Figure 9 illustrates the comparative box plots for the downlink datarate, uplink datarate, and Round trip time (RTT) connection metrics when the patient was at home versus on the go. While there are evident differences in the distributions of these metrics between the two environments, the points representing synchronization failures do not predominantly cluster around areas of low data rate or high RTT.

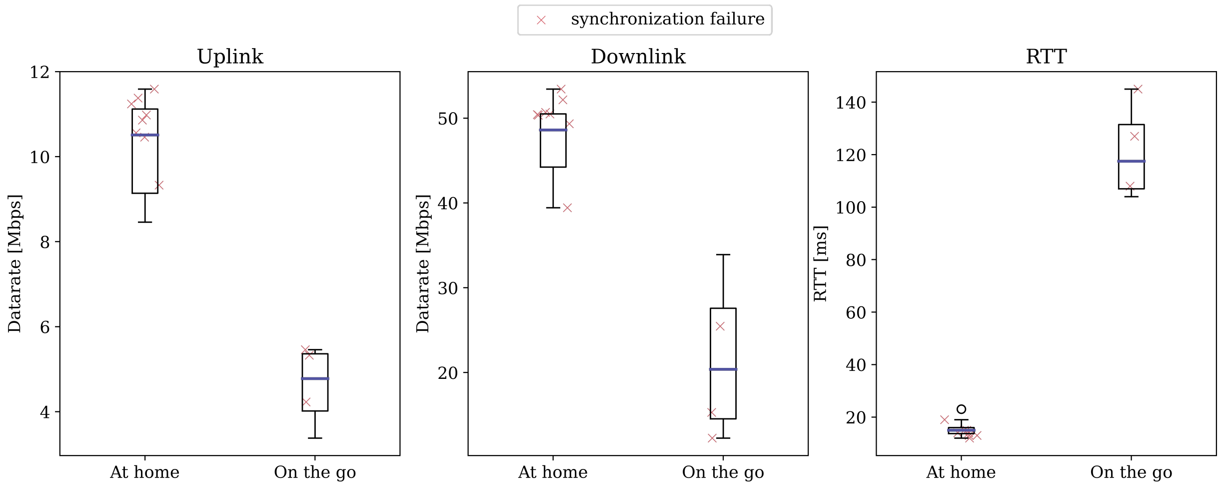


Figure 9: Connection quality and synchronization failures.

A reaction delay t_r existed from when a notification was dispatched until the subject visited the Medwings website to take measurements. The average ($\overline{t_{r,\text{home}}} = 36$ min) and median ($M_{t_{r,\text{home}}} = 33$ min) delay was significantly lower when the patient was at home, compared to when they were out of the house ($\overline{t_{r,\text{on the go}}} = 68$ min, $M_{t_{r,\text{on the go}}} = 70$ min). The patient reported feeling fatigued by the regularity of the notifications from the second trial day onward.

The average time it took the patient to carry out all three measurements was 4.5 minutes, with no significant difference between the "at home" and "on the go" environments.

In all cases where vitals measurements were taken using the devices, the vitals data was captured and stored by Medwings. In cases where the measurement data was not uploaded to the Withings Cloud quickly enough for Medwings to calculate the MEWS, the recorded vitals data was still pulled into the Medwings database. Across all measurements, the subject's vital signs were within normal ranges, with the exception of two outliers where a slightly increased heart rate was measured. Both outliers were detected by Medwings in the form of an elevated MEWS.

The complete trial data is listed in Appendix A.

4 Discussion

The usability study of the Medwings system provided valuable insights into the system's performance, reliability, and user interaction experience. Classifying measurement failures into types helped to identify bottlenecks and other areas for improvement. Overall, the Medwings system was successful in retrieving a wide range of vital signs from the patient at regular intervals, and detected abnormal readings using the MEWS. The system successfully aggregated data from multiple sources to compute the MEWS, and all MEWS calculations carried out by Medwings resulted in the correct value based on the recorded vitals data. Both at home and on the go, the patient's vital parameters could be monitored using the system. While at home, the patient was able to take all vitals measurements quickly and accommodate the measurement process into their daily routine, leading to a high rate of interaction with the system. Within the limited trial period, Medwings was able to detect abnormal readings effectively.

A significant portion of recorded vitals data, however, could not successfully be converted into MEWS records. These calculation failures pertained to device synchronization delay with the Withings Cloud, highlighting a critical issue. The BPM Core and Thermo devices synchronize only when turned on through manual interaction. This leads to longer sync times for these devices, inhibiting Medwings from accessing new vitals data swiftly and performing a timely MEWS calculation. A timeout period more lenient than the ten minute window imposed by Medwings may reduce the rate of synchronization failures, but it may also negatively impact the validity of a MEWS record if implemented. The study found that connection metrics such as data transmission rates and round-trip times did not show a significant correlation with synchronization failures. This suggests that other factors, likely server-side processing delays on the Withings Cloud, contribute to these failures.

The study also revealed that the system is generally more reliable when the patient is at home, as indicated by the low interaction rate while on the go. One reason was that carrying a a range of vitals sensors while out of the house is not always feasible. Another was the subject's reluctance to take measurements in public spaces, suggesting a need for more discreet solutions for on the go vitals monitoring. However, when measurements were made in the mobile environment, Medwings was successful at aggregating the measured data and, aside from the aforementioned synchronization issues, was able to calculate the subject's MEWS.

While at home, the test subject was able to adhere well to the measurement schedule, missing measurements only twice throughout the week. With a three-hour window to respond to each notification, the average response time of 36 minutes and the minimal number of P_1 failures show that the 4.5-minute measurements were manageable within the home setting. On the go however, a significant portion of the received notifications were not followed up by vitals measurements. When leaving the house for extended periods of time, the subject was not always able to bring the whole array of medical devices with them. Additionally, taking measurements could not always be done discreetly in public spaces, and finding a private area to take measurements was not always possible. This lead to a high rate of P_1 failures on the go, coupled with a comparatively long average reaction time of $\overline{t_{r,\text{on the go}}} = 68$ minutes.

The rate at which device synchronization failures occurred was high, with 39% of successful measurements not being pushed to the Withings cloud in time for a MEWS calculation to be valid. A combination of three factors was determined to be the cause for this.

Firstly, while the Scanwatch is constantly connected to the patient's phone, the BPM Core and Thermo devices only establish their Bluetooth connection intermittently. Presumably, measurement data updates from these devices are sent to the phone less frequently than for the Scanwatch. This is strongly underlined by the fact that 93% of all synchronization timeouts were caused by the BPM Core or Thermo.

The second factor becomes apparent after examining the likelihood of each device aborting its measurement due to inconclusive sensor data, as displayed in Figure 8. Although the aborted measurements did not cause synchronization failures directly, the time taken to repeat measurements impacted the likelihood of the MEWS calculation timing out before all vitals data was synchronized. The Scanwatch was particularly prone to prolonging the overall time it took the patient to complete all readings.

The third factor was the time it took the Withings app to push vitals data to the Cloud, and data being available for retrieval through the Withings API. While no concrete data to quantify this duration could be gathered, it is clear that the two minute delay estimate provided by the manufacturer[63] was exceeded substantially in many cases. The relationship between the connection quality and the likelihood of synchronization failures was examined, as shown in Figure 9, but no correlation was found, suggesting that synchronization failures were not majorly influenced by the current connection quality of the subject's end device.

Ultimately, while 61% of notifications to which the patient responded did result in a successful MEWS calculation, the high rate of device synchronization timeouts suggests that routing data from the device, to the mobile app, to the Withings cloud, and finally to the Medwings server introduces substantial delays, thereby affecting the system's usability for its near-real-time calculation requirement.

In terms of its software design, the Medwings application successfully met its predetermined software requirements. The system demonstrated robust user authentication mechanisms and offered portability by being accessible on mobile phones. Additionally, it provided an intuitive interface for data visualization. Vital signs were collected and stored automatically from all three Withings smart medical sensors, and the respiration score was able to be determined interactively. The system was consistently available and ensured data validity, while maintaining stringent security protocols. While certain challenges were encountered during the usability trial, the software's overarching objectives in terms of functional and non-functional requirements were successfully achieved.

4.1 Limitations

Several limitations of the current study and the Medwings system must be noted.

Firstly, the original MEWS algorithm could not be used in its unaltered form to facilitate automated deterioration scoring. Measuring the respiration rate and AVPU of a mobile patient presented a challenge, which had to be overcome by disregarding the AVPU from the calculation and replacing the respiration rate in favor of a custom respiration score and SPO_2 measurements.

Furthermore, the usability study had only a single test subject, which does not capture the diversity of potential user experiences. Due to time constraints, the trial period was limited to lasting only one week, reducing the sample size and potentially introducing bias in the gathered data.

Measurement prompts were dispatched every 3 hours during the day. This allows for just a restricted, intermittent view of a patient's physiological state, and the chosen sampling period may require adequate adjustment.

Moreover, although designed and implemented as a multi-user system, Medwings was only tested with one active user. When used by many more users, the proof-of-concept system may encounter scalability issues, such as exceeding the API rate limits imposed by Withings. The non-enterprise Withings API enforces a rate limit of 120 requests per minute. Medwings polls the API regularly to retrieve the latest health data for patients. At scale, with many patient users, the rate limit would quickly be reached. The Withing API does provide functionality to notify client applications upon availability of new data, making it possible to avoid polling. Given that Medwings was only used by a single patient user during the trial phase, falling back to polling was an acceptable compromise to lower complexity while still operating within the rate limit.

Another significant limitation pertains to data security and privacy. The Medwings system replicates sensitive patient data, which is already stored in the Withings Cloud, in its own database. This dual storage increases the attack surface for breaches of sensitive data, posing a risk to patient privacy. Ideally, removing the need to store vitals data either in the Withings Cloud or in the Medwings database would improve the system's privacy and security.

Furthermore, the system's complexity during initial setup poses a notable limitation. Users must undergo a multi-step process: signing up for Withings, pairing medical devices, registering for a Medwings account, and finally, logging in to the Gotify application. This makes the system less accessible, particularly for elderly patients or those less technically inclined. Although necessitated by current resource limitations, a more streamlined setup process could have been achieved with additional development time and funding. For example, integrating Medwings and Gotify into a single mobile application would significantly ease the setup process. The Withings enterprise API plan can be utilized to manage OAuth2 user accounts[68], eliminating the need for a separate Medwings user database and thus further simplifying user registration.

Lastly, using Medwings and the smart medical devices requires the patient to have internet access, which will negatively impact the system's effectiveness in some circumstances where a stable connection is not available.

4.2 Future Work and Improvements

The Medwings system, while successful in its current iteration, offers multiple avenues for improvement.

Its dependence on web-based access to the Withings API to retrieve vitals readings results in significant delays and mandates an internet connection. A native mobile application offering direct Bluetooth access to sensor measurements would enhance real-time responsiveness and negate the necessity for a stable internet connection. Unfortunately, Withings do not offer such an option to developers. Vendor dependence in general introduces a risk to Medwings' continued operation. Service outages, discontinued device updates, or the vendor ceasing business operations all render the smart devices, and consequently Medwings, unusable. Vendor-independent access and open-source firmware for the medical devices would mitigate these risks and open up exciting possibilities for further system integrations.

Additionally, expanding the range of monitored vitals could allow implementation of more comprehensive RWSM techniques. The integration of a smart device capable of accurately measuring the respiration rate of a mobile patient would refine the MEWS calculations, leading to a more accurate deterioration monitoring system. The system could also benefit from real-time alerting for emergency situations, rather than relying solely on periodic MEWS calculations. This would not only make the system more robust but would also be crucial for immediate medical intervention. For healthcare providers, a monitoring platform could be developed to allow medical staff to have direct visibility into their patient's vitals and recent developments.

Intermittent vitals monitoring presents an incomplete picture of the patient's health status. A continuous monitoring system would not only improve the system's efficacy[36, 14], but could greatly enhance the sampling frequency and obviate the need for manual patient interaction for taking measurements.

Given more development time, a range of auxiliary features could be integrated into Medwings. Native mobile notifications, more detailed vitals analysis, and utilization of additional functionalities available in Withings devices would elevate the system's overall capabilities and usefulness. As technology advances, future work could explore machine learning models to predict potential health anomalies based on historical data.

5 Conclusion

The objective of this research was to explore the feasibility and of an RWSM system for use by outpatients, using commercially available smart medical devices. The Medwings system was successful in demonstrating the feasibility of such an approach. Key operational challenges and successes were identified, providing insights for the future development and refinement of systems in this domain.

The research found that RWSM is feasible. While the MEWS could not be directly applied in its unaltered form, the use of consumer-grade smart devices in the Medwings system successfully facilitated remote patient monitoring in combination with EWS assessments.

Given the rapidly evolving market for advanced smart medical devices, the implications for healthcare providers are significant. Potentially freeing up medical resources and improving patient mobility and autonomy by allowing for earlier dismissal of patients from care facilities, systems such as Medwings may hold considerable value.

While the Medwings system has demonstrated the feasibility of RWSM, it remains somewhat rough around the edges. Continued research in this area is essential to enhance the robustness and effectiveness of RWSM systems. The potential for life-saving interventions via automated alerts makes the case for a more robust system compelling. Although the current system uses a web-based client-server architecture, alternative approaches should be explored. Research into the development of a local, body-area-network system could offer improved reliability and responsiveness.

In conclusion, the research has successfully filled an important knowledge gap in the field of remote patient monitoring with early warning scores, and outlines the scope for future advancements. Given the continuing technological advancements in smart medical devices, the future appears promising for the adoption and refinement of systems like Medwings for better patient care and resource optimization in healthcare.

Glossary

Application Programming Interface

A set of rules and protocols that allow different software entities to communicate with each other. It defines the methods and data formats that applications can use to request and exchange information. APIs are utilized to enable the integration between different systems and devices, streamlining their functionalities and expanding capabilities.

AVPU Score

A rapid assessment method to determine a patient's level of consciousness. The AVPU scale is used to quickly identify potential neurological impairment or altered mental status in emergency settings. The four possible findings are:

- **Alert**: Patient is fully alert and oriented.
- **Voice**: Patient responds to verbal stimuli but is not fully alert.
- **Pain**: Patient responds only to painful stimuli.
- **Unresponsive**: Patient does not respond to any external stimuli.

Blood Oxygen Saturation

A percentage measure indicating the level of oxygen saturation in the blood. The blood oxygen saturation represents the proportion of hemoglobin molecules in the bloodstream that are saturated with oxygen[69].

deterioration

A decline in a patient's health status marked by worsening of clinical signs and symptoms, often necessitating escalated medical intervention.

downlink datarate

The rate at which data is received by a client device from a central server or network. Expressed often in Mbps, it reflects the downloading or data reception efficiency of a network connection.

Early Warning Score

A clinical tool used to assess the severity and likelihood of patient deterioration by scoring multiple vital signs.

Electrocardiogram

A medical test that measures the electrical activity of the heartbeat to diagnose various heart conditions.

Modified Early Warning Score

An adaptation of the Early Warning Score, which provides a simplified scoring system based on fewer physiological parameters to predict medical deterioration.

National Early Warning Score 2

The second iteration of a standardized scoring system used in the UK to detect and respond to clinical deterioration in adult patients. It builds upon and refines the original NEWS score.

Pediatric Early Warning Score

An early warning score used to identify early signs of deterioration in pediatric patients.

Remote Warning Score Monitoring

An approach that integrates RPM of mobile patients with the automated calculation of an EWS. It enables real-time assessment of patient deterioration risk based on data gathered remotely.

remote patient monitoring

A technology to enable monitoring of patients outside of conventional clinical settings, such as in the home or in a remote area, which may increase access to care and decrease healthcare delivery costs.

Round trip time

The time taken for a data packet to travel from a source to a destination and back again. It provides an indication of the latency or delay inherent in a network connection and is usually measured in milliseconds (ms).

uplink datarate

The speed at which data is transmitted from a client device, such as a computer or smartphone, to a server or central network. Typically measured in Mbps (megabits per second), it represents the efficiency of data sending capabilities of a network connection.

Acronyms

API

Application Programming Interface

AVPU

AVPU Score

ECG

Electrocardiogram

EWS

Early Warning Score

GUI

Graphical User Interface

ICU

intensive care unit

IoT

Internet of Things

MEWS

Modified Early Warning Score

NEWS2

National Early Warning Score 2

PEWS

Pediatric Early Warning Score

RPM

Remote patient monitoring

RTT

Round trip time

RWSM

Remote Warning Score Monitoring

SPO_2

Blood Oxygen Saturation

UI

User Interface

List of Figures

List of Tables

List of Algorithms

References

1. Downey C, Tahir W, Randell R, Brown J, and Jayne D. Strengths and limitations of early warning scores: A systematic review and narrative synthesis. International Journal of Nursing Studies. 2017; 76:106–19. DOI: 10.1016/j.ijnurstu.2017.09.003
2. Subbe C, Kruger M, Rutherford P, and Gemmel L. Validation of a modified Early Warning Score in medical admissions. QJM: An International Journal of Medicine. 2001 Oct 1; 94:521–6. DOI: 10.1093/qjmed/94.10.521. Available from: https://doi.org/10.1093/qjmed/94.10.521 [Accessed on: 2023 Apr 30]
3. Buist M, Bernard S, Nguyen TV, Moore G, and Anderson J. Association between clinically abnormal observations and subsequent in-hospital mortality: a prospective study. Resuscitation. 2004 Aug 1; 62:137–41. DOI: 10.1016/j.resuscitation.2004.03.005. Available from: https://www.sciencedirect.com/science/article/pii/S0300957204001236 [Accessed on: 2023 Apr 26]
4. Paterson R, MacLeod DC, Thetford D, Beattie A, Graham C, Lam S, and Bell D. Prediction of in-hospital mortality and length of stay using an early warning scoring system: clinical audit. Clinical Medicine. 2006 May 1; 6. Publisher: Royal College of Physicians Section: Original Papers:281–4. DOI: 10.7861/clinmedicine.6-3-281. Available from: https://www.rcpjournals.org/content/clinmedicine/6/3/281 [Accessed on: 2023 Apr 26]
5. Gardner-Thorpe J, Love N, Wrightson J, Walsh S, and Keeling N. The Value of Modified Early Warning Score (MEWS) in Surgical In-Patients: A Prospective Observational Study. Annals of The Royal College of Surgeons of England. 2006 Oct; 88:571–5. DOI: 10.1308/003588406X130615. Available from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1963767/ [Accessed on: 2023 Aug 27]
6. Alam N, Vegting IL, Houben E, Berkel B van, Vaughan L, Kramer MHH, and Nanayakkara PWB. Exploring the performance of the National Early Warning Score (NEWS) in a European emergency department. Resuscitation. 2015 May 1; 90:111–5. DOI: 10.1016/j.resuscitation.2015.02.011. Available from: https://www.sciencedirect.com/science/article/pii/S0300957215000787 [Accessed on: 2023 Apr 27]
7. Bilben B, Grandal L, and Søvik S. National Early Warning Score (NEWS) as an emergency department predictor of disease severity and 90-day survival in the acutely dyspneic patient – a prospective observational

study. Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine. 2016 Dec; 24. Number: 1 Publisher: BioMed Central:1–8. DOI: 10.1186/s13049-016-0273-9. Available from: https://sjtrem.biomedcentral.com/articles/10.1186/s13049-016-0273-9 [Accessed on: 2023 Apr 27]

8. Brekke IJ, Puntervoll LH, Pedersen PB, Kellett J, and Brabrand M. The value of vital sign trends in predicting and monitoring clinical deterioration: A systematic review. PLOS ONE. 2019 Jan 15; 14. Publisher: Public Library of Science:e0210875. DOI: 10.1371/journal.pone.0210875. Available from: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0210875 [Accessed on: 2023 Apr 26]
9. Ehara J, Hiraoka E, Hsu HC, Yamada T, Homma Y, and Fujitani S. The effectiveness of a national early warning score as a triage tool for activating a rapid response system in an outpatient setting: A retrospective cohort study. Medicine. 2019 Dec; 98:e18475. DOI: 10.1097/MD.0000000000018475. Available from: https://journals.lww.com/md-journal/Fulltext/2019/12270/The_effectiveness_of_a_national_early_warning.30.aspx [Accessed on: 2023 Apr 26]
10. Burgos-Esteban A, Gea-Caballero V, Marín-Maicas P, Santillán-García A, Cordón-Hurtado MdV, Marqués-Sule E, Giménez-Luzuriaga M, Juárez-Vela R, Sanchez-Gonzalez JL, García-Criado J, and Santolalla-Arnedo I. Effectiveness of Early Warning Scores for Early Severity Assessment in Outpatient Emergency Care: A Systematic Review. Frontiers in public health. 2022 Jan 1; 10:894906. DOI: 10.3389/fpubh.2022.894906. Available from: https://europepmc.org/articles/PMC9330632 [Accessed on: 2023 Apr 27]
11. Paganelli AI, Velmovitsky PE, Miranda P, Branco A, Alencar P, Cowan D, Endler M, and Morita PP. A conceptual IoT-based early-warning architecture for remote monitoring of COVID-19 patients in wards and at home. Internet of Things. 2022 May 1; 18:100399. DOI: 10.1016/j.iot.2021.100399. Available from: https://www.sciencedirect.com/science/article/pii/S2542660521000433 [Accessed on: 2023 Apr 26]
12. National Early Warning Score (NEWS) 2. RCP London. 2017 Dec 19. Available from: https://www.rcplondon.ac.uk/projects/outputs/national-early-warning-score-news-2 [Accessed on: 2023 May 1]
13. Eisenkraft A, Goldstein N, Merin R, Fons M, Ishay A, Nachman D, and Gepner Y. Developing a real-time detection tool and an early warning score using a continuous wearable multi-parameter monitor. Frontiers in Physiology. 2023; 14. DOI: 10.3389/fphys.2023.1138647

14. Shaik T, Tao X, Higgins N, Li L, Gururajan R, Zhou X, and Acharya UR. Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. WIREs Data Mining and Knowledge Discovery. 2023; 13. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/widm. DOI: 10.1002/widm.1485. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/widm.1485 [Accessed on: 2023 Apr 26]
15. Filho IdMB, Aquino G, Malaquias RS, Girão G, and Melo SRM. An IoT-Based Healthcare Platform for Patients in ICU Beds During the COVID-19 Outbreak. IEEE Access. 2021; 9. Conference Name: IEEE Access:27262–77. DOI: 10.1109/ACCESS.2021.3058448
16. Un KC, Wong CK, Lau YM, Lee JCY, Tam FCC, Lai WH, Lau YM, Chen H, Wibowo S, Zhang X, Yan M, Wu E, Chan SC, Lee SM, Chow A, Tong RCF, Majmudar MD, Rajput KS, Hung IFN, and Siu CW. Observational study on wearable biosensors and machine learning-based remote monitoring of COVID-19 patients. Scientific Reports. 2021 Feb 23; 11. Number: 1 Publisher: Nature Publishing Group:4388. DOI: 10.1038/s41598-021-82771-7. Available from: https://www.nature.com/articles/s41598-021-82771-7 [Accessed on: 2023 Apr 26]
17. Karvounis E, Vavva M, Giannakeas N, Tzallas AT, Smanis I, and Tsipouras MG. A Hospital Healthcare Monitoring System Using Internet of Things Technologies. *2021 6th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM)*. 2021 6th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM). 2021 Sep :1–6. DOI: 10.1109/SEEDA-CECNSM53056.2021.9566252
18. Gidari A, De Socio GV, Sabbatini S, and Francisci D. Predictive value of National Early Warning Score 2 (NEWS2) for intensive care unit admission in patients with SARS-CoV-2 infection. Infectious Diseases. 2020 Oct 2; 52. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/23744235 704. DOI: 10.1080/23744235.2020.1784457. Available from: https://doi.org/10.1080/23744235.2020.1784457 [Accessed on: 2023 Apr 27]
19. Otoom M, Otoum N, Alzubaidi MA, Etoom Y, and Banihani R. An IoT-based framework for early identification and monitoring of COVID-19 cases. Biomedical Signal Processing and Control. 2020 Sep 1; 62:102149. DOI: 10.1016/j.bspc.2020.102149. Available from: https://www.sciencedirect.com/science/article/pii/S1746809420302949 [Accessed on: 2023 Apr 27]

20. Carr E, Bendayan R, Bean D, Stammers M, Wang W, Zhang H, Searle T, Kraljevic Z, Shek A, Phan HTT, Muruet W, Gupta RK, Shinton AJ, Wyatt M, Shi T, Zhang X, Pickles A, Stahl D, Zakeri R, Noursadeghi M, O'Gallagher K, Rogers M, Folarin A, Karwath A, Wickstrøm KE, Köhn-Luque A, Slater L, Cardoso VR, Bourdeaux C, Holten AR, Ball S, McWilliams C, Roguski L, Borca F, Batchelor J, Amundsen EK, Wu X, Gkoutos GV, Sun J, Pinto A, Guthrie B, Breen C, Douiri A, Wu H, Curcin V, Teo JT, Shah AM, and Dobson RJB. Evaluation and improvement of the National Early Warning Score (NEWS2) for COVID-19: a multi-hospital study. BMC Medicine. 2021 Jan 21; 19:23. DOI: 10.1186/s12916-020-01893-3. Available from: https://doi.org/10.1186/s12916-020-01893-3 [Accessed on: 2023 Apr 27]
21. Anzanpour A, Rahmani AM, Liljeberg P, and Tenhunen H. Internet of things enabled in-home health monitoring system using early warning score. MOBIHEALTH 2015 - 5th EAI International Conference on Wireless Mobile Communication and Healthcare - Transforming Healthcare through Innovations in Mobile and Wireless Technologies. 2015. DOI: 10.4108/eai.14-10-2015.2261616
22. Anzanpour A, Rahmani AM, Liljeberg P, and Tenhunen H. Context-Aware Early Warning System for In-Home Healthcare Using Internet-of-Things. *Internet of Things. IoT Infrastructures*. Ed. by Mandler B, Marquez-Barja J, Mitre Campista ME, Cagáňová D, Chaouchi H, Zeadally S, Badra M, Giordano S, Fazio M, Somov A, and Vieriu RL. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering. Cham: Springer International Publishing, 2016 :517–22. DOI: 10.1007/978-3-319-47063-4_56
23. Archip A, Botezatu N, Şerban E, Herghelegiu PC, and Zală A. An IoT based system for remote patient monitoring. *2016 17th International Carpathian Control Conference (ICCC)*. 2016 17th International Carpathian Control Conference (ICCC). 2016 May :1–6. DOI: 10.1109/CarpathianCC.2016.7501056
24. Arnil J, Punsawad Y, and Wongsawat Y. Wireless sensor network-based smart room system for healthcare monitoring. *2011 IEEE International Conference on Robotics and Biomimetics*. 2011 IEEE International Conference on Robotics and Biomimetics. 2011 Dec :2073–6. DOI: 10.1109/ROBIO.2011.6181597
25. Athira A, Devika T, Varsha K, and Bose S. SS. Design and Development of IOT Based Multi-Parameter Patient Monitoring System. *2020 6th International Conference on Advanced Computing and Communication*

Systems (ICACCS). 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS). ISSN: 2575-7288. 2020 Mar :862–6. DOI: 10.1109/ICACCS48705.2020.9074293

26. Azimi I, Anzanpour A, Rahmani AM, Liljeberg P, and Salakoski T. Medical warning system based on Internet of Things using fog computing. *2016 International Workshop on Big Data and Information Security (IWBIS)*. 2016 International Workshop on Big Data and Information Security (IWBIS). 2016 Oct :19–24. DOI: 10.1109/IWBIS.2016.7872884
27. Azimi I, Anzanpour A, Rahmani A, Liljeberg P, and Tenhunen H. Self-aware early warning score system for IoT-based personalized healthcare. Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST. 2017; 181 LNICST. ISBN: 9783319496542:49–55. DOI: 10.1007/978-3-319-49655-9_8
28. B V SK, Sharma S, Swathi KS, Yamini KR, Kiran CP, and Chandrika K. Review on IoT based Healthcare systems. *2022 International Conference on Advanced Computing Technologies and Applications (ICACTA)*. 2022 International Conference on Advanced Computing Technologies and Applications (ICACTA). 2022 Mar :1–5. DOI: 10.1109/ICACTA54488.2022.9753547
29. Chen CL and Chuang CT. A QRS Detection and R Point Recognition Method for Wearable Single-Lead ECG Devices. Sensors. 2017 Sep; 17. Number: 9 Publisher: Multidisciplinary Digital Publishing Institute:1969. DOI: 10.3390/s17091969. Available from: https://www.mdpi.com/1424-8220/17/9/1969 [Accessed on: 2023 Apr 26]
30. Chiuchisan I, Costin HN, and Geman O. Adopting the Internet of Things technologies in health care systems. *2014 International Conference and Exposition on Electrical and Power Engineering (EPE)*. 2014 International Conference and Exposition on Electrical and Power Engineering (EPE). 2014 Oct :532–5. DOI: 10.1109/ICEPE.2014.6969965
31. Chowdary KC, Lokesh Krishna K, Prasad KL, and Thejesh K. An Efficient Wireless Health Monitoring System. *2018 2nd International Conference on 2018 2nd International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*. 2018 2nd International Conference on 2018 2nd International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC). 2018 Aug :373–7. DOI: 10.1109/I-SMAC.2018.8653716

32. Silva DB da, Schmidt D, Costa CA da, Rosa Righi R da, and Eskofier B. DeepSigns: A predictive model based on Deep Learning for the early detection of patient health deterioration. Expert Systems with Applications. 2021 Mar 1; 165:113905. DOI: 10.1016/j.eswa.2020.113905. Available from: https://www.sciencedirect.com/science/article/pii/S0957417420307004 [Accessed on: 2023 Apr 27]
33. Dagan A and Mechanic O. Use of ultra-low cost fitness trackers as clinical monitors in low resource emergency departments. Clinical and Experimental Emergency Medicine. 2020; 7:144–9. DOI: 10.15441/ceem.19.081
34. Mello Dantas H de and Miceli de Farias C. A data fusion algorithm for clinically relevant anomaly detection in remote health monitoring. *2020 International Symposium on Networks, Computers and Communications (ISNCC)*. 2020 International Symposium on Networks, Computers and Communications (ISNCC). 2020 Oct :1–8. DOI: 10.1109/ISNCC49221.2020.9297315
35. Gómez J, Oviedo B, and Zhuma E. Patient Monitoring System Based on Internet of Things. Procedia Computer Science. The 7th International Conference on Ambient Systems, Networks and Technologies (ANT 2016) / The 6th International Conference on Sustainable Energy Information Technology (SEIT-2016) / Affiliated Workshops 2016 Jan 1; 83:90–7. DOI: 10.1016/j.procs.2016.04.103. Available from: https://www.sciencedirect.com/science/article/pii/S1877050916301260 [Accessed on: 2023 Apr 26]
36. Grønbæk KK, Rasmussen SM, Langer NH, Vincentz M, Oxbøll AB, Søgaard M, Awada HN, Jensen TO, Jensen MT, Sørensen HBD, Aasvang EK, and Meyhoff CS. Continuous monitoring is superior to manual measurements in detecting vital sign deviations in patients with COVID-19. Acta Anaesthesiologica Scandinavica. 2023; 67. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/aas.14221:640–8. DOI: 10.1111/aas.14221. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1111/aas.14221 [Accessed on: 2023 Apr 26]
37. Imtyaz Ahmed M and Kannan G. Secure and lightweight privacy preserving Internet of things integration for remote patient monitoring. Journal of King Saud University - Computer and Information Sciences. 2022; 34:6895–908. DOI: 10.1016/j.jksuci.2021.07.016
38. Jagadish D, Priya N, and Suganya R. Remote Continuous Health Monitoring System for Patients. *Data Science Analytics and Applications*. Ed. by R S and Sharma M. Communications in Computer and Informa-

tion Science. Singapore: Springer, 2018 :129–38. DOI: 10.1007/978-981-10-8603-8_11

39. Javanbakht M, Mashayekhi A, Trevor M, Rezaei Hemami M, L. Downey C, Branagan-Harris M, and Atkinson J. Cost utility analysis of continuous and intermittent versus intermittent vital signs monitoring in patients admitted to surgical wards. Journal of Medical Economics. 2020 Jul 2; 23. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/13696998.2 36. DOI: 10.1080/13696998.2020.1747474. Available from: https://doi.org/10.1080/13696998.2020.1747474 [Accessed on: 2023 Apr 26]
40. Joshi M, Ashrafian H, Aufegger L, Khan S, Arora S, Cooke G, and Darzi A. Wearable sensors to improve detection of patient deterioration. Expert Review of Medical Devices. 2019 Feb 1; 16. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/17434440.2019.1563480:145–54. DOI: 10.1080/17434440.2019.1563480. Available from: https://doi.org/10.1080/17434440.2019.1563480 [Accessed on: 2023 Apr 26]
41. Kale YS, Rathkanthiwar SV, and Gawande PD. Intelligent Healthcare. *Intelligent Healthcare: Applications of AI in eHealth*. Ed. by Bhatia S, Dubey AK, Chhikara R, Chaudhary P, and Kumar A. EAI/Springer Innovations in Communication and Computing. Cham: Springer International Publishing, 2021 :19–31. DOI: 10.1007/978-3-030-67051-1_2. Available from: https://doi.org/10.1007/978-3-030-67051-1_2 [Accessed on: 2023 Apr 26]
42. Lee S, Gandla S, Naqi M, Jung U, Youn H, Pyun D, Rhee Y, Kang S, Kwon HJ, Kim H, Lee M, and Kim S. All-day mobile healthcare monitoring system based on heterogeneous stretchable sensors for medical emergency. IEEE Transactions on Industrial Electronics. 2020; 67:8808–16. DOI: 10.1109/TIE.2019.2950842
43. Martín-Rodríguez F, Castro-Villamor MÁ, Pozo Vegas C del, Martín-Conty JL, Mayo-Iscar A, Delgado Benito JF, Brio Ibañez P del, Arnillas-Gómez P, Escudero-Cuadrillero C, and López-Izquierdo R. Analysis of the early warning score to detect critical or high-risk patients in the prehospital setting. Internal and Emergency Medicine. 2019 Jun 1; 14:581–9. DOI: 10.1007/s11739-019-02026-2. Available from: https://doi.org/10.1007/s11739-019-02026-2 [Accessed on: 2023 Apr 28]
44. Pahlevanynejad S, Niakan Kalhori S, Katigari M, and Eshpala R. Personalized Mobile Health for Elderly Home Care: A Systematic Review of Benefits and Challenges. International Journal of Telemedicine and Applications. 2023; 2023. DOI: 10.1155/2023/5390712

45. Phaltankar S, Tyagi K, Prabhu M, Jaguste P, Sahu S, and Kalbande D. CuraBand: Health Monitoring and Warning System. *International Conference on Innovative Computing and Communications*. Ed. by Gupta D, Khanna A, Bhattacharyya S, Hassanien AE, Anand S, and Jaiswal A. Advances in Intelligent Systems and Computing. Singapore: Springer, 2021 :1017–26. DOI: 10.1007/978-981-15-5113-0_86
46. Quraishi SJ and Yusuf H. Internet of Things in Healthcare, A Literature Review. *2021 International Conference on Technological Advancements and Innovations (ICTAI)*. 2021 International Conference on Technological Advancements and Innovations (ICTAI). 2021 Nov :198–202. DOI: 10.1109/ICTAI53825.2021.9673369
47. Sahu ML, Atulkar M, Ahirwal MK, and Ahamad A. Vital Sign Monitoring System for Healthcare Through IoT Based Personal Service Application. Wireless Personal Communications. 2022 Jan 1; 122:129–56. DOI: 10.1007/s11277-021-08892-4. Available from: https://doi.org/10.1007/s11277-021-08892-4 [Accessed on: 2023 Apr 26]
48. Sahu ML, Atulkar M, Ahirwal MK, and Ahamad A. Internet-of-Things-Enabled Early Warning Score System for Patient Monitoring. IETE Journal of Research. 2022 Aug 15; 0. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/03772063.2022.2110528:1–12. DOI: 10.1080/03772063.2022.2110528. Available from: https://doi.org/10.1080/03772063.2022.2110528 [Accessed on: 2023 Apr 26]
49. Sahu ML, Atulkar M, Ahirwal MK, and Ahamad A. Cloud-Based Remote Patient Monitoring System with Abnormality Detection and Alert Notification. Mobile Networks and Applications. 2022 Oct 1; 27:1894–909. DOI: 10.1007/s11036-022-01960-4. Available from: https://doi.org/10.1007/s11036-022-01960-4 [Accessed on: 2023 Apr 26]
50. Thippeswamy V, Shivakumaraswamy P, Chickaramanna S, Iyengar V, Das A, and Sharma A. Prototype development of continuous remote monitoring of ICU patients at home. Instrumentation Mesure Metrologie. 2021; 20:79–84. DOI: 10.18280/i2m.200203
51. Tiwari D, Prasad D, Guleria K, and Ghosh P. IoT based Smart Healthcare Monitoring Systems: A Review. *2021 6th International Conference on Signal Processing, Computing and Control (ISPCC)*. 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC). ISSN: 2643-8615. 2021 Oct :465–9. DOI: 10.1109/ISPCC53510.2021.9609393
52. Rossum MC van, Vlaskamp LB, Posthuma LM, Visscher MJ, Breteler MJM, Hermens HJ, Kalkman CJ, and Preckel B. Adaptive threshold-

based alarm strategies for continuous vital signs monitoring. Journal of Clinical Monitoring and Computing. 2022 Apr 1; 36:407–17. DOI: 10.1007/s10877-021-00666-4. Available from: https://doi.org/10.1007/s10877-021-00666-4 [Accessed on: 2023 Apr 26]

53. Wu KH, Cheng FJ, Tai HL, Wang JC, Huang YT, Su CM, and Chang YN. Predicting in-hospital mortality in adult non-traumatic emergency department patients: a retrospective comparison of the Modified Early Warning Score (MEWS) and machine learning approach. PeerJ. 2021 Aug 24; 9. Publisher: PeerJ Inc.:e11988. DOI: 10.7717/peerj.11988. Available from: https://peerj.com/articles/11988 [Accessed on: 2023 Apr 28]

54. Yeri V and Shubhangi D. IoT based Real Time Health Monitoring. *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*. 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA). 2020 Jul :980–4. DOI: 10.1109/ICIRCA48905.2020.9183194

55. Youssef Ali Amer A, Wouters F, Vranken J, Korte-de Boer D de, Smit-Fun V, Duflot P, Beaupain MH, Vandervoort P, Luca S, Aerts JM, and Vanrumste B. Vital Signs Prediction and Early Warning Score Calculation Based on Continuous Monitoring of Hospitalised Patients Using Wearable Technology. Sensors. 2020 Jan; 20. Number: 22 Publisher: Multidisciplinary Digital Publishing Institute:6593. DOI: 10.3390/s20226593. Available from: https://www.mdpi.com/1424-8220/20/22/6593 [Accessed on: 2023 Apr 26]

56. Zarabzadeh A. Features of electronic Early Warning systems which impact clinical decision making | IEEE Conference Publication | IEEE Xplore. 2012. Available from: https://ieeexplore.ieee.org/document/6266394 [Accessed on: 2023 Apr 26]

57. PM6750 Handheld Patient Monitor. Berry Medical. Available from: https://www.shberrymed.com/products/handheld-pm6750 [Accessed on: 2023 Apr 26]

58. Monaghan A. Detecting and managing deterioration in children: Alan Monaghan describes how the introduction of a critical care outreach service and a Paediatric Early Warning Score improved management of acutely ill children. Paediatric Care. 2005 Feb; 17:32–5. DOI: 10.7748/paed2005.02.17.1.32.c964. Available from: http://rcnpublishing.com/doi/abs/10.7748/paed2005.02.17.1.32.c964 [Accessed on: 2023 Aug 27]

59. The world's first analog watch with clinically validated ECG - ScanWatch | Withings. Available from: https://www.withings.com/de/en/scanwatch [Accessed on: 2023 Aug 22]
60. BPM Core | Withings. Available from: https://www.withings.com/de/en/bpm-core [Accessed on: 2023 Aug 22]
61. Smart Temporal Thermometer - Thermo | Withings. Available from: https://www.withings.com/de/en/thermo [Accessed on: 2023 Aug 27]
62. Hardt D. The OAuth 2.0 Authorization Framework. Request for Comments RFC 6749. Num Pages: 76. Internet Engineering Task Force, 2012 Oct. DOI: 10.17487/RFC6749. Available from: https://datatracker.ietf.org/doc/rfc6749 [Accessed on: 2023 Aug 21]
63. Keep user's data up to date | Withings. Available from: https://developer.withings.com/developer-guide/v3/integration-guide/public-health-data-api/data-api/keep-user-data-up-to-date [Accessed on: 2023 Aug 22]
64. Gotify · a simple server for sending and receiving messages. Available from: https://gotify.net/ [Accessed on: 2023 Aug 21]
65. ScanWatch - Performing a SpO2 measurement. Withings | Support. Available from: https://support.withings.com/hc/en-us/articles/360010097498-ScanWatch-Performing-a-SpO2-measurement [Accessed on: 2023 Aug 22]
66. BPM Core - Positioning myself and the BPM for the measurement. Withings | Support. Available from: https://support.withings.com/hc/en-us/articles/360024168954-BPM-Core-Positioning-myself-and-the-BPM-for-the-measurement [Accessed on: 2023 Aug 22]
67. Guides documents | Withings. Available from: https://www.withings.com/de/en/guides [Accessed on: 2023 Aug 22]
68. Withings API Reference. Withings API Reference. Available from: https://developer.withings.com/api-reference [Accessed on: 2023 Sep 11]
69. Hafen BB and Sharma S. Oxygen Saturation. *StatPearls*. Treasure Island (FL): StatPearls Publishing, 2023. Available from: http://www.ncbi.nlm.nih.gov/books/NBK525974/ [Accessed on: 2023 Aug 22]

Trial Data

		Day 1					Day 2				
Notification	Time of dispatch	10:00	13:00	16:00	19:00	22:00	10:00	13:00	16:00	19:00	22:00
Mews	Value [n]		0		0				0	0	0
	Time of calculation		13:06:18		19:07:22				16:16:55	19:40:31	22:37:55
Blood Pressure	Value (systolic) [mmHg]	131	117	126	124	114			115	114	114
	Value (diastolic) [mmHg]	86	75	85	86	86			83	80	78
	Time of measurement	10:26:35	13:05:06	16:48:16	19:06:01	22:27:50			16:13:28	19:37:37	22:37:09
Body Temperature	Value [°C]	36.98	37.49	37.16	37.28	37.32			37.64	37.33	37.27
	Time of measurement	10:25:48	13:04:18	16:47:12	19:05:10	22:27:12			16:12:25	19:36:32	22:36:27
Heart Rate	Value [bpm]	90	71	73	82	56			84	75	63
	Time of measurement	10:26:35	13:05:06	16:48:16	19:06:01	22:27:50			16:13:28	19:37:37	22:37:09
SPO2	Value [%]	96	97	98	96	98			96	97	99
	Time of measurement	10:25:35	13:03:59	16:46:57	19:04:57	22:26:54			16:12:03	19:36:19	22:36:09
Respiration Score	Value [n]	0	0	0	0	0			0	0	0
	Time of measurement	10:24:51	13:03:24	16:46:18	19:03:39	22:24:14			16:11:23	19:35:07	22:35:34
Measurement Failure	S1 [n]	0	0	0	1	3			0	1	0
	B1 [n]	0	0	0	0	0			0	0	0
	T1 [n]	0	0	0	0	0			0	0	0
	S2 [bool]	✗	✗	✗	✗	✗			✗	✗	✗
	B2 [bool]	✓	✗	✓	✗	✓			✗	✗	✗
	T2 [bool]	✗	✗	✓	✗	✗			✗	✗	✗
	P1 [bool]	✗	✗	✗	✗	✗	✓	✓	✗	✗	✗
	P2 [bool]	✗	✗	✗	✗	✗			✗	✗	✗
Environment	Home [bool]	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓
	On the go [bool]	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗
Connection	Uplink [Mbps]	11.38	11.24	5.33	8.46	9.33			11.39	9.33	9.03
	Downlink [Mbps]	50.42	46.29	15.3	39.94	39.44			50.21	44.34	41.03
	RTT [ms]	14	16	145	15	15			15	15	16

Page 1 of 3

Trial Data

Day 3					**Day 4**					**Day 5**				
10:00	13:00	16:00	19:00	22:00	10:00	13:00	16:00	19:00	22:00	10:00	13:00	16:00	19:00	22:00
0 10:34:58			0 20:15:42	0 23:18:50			0 16:54:15	0 20:13:09	0 22:50:02	0 10:55:50	0 13:34:01		2 19:41:43	
112 82 10:33:29	119 93 14:38:04	118 83 16:47:26	118 81 20:12:49	125 74 23:18:08	112 79 11:01:05	118 82 14:27:40	121 71 16:53:03	129 69 20:12:24	121 81 22:47:55	124 75 10:54:12	123 86 13:32:51	122 83 16:39:14	123 75 19:38:58	
37.39 10:32:39	37.65 14:36:55	37.64 16:45:42	37.52 20:11:58	37.65 23:15:39	37.05 11:00:04	37.43 14:27:09	37.73 16:52:21	37.46 20:11:32	36.79 22:47:18	37.34 10:53:27	37.09 13:32:16	37.13 16:37:22	37.65 19:36:37	
93 10:33:29	72 14:38:04	89 16:47:26	97 20:12:49	85 23:18:08	87 11:01:05	80 14:27:40	83 16:53:03	73 20:12:24	95 22:47:55	73 10:54:12	61 13:32:51	73 16:39:14	114 19:38:58	
96 10:32:23	97 14:36:42	98 16:45:28	98 20:11:35	99 23:15:17	95 10:59:48	98 14:26:45	98 16:51:58	96 20:11:13	97 22:46:54	96 10:53:12	97 13:31:55	96 16:37:02	95 19:36:14	
0 10:31:39	0 14:36:04	0 16:44:39	0 20:10:52	0 23:13:39	0 10:58:59	0 14:25:59	0 16:50:34	0 20:10:31	0 22:46:04	0 10:51:36	0 13:29:25	0 16:36:14	0 19:35:24	
0 0 0	0 0 0	0 1 0	0 0 0	1 2 0	0 0 0	0 0 0	1 0 0	0 0 0	0 0 0	1 0 0	2 0 0	0 1 0	0 1 0	
✗ ✗ ✗	✗ ✗ ✓	✗ ✗ ✓	✗ ✗ ✗	✗ ✗ ✗	✗ ✓ ✗	✗ ✓ ✓	✗ ✗ ✗	✗ ✗ ✗	✗ ✗ ✗	✗ ✗ ✗	✗ ✗ ✗	✓ ✗ ✗	✗ ✗ ✗	
✗ ✗	✗ ✗	✗ ✗	✗ ✗	✗ ✗	✗ ✗	✗ ✗	✗ ✗	✗ ✗	✗ ✗	✗ ✗	✗ ✗	✗ ✗	✗ ✗	✓
✓ ✗	✗ ✓	✓ ✗	✓ ✗	✓ ✗	✓ ✗	✓ ✗	✓ ✗	✓ ✗	✓ ✗	✓ ✗	✓ ✗	✓ ✗	✗ ✓	✗ ✓
10.65 47.88 12	5.46 25.47 127	11.59 50.34 15	8.81 41.72 14	8.91 43.93 18	10.56 49.34 14	10.98 50.49 19	10.04 52.47 16	9.11 47.04 23	8.62 45.86 12	11.08 51.17 16	10.62 50.12 14	11.24 52.16 12	3.38 33.91 104	

Day 6					Day 7				
10:00	13:00	16:00	19:00	22:00	10:00	13:00	16:00	19:00	22:00
	1 13:27:13							0 19:12:52	0 22:29:09
121 76 11:36:26	120 73 13:24:56					119 82 13:21:35	118 79 16:13:04	120 82 19:06:47	115 73 22:25:47
37.5 11:35:24	37.31 13:24:02					37.29 13:20:44	37.38 16:12:05	37.25 19:05:37	37.45 22:25:06
54 11:36:26	106 13:24:56					83 13:21:35	95 16:13:04	93 19:06:47	83 22:25:47
98 11:35:05	96 13:23:43					98 13:20:20	97 16:11:52	97 19:05:23	97 22:24:51
0 11:34:30	0 13:21:46					0 13:18:46	0 16:10:40	0 19:04:47	0 22:23:27
0 0 0	2 0 0					1 0 0	1 0 0	0 0 0	1 0 0
✗ ✓ ✓	✗ ✗ ✗					✗ ✗ ✓	✗ ✓ ✓	✗ ✗ ✗	✗ ✗ ✗
✗ ✗	✗ ✗	✓	✓	✓	✓	✗ ✗	✗ ✗	✗ ✗	✗ ✗
✗ ✓	✓ ✗	✗ ✓	✗ ✓	✗ ✓	✗ ✓	✓ ✗	✓ ✗	✓ ✗	✓ ✗
4.23 12.27 108	11.29 50.55 13					10.86 50.69 13	10.46 53.43 13	9.16 42.21 17	9.15 46.81 15

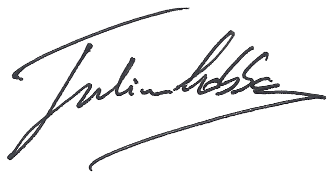
Aufgabenstellung zur Abschlussarbeit im Studiengang Informatik

Name Student*in:	Julian Lobbes
Matrikelnummer:	4343013
Abschluss:	Bachelor
Name Erstgutachter*in:	Prof. Dr. med. Dr.-Ing. Michael Marschollek
Name Betreuer*in:	Prof. Dr. Sharareh R. Niakan Kalhori
Titel der Arbeit:	Early detection of patient deterioration at home using smart medical sensors

Aufgabenbeschreibung

The goal of this bachelor thesis is the development of a software application capable of calculating an early warning score for patient deterioration using smart medical devices, followed by a usability trial of the application. With the help of the trial data, the developed software system should be evaluated regarding its feasibility for daily use by patients.

Braunschweig, 12.09.2023



Eigenständigkeitserklärung

Hiermit versichere ich, dass ich die vorliegende Abschlussarbeit selbstständig und ohne unzulässige fremde Hilfe erbracht habe. Ich habe keine anderen als die angegebenen Quellen und Hilfsmittel benutzt. Die wörtliche oder sinngemäße Übernahme von Abschnitten aus Texten Dritter sowie aus eigenen vorangegangenen Veröffentlichungen habe ich kenntlich gemacht.

Ferner versichere ich, dass es sich hier um eine Originalarbeit handelt, die noch nicht in einer anderen Prüfung vorgelegen hat.

Braunschweig, 12.09.2023

Erklärung zur Abgabe der gedruckten Abschlussarbeit

Hiermit versichere ich, dass die vorliegende gedruckte Abschlussarbeit mit der elektronisch abgegebenen (hochgeladenen) Abschlussarbeit exakt übereinstimmt und dass ich keine unerlaubten Änderungen vorgenommen habe.

Braunschweig, 12.09.2023