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Consumer Smartwatches for Collecting Self-Report and Sensor Data: App Design and Engagement

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Abstract. Longitudinal data from patients' natural environments would benefit chronic disease care, yet most devices cannot collect sensor data alongside patient-reported outcomes. Here we describe *Koalap,* a consumer cellular smartwatch application that collects patient-reported outcomes alongside physical activity data from various sensors. Additionally, we show preliminary results indicating high engagement of our 26 participants with knee osteoarthritis. Our future work will show whether data collection with consumer smartwatches is feasible in terms of user engagement, acceptability, data quality and consistency.

Keywords. mHealth, Smartwatch, Feasibility, Engagement

1. Introduction

In chronic disease care and research, longitudinal data collected in patients' natural environments could provide valuable insights into patterns of disease activity and trajectories of symptoms. It is especially interesting to relate patient-reported outcomes to patient behavior, measured with sensors [1].

Wearable devices such as smartwatches provide an opportunity for longitudinal data collection. This can support telemonitoring progression of diseases such as Parkinson's disease [2] and serious mental illnesses [3]. Consumer smartwatches with a touch screen enable collection of patient-reported outcomes alongside passively collected sensor data. In contrast to research devices, consumer technology is already integrated in users' daily lives [4]. Lack of user engagement could, however, hamper the success of smartwatches and mHealth [5]. If participants drop out early, do not wear the watch or do not answer questionnaires, the data may not be as rich as expected.

To investigate feasibility of consumer smartwatches for chronic disease monitoring and research, we launched the consumer cellular smartwatch study *'Knee osteoarthritis: linking activity and pain'* (KOALAP). In this study, we collect patient-reported outcomes and passively-measured physical activity data through consumer

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smartwatches. In this article, we describe study objectives, the *Koalap* app and preliminary results on user engagement.

2. *Koalap* study objectives and design

2.1. Background and objectives

Koalap aims to investigate the association between physical activity and pain in patients with osteoarthritis of the knee. While clinicians generally agree that physical activity is beneficial for these patients, exercise is known to increase pain and pain is known to limit the amount of activity. There is a need to understand this relationship to guide physical activity interventions.

The objectives of *Koalap* are to examine (a) the feasibility of consumer cellular smartwatches for collection of patient-reported outcomes alongside continuous sensor data and (b) the relationship between pain and physical activity. This paper focuses on preliminary results of user engagement with our smartwatch app and data completeness.

2.2. Study design and participant recruitment

Koalap is a prospective cohort study of 26 people with knee osteoarthritis who wear a Huawei Watch 2 consumer smartwatch for 100 consecutive days on first waking until bedtime. The watches are provided with a pre-installed *Koalap* app, collecting patient-reported outcomes and sensor data related to physical activity. The smartwatches were loaned by Google Android Wear, which also was our partner in co-creation of the *Koalap* app, developing system architecture and user interface design.

When users wear the watch, it collects sensor data as shown in Table 1. These data allow us to derive gait outcomes of interest (characteristics of painful walking and activity patterns that may aggravate pain). Of note, algorithms to derive these outcomes from a wrist-worn consumer device will need to be validated. The choice of sensors and sampling frequencies is based on our data requirements, balanced against the required battery life. Patient-reported outcomes will be collected on the watch with the questionnaires shown in Table 2.

Table 1. Outcomes of interest, corresponding smartwatch sensors and chosen frequencies

Outcome of interest	Sensors	Sampling frequency
Step count	Accelerometer, magnetometer, gyroscope	50 Hz
Walking inclines	Barometer	1 per minute
Doing strenuous activity	Heart rate	1 Hz

Table 2. Overview of self-reported data collected with *Koalap app*: questionnaire, frequency and time window for completion. KOOS = clinically validated Knee injury and Osteoarthritis Outcome Score

	Question	Frequency	Window
Q1	Level of knee pain this morning Level of knee pain this afternoon	Twice daily	12.22-16.22 18.22-22.22
Q2	Pain affecting daily activities	Daily	17.00-00.00
Q3	Pain during aggravating activity		
Q4	Pain preventing important activity	Weekly	Wed 12.00-00.00
Q5	Pain affecting quality of life	Weekly	Sun 12.00-00.00
Q6	KOOS (28 questions)	Monthly	1st-7th of every month

All items are answered on a 10-point numeric rating scale, except for Q6, which uses a 4-point Likert scale. This data is stored in an SQLite database on the watch. Users are instructed to charge the watches overnight. When on charger, the watch securely (encrypted-at-rest) uploads the depersonalized data to our servers and deletes the data from the watch. The smartwatches contain a SIM card with a 24 GB data bundle, allowing for data collection and transmission without pairing with a smartphone.

User interaction designers at Google developed the user interface, shown in Figure 1. When not answering questionnaires, the watch shows either a dashboard showing ‘outstanding survey questions’ or the home screen with four icons showing remaining battery, heart rate, step count and number of outstanding surveys. In the question screen (Figure 1b) the left lower corner is obscured, indicating that the user can scroll down further. Upon swiping downwards, the data entry screen will present itself.

a b c

Figure 1. Images of the user interface. (a) Notification of an active survey and start screen of questionnaire (b) Data entry screen for survey ‘level of knee pain’ (c) Data is entered by swiping the numeric rating scale icon.

The study was advertised in local newspapers and via social media. Interested participants contacted the study team for the patient information sheet. People were eligible if they had a diagnosis of knee osteoarthritis (self-reported), were 50 years or older, and willing to travel to Manchester (UK) and owned a smartphone. In total, 75 people expressed interest, of which 26 eventually took part in the study. Reasons for not taking part were: not eligible to enroll (*N* = 13), unavailable on current dates (*N* = 13), unwell (*N* = 3) not interested (*N* = 4) and unknown (*N* = 12). Participants were invited to visit the University, where they provided written consent, received a study watch and received a user guide (but no specific training).

3. Results

In this section we present preliminary results on data completeness and engagement of participants during the first study month (from September 23, 2017 to October 23, 2017). Updated figures will be presented at the conference.

3.1. Summary of data

During the first study month, we collected 302 GB of sensor data and 2407 questionnaires. On average, questionnaires are completed by 16 (afternoon pain questionnaire, 62% completeness) to 23 (monthly questionnaire, 88% completeness) with no clear trends over time (graph not shown). Only two participants entered no data throughout the last week, user 16 having informed us of a stay abroad, hampering upload of study data.

Table 3. Data completeness: number of submitted questionnaires by 26 participants over 30 days, % of maximum expected questionnaires based on frequency, average engaged users per submission time point.

Questionnaire	Submitted (#)	Completeness (%)	Users (mean)
Pain (twice daily) - morning	557	71	19
afternoon	481	62	16
Painful activity (daily)	588	75	20
Daily function (daily)	585	75	20
Important activity (weekly)	76	73	19
Quality of life (weekly)	97	75	19
KOOS (monthly)	23	88	23

Most participants wear the watch most of the days (square, triangle or dot in Figure 2) – based on the presence of sensor data for that day, as sensor data is only collected when the watch is off charger. If we receive self-reported data only (red dot), this indicates a technical issue, hampering uploading of sensor data (usually: lack of cellular signal at home, as confirmed by smartwatch metadata).

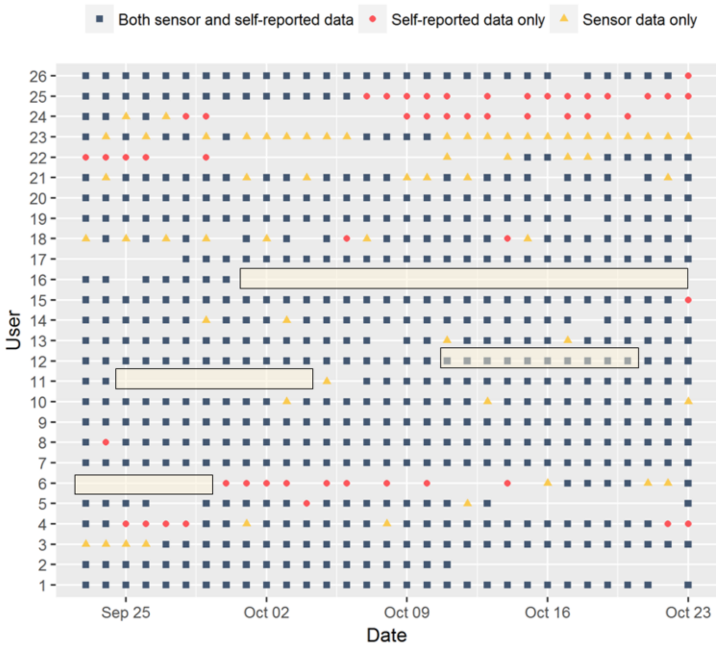

Figure 2. Engagement of users over the 30-day study period. A blue square indicates sensor and self-reported symptom data, a red circle indicates that only self-reported symptom data was received, a yellow triangle indicates that only sensor data was received, and no symbol means that no data was received. Yellow rectangles indicate periods that participants reported to be abroad.

4. Discussion

This study introduces an application for collection of patient-reported outcomes alongside passively-collected physical activity data with a consumer smartwatch.

Preliminary results show that data collection through consumer smartwatches is feasible, although not all participants may provide all data all of the days.

Previous research mostly focused on data collection with dedicated research wearables. Our approach to collecting both patient-reported outcomes and physical activity data with a consumer smartwatch is therefore novel.

During preparation of consumer smartwatches for research, co-creation and collaboration with industry was valuable. We benefited from Google's expertise in user interaction design, system architecture and cloud storage. During co-creation, the consumer smartwatch app was tweaked to our research needs. Typically, consumer smartwatches store processed, aggregated data rather than raw sensor data, which is required for (our) research, and storing continuous raw data is often not straight forward (and sometimes not possible).

Through the *Koalap* study, we will do both quantitative and qualitative research to investigate user acceptability and user engagement with consumer smartwatches, as well as data quality and consistency. If data collection through consumer smartwatches is feasible, further studies are necessary to validate physical activity measures derived from the raw sensor data generated with these wrist-worn devices. Furthermore, improvements in battery life are needed for continuous data collection of high-frequency sensor data from dawn to dusk.

5. Conclusion

We successfully co-created a smartwatch application for consumer smartwatches with Google Android Wear. The *Koalap* app collects physical activity sensor data alongside patient-reported outcomes related to knee pain. Preliminary results show that most participants wear the watch daily, accumulating 302GB of sensor data in 30 days of data collection, answering the majority of daily, weekly and monthly questionnaires.

This study had a limited sample size of 26 participants, and focused only on user engagement. In future, we will assess data quality and consistency. To investigate the association between knee pain and daily physical activity, we will develop algorithms to convert the raw sensor data to clinically meaningful outcomes.

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