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Research-in-progress

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Abstract

Wearable technology in the form of smartwatches and advanced analytics are set to reshape healthcare by facilitating prevention, early diagnosis, personalized treatment, and management of chronic diseases. However, gaining insights from vast amounts of smartwatch data remains challenging for healthcare providers due to complex data formats and a lack of training. To mitigate this shortcoming, healthcare professionals need tools that support them in analysing and presenting smartwatch data in an easy-to-understand way. Therefore, this study uses a design science approach to co-design, develop and evaluate an application prototype that analyses smartwatch data and allows healthcare providers to use this data to manage aspects of patients' health. The preliminary results of the co-design and development phases are reported. The meaningful involvement of healthcare providers in designing and evaluating such analytical tools would help develop relevant and useful health monitoring applications that can be scaled in real-world settings.

Keywords Smartwatch, data visualization, anomaly detection, machine learning, health monitoring

1 Introduction

The COVID-19 pandemic has profoundly affected global attitudes towards health, with consumers becoming increasingly conscious of their health decisions (Wire 2020). Using wearable technology such as smartwatches, healthcare providers can monitor patients' biometric parameters remotely, thus automating certain time-consuming routine checks. Smartwatch data qualifies as user-generated data or Big Data due to the constant stream of vast data generation, which can overwhelm users and healthcare providers who want to gain insights. As a result of highly relevant phenomena revolving around healthcare and massive amounts of user-generated data, smartwatch data analytics has gained popularity among IS scholars (Philipp et al. 2022). Therefore, a smartwatch-based health monitoring application is highly relevant in reducing the burden of information overload on clinicians when integrating smartwatch data in clinical workflows (Philipp et al. 2022).

Health monitoring approaches using smartwatches have focused on two main processes: data visualization and data analytics in a disconnected way. Data visualization refers to the graphical representation of data that is easy to understand (Kheirkhahan et al. 2019). Data analytics involves transforming raw data to extract useful information for decision-making and insightful conclusions using machine learning, artificial intelligence, and big data analytics (Sabry et al. 2022; Singhal et al. 2020). Therefore, analysing smartwatch data to extract meaning, detect health anomalies, and present it visually appealingly will prove beneficial in understanding an individual's current health conditions (Frink et al. 2017; Sunny et al. 2022). While it is worth acknowledging that machine learning algorithms support the identification of anomalous behavior, there is a need to provide adequate clinician support to interpret machine learning results and involve clinicians in the underlying detection process (Javaid et al. 2022; Riveiro 2014) . Thus, visualization and interaction play a crucial role in providing adequate clinician support and involving the clinicians (human expert knowledge) in guiding the detection of health anomalies. However, existing studies have not successfully captured these aspects in the design, implementation, and use of information systems. We aim to fill this gap. A multimethodological approach such as design science research (DSR) would be a good fit for our objectives.

Therefore, this study aims to co-design, develop and evaluate a web-based dashboard for monitoring health data from smartwatches for adaptive prescription of medical checks. We employ the DSR approach (Hevner et al. 2004; Nunamaker Jr et al. 1990; Peffers et al. 2007) and used Diffusion of Innovation (DoI) (Rogers 2003; Sanson-Fisher 2004) as an overarching framework during the co-design and evaluation phases of the artefact development. The intention is for the application to be available for healthcare providers, with functionalities to detect possible health anomalies, display visualizations, and notify individuals about health anomalies filtered by healthcare providers using their domain knowledge. Large datasets generated by smartwatches are analyzed and transformed into insightful visual representations, so that vast amounts of data do not overwhelm clinicians. The insights from data analysis assist them with improved clinical decision-making and early detection and diagnosis of possible health disorders (Singhal et al. 2020). The meaningful involvement of healthcare providers in the prototype design and evaluation may help develop a relevant and practical research artefact that can be scaled in the future (Noorbergen et al. 2021).

This research-in-progress paper presents the first two phases of the study: co-design and development. This paper's contribution to knowledge is directed at the experiences we gain while co-designing the prototype with healthcare providers and how involving the end users influences the DSR process. The outcomes of this study are expected to contribute to practice by supporting healthcare providers to deliver evidence-based personalized care for better health management and may provide a foundational element for integrating smartwatch data with official electronic health records. In this paper, the terms healthcare providers and clinicians are used interchangeably.

2 Literature review

Smartwatches offer a potential solution for remote health monitoring by continuously monitoring physiological parameters such as heart rate, step count, and calories. The last few years have witnessed a considerable increase in clinical health monitoring applications based on smartwatches as assistive devices that help inform patient care (Jat and Grønli 2022). Smartwatch data has received significant attention as it can benefit healthcare providers by supplying frequent temporal information about patients, fostering better communication, improving care coordination, and strengthening patient engagement (Alpert et al. 2020). Previous research has explored the potential of designing smartwatch-based applications for data visualization (Frink et al. 2017; Reddy et al. 2020) and Covid-19 prediction (Zhu et al. 2020) and detection (Bogu and Snyder 2021; Mishra et al. 2020) by employing anomaly detection algorithms. However, a comprehensive solution combining visualization, anomaly detection, and adaptive prescriptions of medical checks based on individuals' data requires further attention due to the difficult interpretability of ML results by clinicians (Javaid et al. 2022). Identifying anomalies in smartwatch data, such as heart rates and other health parameters, can assist healthcare providers with further diagnosis and treatment plans (Sunny et al. 2022). Moreover, involving healthcare providers in the design phase of the application result in a practical and usable solution (Noorbergen et al. 2021). Therefore, we aim to co-design, develop and evaluate the application prototype tailored to healthcare providers' needs and functional requirements. We used the DoI principles and attributes in the design phase for prototypes' chances of being positively perceived, adopted, adapted, and implemented, thus successfully crossing the research-to-practice differences (Alpert et al. 2020; Dearing and Cox 2018).

2.1 Diffusion of Innovation

For this study, Rogers's Diffusion of Innovations theory (Rogers 2003) was used as a framework in the design and evaluation phases of the artefact development. Five attributes of innovations determine how innovation will be responded to by a potential end-user: relative advantage, compatibility, complexity, trialability, and observability. The relative advantage is the degree to which the potential user perceives the innovation to be better than what it is replacing. Compatibility is how consistent the innovation is with the values, experiences, and needs of the potential user. The complexity is how difficult the innovation is to understand and/or use. Trialability is the extent to which the innovation may be tested or experimented with before full-scale use. Finally, observability is the degree to the innovation provides tangible results. According to DOI theory, diffusion is the process in which innovation is communicated over time among the members of a social system.

Smartwatch data analytics implementation in healthcare is slow because of the limited interpretability of advanced analytics and increased workload risk, creating a knowledge gap (Javaid et al. 2022). This knowledge gap needs to be narrowed with the planned transmission of smartwatch data analytics information. Collaboration between healthcare providers, developers, and researchers to facilitate designing the prototype and provide necessary hands-on experience and infrastructure is recommended for the successful diffusion of these solutions in practice (Dearing and Cox 2018; Noorbergen et al. 2021). Therefore, a survey of key end-users (healthcare providers) was conducted in the co-design phase to understand the important aspects of the application's functionality and ease of use.

3 Design Science Research Methodology

DSR is a problem-focused research paradigm for addressing a specific organizational problem (Hevner et al. 2004; Nunamaker Jr et al. 1990; Peffers et al. 2007). Since our research aims to implement an artefact to assist healthcare providers with clinical decision-making by analyzing and visualizing smartwatch data, the DSR approach is suitable for this study. We follow a multimethodological approach to IS research by Nunamaker Jr et al. (1990) that includes observation, theorisation, systems development, and experimentation in an iterative cycle where each phase complements the other and provides valuable feedback to different phases. The first and the second step of the research cycle were accomplished by literature analysis. Observation is about identifying the problem that we intend to address with our research using an appropriate theoretical framework. We aim to solve the challenges associated with using smartwatch data by healthcare providers for clinical decision-making. Specifically, we aim to design, develop and evaluate a clinician-focused web-based application prototype capable of visualizing long-term smartwatch data, analyzing health trends (anomaly detection), and communicating areas of concern to stakeholders for early or preventative treatment (Sunny et al. 2022). A dashboard revolving around health trends that can also make insights into the data would fill the market vacancy due to the shortcomings of existing consumer-oriented applications and the inaccessibility to medical monitoring tools that doctors typically prescribe to at-risk patients. The study is divided into three phases: co-design, development, and evaluation. The first phase seeks clinicians' views and opinions to understand how such an application would best suit their needs. We recruited clinicians involved in using or monitoring health outcomes and smartwatch data, or those interested in this health care monitoring field, to assist with designing the prototype application. Clinicians completed a survey on how they would like such an application to function, providing information on what smartwatch data is valuable and useful and how they would like to view the smartwatch data on the application. The information and feedback obtained from the survey during this co-design phase drive the development of the prototype (phase II), where smartwatch data (FitBit®) from a publicly available dataset PMData: A sports logging dataset Simula PMData (Thambawita et al. 2020) has been used for anomaly detection using a machine learning algorithm. Anomaly detection is finding rare items, events, or observations that deviate significantly from most of the data and do not conform to expected behaviour (Chandola et al. 2009). The goal is to build a machine learning model to detect irregular heartbeats based on heart rate, calories, steps, and distance data over time. Once the prototype is fully designed and implemented, we aim to evaluate it (phase III) by testing its usability in the same group of clinicians. Clinicians will first be presented with a demonstration of the prototype through an online video and the URL of the web-based prototype. They will then be asked to complete an online questionnaire about the prototype's usability. Thus, the co-design and evaluation phases use primary data, while machine-learning analysis uses secondary datasets.

4 Phase I – Co-design

To understand clinicians' requirements, we surveyed Physiotherapists (1), Clinical exercise physiologists (4), personal trainers (2), and General Practitioners (1) on the important aspects of applications' functionality and ease of use. Diffusion of innovation (DOI) (Rogers 2003; Sanson-Fisher 2004) was used as a framework to develop the survey questions. The five main attributes of DOI are relative advantage, compatibility, complexity, trialability, and observability. The first two attributes were used during the co-design phase, and the remaining attributes would be considered in the evaluation phase. Based on the requirements, the objectives of the prototype were identified from the survey responses. We analyzed data to identify themes and conceptual patterns between ideas and functional requirements that guided the prototype's development. Descriptive statistics were used to tabulate the frequencies of closed-ended questions. The resulting requirements and objectives are shown in Table 1. Requirements were categorized into 1) DoI attributes - relative advantage and compatibility of the prototype, 2) Visualization and customization of user interface features, and 3) Anomaly detection and alert features of the prototype. Clinicians' responses are reported in the order from most to least preferred requirements. Heart rate is the most valuable parameter indicated for visualization and anomaly detection, with charts and bar graphs as the preferred way to view the summary reports, as examining heart rate over intervals of different durations helps assess patients' overall health. Clinicians also indicated that healthcare administrators should view the summary reports for further actions, who can then notify clinicians for decision-making, as this will decrease clinicians' burden with the additional data work (Philipp et al. 2022).

No.	Requirements	Most to least preferred (Objectives)	
1.	**Diffusion of Innovation attributes**		
	Relative advantage: How monitoring smartwatch data benefit clinicians and patients	I.	Improved communication
		II.	Patient / client empowerment
		III.	Behaviour change
		IV.	Informed decision making
	Compatibility: How integrating smartwatch data assist clinicians with patient care	I.	It will be a good starting point and would provoke more productive discussions
		II.	It will support evidence-based practice
		III.	Good way to review the data and plan before the consultation
		IV.	It will reduce the consultation time spent gathering information on lifestyle and health data
		V.	It will increase the workload
2	**Data visualization and customization**		
	Most valuable activity and physiological parameters	I.	Heart rate
		II.	Step count
		III.	Calories burned
		IV.	Sleep score, ECG, blood glucose
		V.	Sedentary minutes
	The preferred way to view the summary reports	I.	Charts
		II.	Bar graphs
		III.	Line graphs
		IV.	Text summaries

	Frequency of summary reports	I. Weekly II. Monthly III. Daily IV. Only if an anomaly is detected
3	**Anomaly detection and alert feature**	
	Type of anomalies	I. Heart rate II. Sleep score III. Pain levels
	Who should view the summary reports for further actions?	I. Healthcare administrators (who can then notify clinicians) II. Clinicians
	Alert feature	60% preferred to have this feature

Table 1. Requirements and objectives resulting from the co-design phase

5 Phase II - Artefact development and results

The artefact development process diagram highlighting different phases and an overview of the software tools that make up the artefact is shown in Figure 1. A web-based dashboard was developed using HTML, CSS, and Javascript. A publicly available dataset that provides five months of Fitbit Versa 2 smartwatch data of 16 individuals that combines regular lifestyle and sporting activities was used for analysis. Smartwatch data (Fitbit) is extracted from JSON files using a program developed in Python, which processes and merges the transformed data from different files into a single JSON file. We used PyCaret, an open-source, low-code machine learning library in Python that automates machine learning workflows to detect anomalies in health data. PyCaret's anomaly detection module (pycaret.anomaly) is an unsupervised machine learning module that identifies rare items, events, or observations that raise suspicions by differing significantly from the majority of the data. We used a clustering algorithm to build a machine learning model using PyCaret to detect irregular heartbeats based on heart rate, calories, steps, and distance data over time. Power BI reports were generated and integrated into the dashboard to display the anomalies detected using the trained machine learning pipeline. After viewing anomaly detection results and corresponding reports, clinicians can notify their patients/clients about the possible health risks via email. Finally, the dashboard would be hosted on a cloud platform with proper user authentication mechanisms.

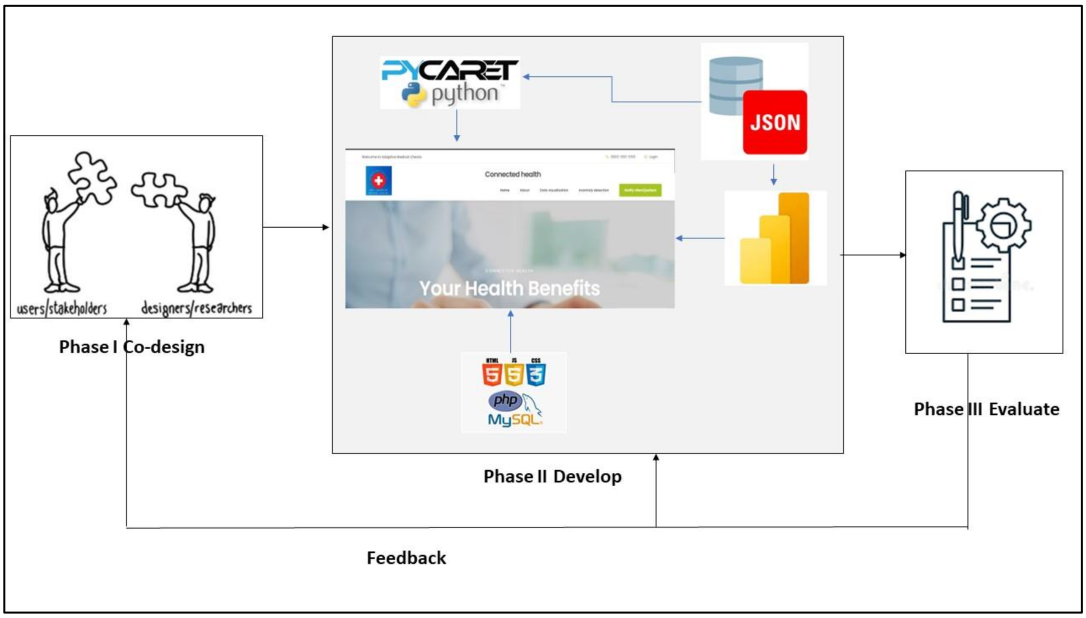

Figure 1. Artefact development process diagram

Figure 2 shows the results of the machine learning algorithm highlighting the anomalies detected. The anomaly detection page is where the main interactions between a clinician and the prototype occur. Clinicians can cycle through the health data of different patients/clients using the drop-down menu. Anomalies will be displayed using an interactive graph, and clinicians can then, using the domain knowledge, filter out the false positives by changing the health parameters relative to individuals' demographics, activity, and physiological parameters.

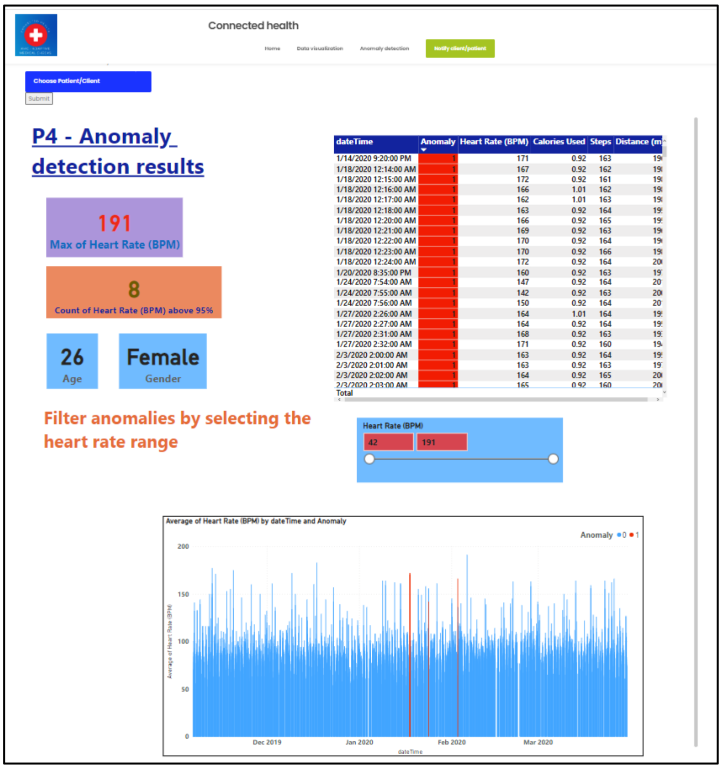

Figure 2. *Anomaly* detection

6 Discussion and next steps

The artefact focuses on providing clinicians with an instrument that detects anomalies and visualizes smartwatch data to improve patient care delivery. In future iterations, our goal is to develop the artefact further to compare the performance of different anomaly detection algorithms, generate visualization reports and notify individuals when possible anomalies are detected. Using the co-design approach, we identified clinicians' requirements through a survey. The next steps encompass the prototype's evaluation by demonstrating the artifact's ability to address the requirements outlined by clinicians in the co-design phase. Design is inherently an iterative activity; therefore, the evaluation phase provides essential feedback to the other phases to assess the quality of the design process and artefact. Through the developed artefact and further evaluation, a contribution to IS research focused on implementing a smartwatch-based health monitoring prototype as a DSR artefact would be made. By addressing clinicians' needs with the prototype, a practical contribution would be to provide them with an instrument that supports their work. Finally, the results of the project will be disseminated by publishing in a scientific article with a detailed explanation of the artefacts' technical features.

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