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Unobtrusive Monitoring of Clinical Deterioration in Smart Homes

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Abstract. Clinical deterioration (CD) is the physiological decompensation that incurs care escalation, protracted hospital stays, or even death. The early warning score (EWS) calculates the occurrence of CD based on five vital signs. However, there are limited reports regarding EWS monitoring in smart home settings. This study aims to design a CD detection system for health monitoring at home (HM@H) that automatically identifies unstable vital signs and alarms the medical emergency team. We conduct a requirement analysis by interviewing experts. We use unified modeling language (UML) diagrams to define the behavioral and structural aspects of HM@H. We developed a prototype using a SQL-based database and Python to calculate the EWS in the front end. A team of five experts assessed the accuracy and validity of the designed system. The requirement analysis for four main users yielded 30 data elements and 10 functions. Three main components of HM@H are the graphical user interface (GUI), the application programming interface (API), and the server. Results show the possibility of using unobtrusive sensors to collect smart home residents' vital signs and calculate their EWS scores in real-time. However, further implementation with real data, for frail elderly and hospital-discharged patients is required.

Keywords. Smart home, clinical deterioration, monitoring, warning, emergency

1. Introduction

CD is an urgent medical concern that can cause major consequences, such as acute care, and death [1]. Healthcare facilities must immediately identify CD cases for further care. An EWS uses five vital signs: heart rate (HR), respiratory rate (RR), SPO2, blood pressure (BP), and body temperature (BT) to predict CD [2]. Hospital wards have employed EWS in manual or electronic charts [3]. However, managing critical care and

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emergencies requires continuous monitoring of health data, especially for vulnerable cases like frail elderly, hospital-discharged patients, and lonely smart home residents [4]. Although hospitals use wearable devices for CD detection in the frame of track and triage systems [5], for private spaces including smart homes these reports are limited. Internet of Things (IoT)-enabled smart homes to monitor various life aspects, including health and biomedical measures [6]. Aided by artificial intelligence (AI), unobtrusively gathered data by smart home sensors helps to detect diseases early and predict health outcomes [7]. This feature is essential for vital sign monitoring and CD detection. Researchers have examined remote vital sign monitoring individually [4]; however, this study aims to develop a Home Monitoring at Home (HM@H) system using non-wearable sensors to calculate Early Warning Scores (EWS) for smart home inhabitants, concurrently detect critical conditions based on five key vital signs, and alert caregivers and medical emergency teams accordingly.

2. Methods

In four sessions, six experts from computer science (n=1), medical informatics (n=4), and electronics (n=1) extracted a system requirements checklist based on facility, data connections, and required skills. We discussed the extracted items in seven focus group online sessions and three personal meetings and calculated the content validity ratio (CVR) using SPSS, version 14 to validate system data elements and functionalities

$$CVR = \frac{\frac{N_e - N_2}{2}}{\frac{N_2}{2}}$$
(1)

where *N* is the total number of experts (*N*=6) and *Ne* refers to the count of experts that chose "Must have" or "Should have" to consider the features as essential requirements. Based on Lawshe table [8], we accepted items with $\text{CVR} \ge 0.99$.

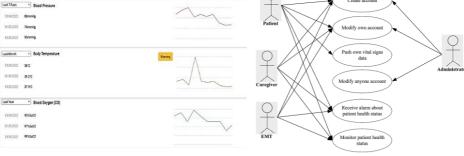
We designed the HM@H's structure and behavior using the UML diagrams. We used activity diagrams to design the system behavior. Class diagrams show the HM@H structure. We developed a system prototype in two steps, encompassing the front and back end. We developed the database using PostgreSQL and implemented each GUI in Python. Multiple API connect the GUIs to the back-end. HM@H calculates the users' EWS score based on vital signs thresholds [3]. Researchers tested the HM@H with machine-generated data for 50 people to check the system's usability.

3. Results

The primary language for the GUIs is English (En-US). The four main users of HM@H are admin, caregiver, patient, and emergency team members. The system has a different front-end view for each user type based on their required functions. Each user opens the browser to log into the system. The main page offers choices to see results, add medical parameters manually, profile settings, etc. The HM@M system's data elements, functionality, and CVR values are in Tables 1 and 2. Authors considered the back-end and system configuration, as non-functional and front-end requirements as functional ones referring to the system capabilities.

Data elements			CVR
Patient	Vital Signs	BP	100%
	-	BT	100%
		Spo2	100%
		HB	100%
		RR	100%
Per	Personal & Demographic data	Age	100%
		sex	100%
		Number of residences	96.67%
		Education level	66.67%
		Blood Group	100%
		Address	66.67%
	Personal medical data	Diabetes	100%
		Heart disease	100%
		Other disease	96.67%
Care provider	Personal Charac	Personal Characteristics	
MET	Personal Charac	Personal Characteristics	
Administrator	Personal Charac	Personal Characteristics	
able 2. The HM@H f	functionalities and their CVR value Functionalities	ues	CVR
Back-end		Connectivity to smart home via API	
Back-end	· · · · · · · · · · · · · · · · · · ·		
		Data storage in the database	
Encode and		Data analysis for trends and EWS calculation	
Front-end		Early Notification of CD	
		MET activation	
		Element for patient account	
		Element for MET account	
		Element for Admin account	
		Element for care provider account	
<u> </u>		Connection to backend via API generation	
System Configuration		Windows 10 or higher	
		512 MB- 2 GB RAM	
	2-4 core 64-bit CPU	@2GHz-3GHz	66.67%
HMEH Hone Vital Signs More +	(O User) Creath	See 0	reate account
Last 70eys Blood Pressure			
13.04.2022 Bitmining	- M	Patient	ify own account
13.05.2022 Scrunity		Mod	
LastMorth • Body Temperature	Varing	Push	own vital signs data
04.05.2022 39.2°C			Admir
13.05.2022 37.9°C	~~~	Caregiver	y anyone account
Last Year * Blood Dxygen (CO)		-	
	- ^		rive alarm about

Table 1. The HM@H data elements and their CVR values are based on each user



a. The front-end of HM@H presents the trend of vital signs and warning points at CD occurrence

b. The HM@H system use-case diagram

Figure 1. The main functionalities of the HM@H system and its user interface

Researchers designed the UML diagrams based on validated requirements defined by experts. Figure 1(a) displays the user interface with vital signs trends over time, while 1(b) describes the system's main functionalities. Figure 2 shows the system's classes and their relationships, which correspond to database tables in the system backend. Figure 3

shows how the system detects clinical deterioration using EWS. Experts checked the functionality of the HM@H system and in 100% of cases, the system worked correctly.

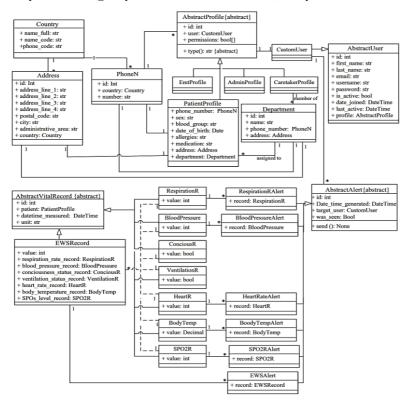


Figure 2. The data model of the system based on its main entities

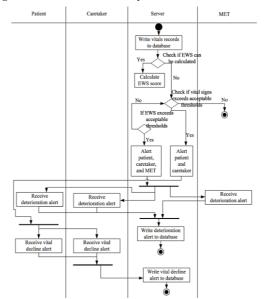


Figure 3. The activity diagram of HM@H for CD detection and alarming

Our results show the possibility of monitoring vital signs and alarming the CD automatically if it at least has the features including a multi-user authentication web interface, a database for storage of vitals data, a public interface to send and store vitals to the server, MEWS calculation [3] based on stored and incoming vitals, and alerting if vitals decline/deteriorate. HM@H consists of two parts: REST API, and a web-based user interface. The API allows third-party applications to interact with the server-side database, to send and store vital records for a specific patient on the server. The WebUI is used for tasks of creating user accounts, configuring notifications, or data visualizing.

4. Discussion

We designed HM@H to monitor vital signs and detect patients' CD risk in smart homes. If needed, the system alarms caregivers and the emergency team. Thus, the HM@H can help caretakers to monitor patients. IoT-based systems have already been developed for remote monitoring of patient's vital signs in homes [4], however, they use sensors attached to the patient's body and, unlike our design, they are not unobtrusive. We integrate sensors for vital sign monitoring in private environments such as the smart home [7] or the smart car [9], which increases patient compliance for continuous use. Our results show the possibility of monitoring vital signs and alarming the CD automatically. Next, we will test the system with real data collected from smart appliances to check the system's functionality and usability.

5. Conclusions

Results show the possibility of monitoring and alarming the health status of patients at smart homes. Despite the system's limitation for testing by real data, it is a practical step toward diagnostic space development targeting home critical care and CD detection.

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