ROAMM: A customizable and interactive smartwatch platform for patient-generated health data

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ABSTRACT

Older citizens experience a large number of falls and hospitalizations per year throughout the world. These intervening health events (IHEs) such as falls/injuries, illnesses, hospitalizations, are strong precipitants of disability in older adults. They are episodic in nature, extremely difficult to study, and require continuous and long-term monitoring.

Wearable technologies with remote capabilities are an ideal solution for capturing information before and after such events. This work presents the ROAMM campaign platform for harnessing sensor and interface capabilities on smart wearables to provide customizable, affordable, and versatile health monitoring that leads to practical remote-based interventions. The platform is flexible, efficient, and scalable for concurrently running multiple studies, each of which consists of patient-reported outcomes, ecological momentary assessments and mental health-related patient responses. Additionally, the system is able to capture and derive ecological, momentary assessments of pain with concurrent mobility tracking that allows life-space mobility ascertainment. The platform supports multiple watches, and we show implementations on both the Samsung Galaxy and Apple series of smartwatches.

KEYWORDS

Smart Wearables, Wrist Accelerometer, Health Monitoring, Realtime mobility Monitoring.

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1 INTRODUCTION

Smartwatch devices are now commonplace among the public with a quickly rising use in clinical care and research settings [13]. The International Data Corporation (IDC) Worldwide Quarterly Wearable Device Tracker published that smartwatches accounted for 44.2% of the wearable market in 2018 and is expected to rise to 47.1% by 2023 [5]. Even health care providers and groups traditionally thought to be less likely to adopt smartwatches, e.g., older adults, show an overall positive view [9]. Smartwatches are quickly gaining the ability to capture more health-related sensor data while enabling direct interaction through the screen. The smartwatch is expected to become a powerful tool to augment traditional clinical care and remote data collection approaches [12].

Despite its potential, there is little evidence in the literature of building smartwatch apps and customizing them for specific clinical and research efforts. There is a good reason for this because there are several barriers to customizing the smartwatch user interface for collecting patient-reported outcomes, harnessing raw sensor data, and sending data to the cloud in a secure manner, with all components being done simultaneously. A smartwatch-based platform to enable practitioners and researchers to customize remotely collected data could improve understanding about intraday variability of symptomatology, environmental exposures, and health behaviors.

Intervening health events (IHEs) such as episodic falls, injuries, severe illnesses, hospitalizations, infections like COVID-19 are emerging scientific area of interest in health care. The available literature suggests that IHEs are strong precipitants of acute losses in physical function and contribute to the onset of new health concerns and chronic losses in physical and cognitive function [4, 17, 18]. However, because of their episodic nature, the predictors of IHEs and factors associated with subsequent recovery are challenging to decipher without long-term data that precedes and follows the IHE. Additionally, surveillance of symptoms and function at a high resolution offers a new look into the usual range of intra-individual variability. Disturbances in this variability can signal a breakdown in homeostatic self-regulation and individual trajectories— e.g. detection of gradual downward trends in cognition. Wearable devices like smartwatches are an innovative solution to meeting these problems because they are both popular and desirable while also containing the necessary elements for tracking meaningful clinical markers of health in a continuous fashion.

Remote health-related data collected with smart devices falls under the global umbrella of patient-generated health data (PGHD), which is divided into two main categories: active and passive data. The essential difference between these two types is the involvement of patients or participants in reporting data. Active data are described as brief questions about symptoms and states of health

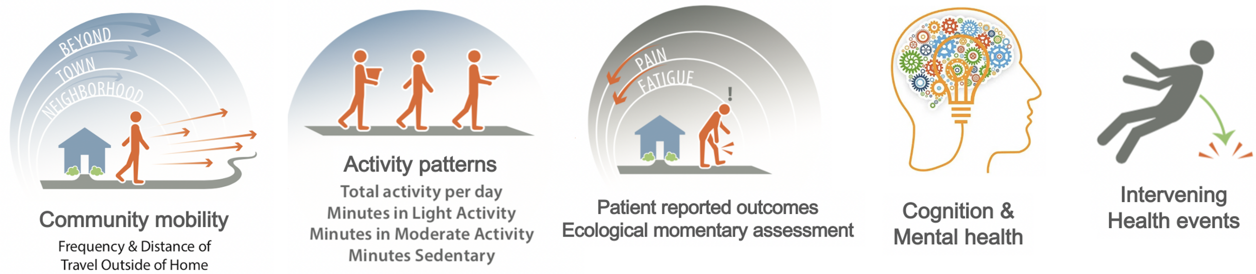

Figure 1: Conceptual diagram of the ROAMM platform. Using accelerometer and GPS sensors, the new generation of mobile devices provides an affordable and more versatile hardware platform upon which monitoring software can be implemented.

or surveys through which people self-report when prompted at specific times. Such an approach capitalizes on the "experience sample method" of data collection, which is commonly described as ecological momentary assessments [8]. This ecological method was originally developed for psychological assessment of the activities people engage in, how they feel, and what they are thinking during their daily lives. Responses about current thoughts and feelings in an individual's environment are recommended because people are poor at reconstructing psychological experiences after they have occurred. For example, in traditional questionnaires, people are asked to recall their pain, physical function, fatigue, or mental health as stable traits. Unfortunately, this approach completely misses the daily variability in complex states and is not considered valid outside of the context in which they occur [2, 14]. Additionally, it is particularly difficult for individuals to assess or recall complex experiences like pain, mood or fatigue after they have occurred. When frequently and randomly sampled, EMAs are often regarded as the "truth" because they estimate an unbiased average that has no tendency to either overestimate or underestimate the state.

Passive data requires no input from people as the smart device continuously collects data through built-in sensors. The type and quality of this data depend on the availability of different sensors. Some of the most common sensors include - GPS, Accelerometer, Gyroscope, Heart rate monitor etc. Global positioning sensor (GPS) that can be used to measure mobility patterns in the community and life-space mobility, which is a measure of the spatial size and frequency of interaction with the surrounding environment. Accelerometer that can be used to track physical activity patterns and energy expenditure whereas gyroscope can be used to measure arm orientation. Sensors like magnetometer, altimeter can be used for compass functions, to measure elevation. The inbuilt barometer can be used to track real time weather patterns. Other sensors like LED lights and light-sensitive photodiodes can be used to measure heart rate, also to understand blood oxygenation levels. The GSM and cellular capabilities of today's smartwatches can be leveraged to collect collect voice samples to be used to extract vocal markers that can serve as a prognostic value for neurological disorders and also extract information about the size and reciprocity of a person's social network. This can also serve as prognostic value for neurological and psychological disorders. Futures sensors may include measurements of blood pressure, galvanic skin response for stress, air pollution, glucose, and gait abnormalities.

We developed the Real-time Online Assessment and Mobility Monitor (ROAMM) platform in 2019 to facilitate the movement towards a connected system of mobile computing and wearable sensing specifically designed for publicly available smartwatches [7]. In this paper, we describe a significantly extended version of ROAMM architecture that uses "campaigns" to customize the interface to control text and on-board sensors of brands of smartwatches across many studies in a secure environment. For the rest of this paper, a campaign is defined as any study with predefined objectives. This approach will aid in the more rapid adoption of smartwatches in both clinical care and research settings to take advantage of the large and growing consumer base for these devices. Our work has the following innovations:

(1) Concurrent execution of multiple patient studies, each of which consists of variable patient-reported outcomes and mental health-related patient responses.
(2) Definition of multiple patient-reported outcomes for each campaign and corresponding responses and the frequency at which each of the outcomes needs to be collected.
(3) Collecting physical and sensor-monitored information on the watch at variable frequencies to optimize battery life.
(4) Evaluation of mental health using standard cognitive tests. These tests require determination of response accuracy as well as response time on the smartwatch.

The system is built using a cloud architecture and provides user interfaces for a study coordinator to build campaigns, manage smartwatches that are part of the campaign, and securely collect and analyze data collected from the campaign.

The ROAMM platform facilitates movement towards a connected system of computing and sensing components. While the use of wearable technology is certainly not new, previous work has been on simple "data loggers" that don't offer connectivity or graphical interfaces in a single package. Our approach is based on the "Internet of Things" that can provide increasingly more detailed metadata on mobility, patient-reported outcomes, cognition, and health events, while also providing an expansive platform to connect other peripheral devices that are becoming smart and connected (e.g., blood pressure devices, refrigerators). Flexible control of the different interconnected and frequently communicating components can provide a rich set of applications that can adapt to the environment dynamically.

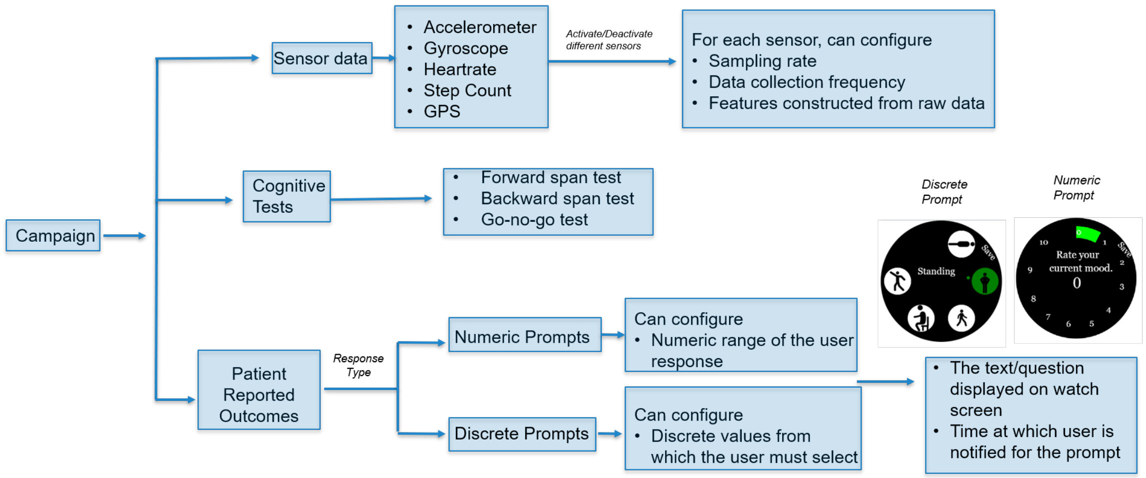

Figure 2: Multiple building blocks that can be configured for a campaign. These building blocks correspond to sensor-based parameters, definitions of patient-reported outcomes, and cognitive tests. Each of these defines and specify the objectives of data collection from the smartwatches for a given campaign.

The rest of the paper is outlined as follows. The logical architecture of the ROAMM platform is presented in section 2, while implementation details of the platform are detailed in section 3. A real-world study demonstrating the effectiveness of the ROAMM platform is presented in section 4. Conclusions are provided in section 5.

2 ROAMM LOGICAL ARCHITECTURE

The novelty of the ROAMM platform is that it can flexibly support executing a study that is customized to needs of the study coordinator (Figure 2). For example, a researcher working on pain-related outcomes might be interested in collecting accelerometry data along with pain-related patient-reported outcomes. Another researcher might be interested in studying the life-space mobility of participants and in collecting GPS data along with activity-related patient-reported outcomes. This platform allows multiple campaigns to run concurrently, each under the auspices of a different researcher. Each campaign is defined as configuration settings of the study that is being executed and consists of three building blocks: sensor-based parameters, definitions of PRO/EMAs, queries about IHEs, and cognitive tests. Each of these define and specify the objectives of data collection for all the smartwatches activated for that campaign. The smartwatch application is programmed to retrieve the campaign definition (configuration settings) from the server and adjust its operation accordingly.

Sensor-Based Data Collection: The data from built-in sensors can be collected at variable sampling rates. The platform enables the choice of which sensors to activate, their sampling rates, raw data aggregation interval, etc. A complete list of all the parameters that can be configured along with their description is provided in Table 1.

Patient-Reported Outcomes and Ecological Momentary Assessments: A patient-reported outcome (PRO) is used for collecting responses from a patient after reflecting on their overall health, quality of life, or functional status associated with health care or

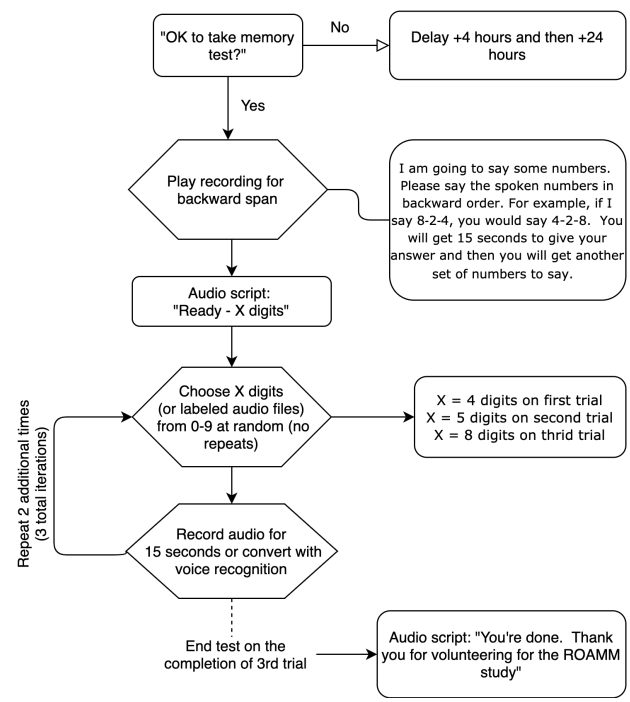

Figure 3: Figure showing flow chart of backward span cognitive test. The user is asked to repeat the digits in backward order, and the test is done for a total of three iterations with 4, 5, and 8 digits, respectively. The voice recording of the user is stored and sent to the server for voice recognition based or human evaluation.

treatment [16] . PROs tend to be a reflection of a static trait, e.g. on

Table 1: List of watch configuration parameters that can be configured for collecting sensor data

Parameter	Description	Value
RECEIVE CONFIG FROM SERVER	When true the watch receives configuration from server	True/False
SAVE LOCALLY	When true stores data locally in the watch	True/False
SEND TO SERVER	When true exports data to server	True/False
RAW MODE	When true exports raw data to server	True/False
VARIABLE CONSTRUCTION RATE	The interval at which raw data are aggregated to construct features	Numeric in seconds
DEFAULT ACCELEROMETER	When true collects accelerometer data	True/False
DEFAULT STEP	When true monitors step count	True/False
DEFAULT HEARTRATE	When true monitors heart rate	True/False
DEFAULT GYRO	When true collects gyroscope data	True/False
DEFAULT BATTERY	When true collects battery information	True/False
ACCELEROMETER RATE	Sampling rate at which accelerometer data are collected	Numeric in Hz
GYRO RATE	Sampling rate at which gyroscope data are collected	Numeric in Hz
GPS RATE	Sampling rate at which GPS data are collected	Numeric in Hz
STEP RATE	Sampling rate at which step count is monitored	Numeric in Hz
SEND DATA INTERVAL	The rate at which data are exported to server from 8:00 AM to 8:00 PM	Numeric in seconds
SEND DATA INTERVAL NIGHT	The rate at which data are exported to server after 8:00 PM	Numeric in seconds
REMINDER INTERVAL	The time interval after which participant is notified if a prompt is missed	Numeric in seconds
APP START TIME	Time to start the app	Time in 24-hr format
APP END TIME	Time to stop the app	Time in 24-hr format

average how much difficulty do you have climbing stairs. An ecological momentary assessment (EMA) differs by asking questions about current experiences or symptoms that represent transient states, e.g. current pain level. We use the watch to elicit different PROs and EMAs from the participant. The platform flexibly allows the study manager to configure the PRO/EMA content remotely

Table 2: List of configurable parameters corresponding to patient-reported outcomes or ecological momentary assessments

Parameter	Description	Value	Constraints
Question	A short form of question to be displayed on watch	String	Length of string should be less than 17 characters
Long question	Question to be displayed	Long string	None
MinValue	Minimum value for the range question asked	Numeric	Value should be between -999 to 999
MaxValue	Maximum value for the range question asked	Numeric	Value should be between -999 to 999
IncrementBy	How much to increment with step	Numeric	Less than or equal to 13
DefaultValue	Default value to be selected when the question is asked	Numeric	Value should be between -999 to 999
Time of day to display prompt	List of times in a day (24-hr format) when to prompt the question	Timestamp	None
Values (for discrete range prompt)	The possible responses that the prompt can have	List of strings/ints	None

based on the study needs and also add, modify, or delete them as necessary. Broadly, there are two kinds of PRO/EMAs that can be defined in the campaign: numeric and discrete. The fundamental difference is the numeric vs. categorical nature of the outcome variable. For numeric prompts, participants are asked to provide ratings on a Likert scale (such as 0-10 range). Whereas, for discrete prompts, participants are asked to make a selection from categorical choices — yes, maybe or no. A complete list of all the parameters that can be configured for the PRO/EMAs is provided in Table 2. Figure 4 shows examples of requests for Patient reported watches for Samsung and Apple Smartwatches. In general, the placement of the question and responses will vary based on the size and shape of the watch interface.

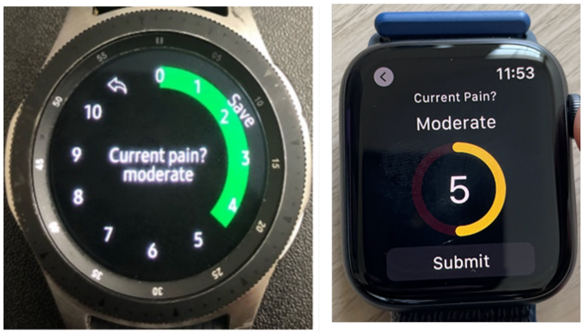

Figure 4: Examples of Patient Reported Outcomes in Samsung and Apple watches. The same question and corresponding responses may appear slightly differently based on the watch interface, aspect ratio and other constraints

Mental Health & Cognitive Tests: Changes in cognitive processing speed/reaction time and executive functioning are implicated in many mental health and normal aging (non-demented) failures of everyday functioning. Falls, motor vehicle crashes, impaired decision making have all been associated with slowing and reduced inhibition. Test performance can be used to identify both daily lability in cognitive functioning, and also when individuals are on a decline trajectory that may be a sentinel for impending IHEs. The ROAMM platform currently supports tests of executive function and motor speed. These tests are established and well-validated, but are traditionally done on paper or with a computer screen. ROAMM miniaturizes the test for a smartwatch interface and uses text and audio to aid self-administration and has the following features:

(1) No-Go for Executive Function: When participants see a particular symbol, e.g., a square or triangle, they must inhibit their response to press a button or tap the screen. When they see any other symbol, they should press a button as quickly as possible. Scores include reaction time to critical letters and accuracy reaction to inhibition trials.
(2) Digit Span for Working Memory: In forward span, participants see a series of digits (4, 3, 2, 7) and are asked to repeat them. In the backward span, participants are asked to repeat backward (i.e., 7, 2, 3, 4). In both tests, several trials are given with increasing span lengths, either 4, 5, or 8 digits. Audio is recorded and stored for manual grading or converted to text with voice recognition. The maximum digit length correctly remembered and the ratio of correct to incorrect responses across all trials are also recorded.
(3) Reaction Time: After a warning (fixation cross), a symbol appears on the screen. Participants are asked to press a side button or screen as quickly as possible when they see the symbol. Three blocks of 10 to 100 trials are completed. Each trial has a different inter-stimulus interval, ranging from 250 to 2000 ms. The reaction time is calculated as the time of screen press subtracted from the time of symbol presentation.

Implementation of such tests is based on developing a flow chart (e.g, Figure 3) and then implementing this flowchart on the smartwatch. The overall process interactively collects both responses and response times.

3 PLATFORM IMPLEMENTATION

We have developed a robust and scalable system that is event driven and leverages a cloud-based architecture. Figure 5 shows the overall architecture of the ROAMM platform. The main components of the platform are as follows:

- Smartwatch application: This is used for data collection and transmission and is customized for Samsung and Apple development platforms.
- Server: A cloud-based computing server manages and configures watches, provides data storage and campaign management.
- Web-based user interface: This is used for managing the watches and configuring them; supporting administrative functions for the study coordinator, including registering research participants, assigning watches to them, data collection on/off, and visualizing data.

We provided details of each of these components in the following.

3.1 Watch Application

The application is designed to support continuous remote data collection and transmission. The application is equipped to

(1) Collect different sensor data with different data structures and resolutions (accelerometer, gyroscope, GPS, heart rate, UV exposure, etc.) then aggregate them as necessary
(2) Interact with the user to elicit PRO/EMAs. These are obtained by prompting the user with questions about predefined outcomes by providing suitable interactivity, including the potential for the user to make changes in their responses.
(3) Execute cognitive tests and collect information about response time etc. and send it back to the server.

Overall, the application requests the server to receive configuration parameters (campaign) and adjusts its utilization accordingly. The configuration received from the server is used to adjust different parameters of the data collection. These parameters include which sensor data to turn on/off, adjusting data collection frequencies, raw data aggregation intervals, selecting data features to summarize from raw data (mean vector magnitude), defining patient reported outcomes of interest and selecting cognitive tests.

3.2 Server

The server acts as the backbone for the whole platform. It supports many functionalities, including interacting with multiple watches concurrently in the field, configuring and receiving data and storing them a centralized database, managing authentication mechanisms, maintaining data privacy between different campaigns, and also supporting the functionality of the Web-user interface.

We now describe different software packages that are used for developing the above functionality using a cloud-based architecture. The main advantages of using a cloud-based architecture are that it provides flexibility, adaptation to changing resource requirements,

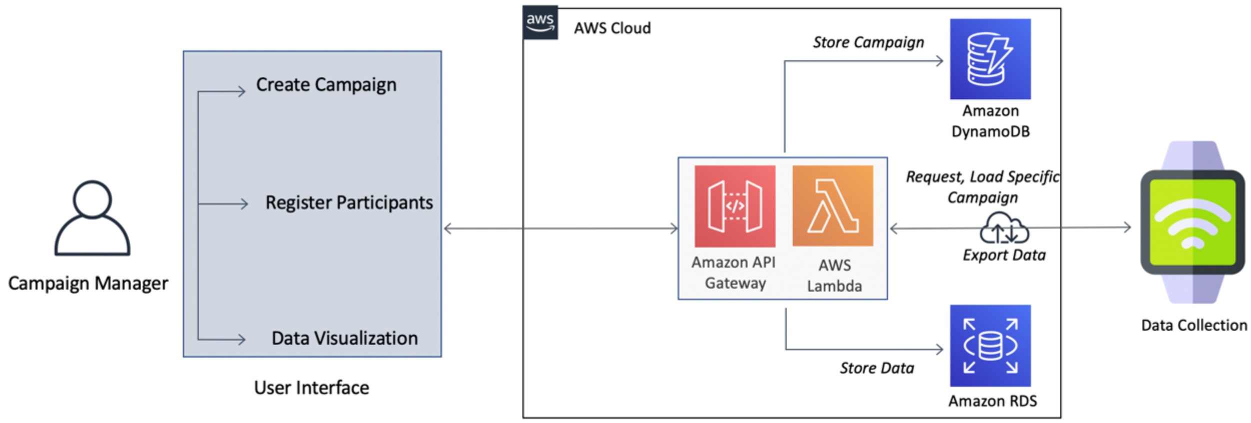

Figure 5: Figure showing the high level architecture of ROAMM platform. The campaign manager can define the campaign by provide campaign configuration information and list of watches that are part of the campaign. Users directly interact with the watches. The server acts as the backbone for the whole platform. Requests from both the user interface and smartwatch are routed to corresponding microservices via API gateway.

and high availability and security. We use Amazon Web Services (AWS) for our implementation (although this can be easily ported to other cloud systems):

- *ROAMM Server* We use the AWS Lambda, serverless compute and event-driven programming platform for this purpose. It can be used to directly run code snippets in the programming language of our choice: Node.js, Python, Java, etc. The main advantages of using Lambda are that it scales with usage, has built-in fault tolerance, and there is no need to manage or provision any servers. Lambda is used for creating new campaigns and managing configuration for each watch with the web-user interface and managing and receiving data from multiple watches simultaneously. Lambda also notifies the watches when a change of configuration is requested by the end user, manages participants and their assigned watches, data visualization, downloading data, and maintaining privacy between different campaigns.
- *Watch Communication:* The AWS API gateway acts as a bridge between the external world and Amazon resources. It acts as a unified API front end for multiple microservices and for all communications to and from the watches. It is used for creating, deploying, and managing a REST application programming interface (API) to expose back end HTTP endpoints. We use this layer instead of directly communicating with the corresponding service because it provides a smartwatch agnostic endpoint, i.e., different watches (Samsung, Apple, etc.) can be easily integrated into the ROAMM platform.
- *Storage:* We use a relational database RDS for this purpose. RDS is Amazon's fully managed fault-tolerant, scalable relational database service. Unstructured infromation is stored in DynamoDB. The data is stored after suitable encryption.

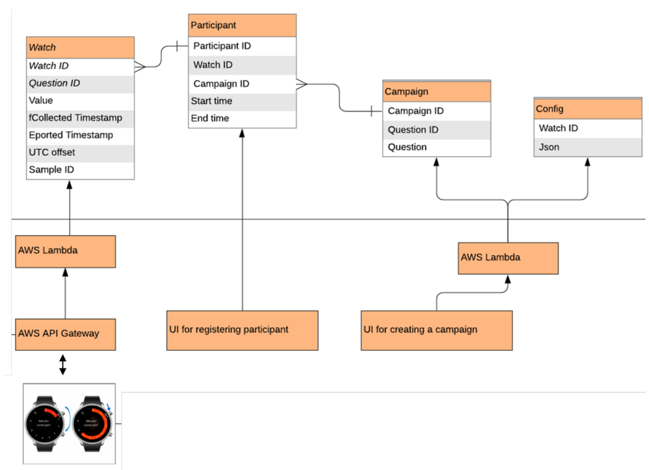

Figure 6: The data storage pipeline used by our system. The collected data from smart watches are stored in Amazon RDS relational tables and routed through API gateway. Other information, such as participant details and start and end dates of the study, is also stored in relational tables. Unstructured data such as campaign information is stored in Dynamo DB.

3.3 Web-Based User Interface

A web-based user interface is designed to provide interaction with watches, supporting administrative functions for the study coordinator (including registering research participants), assigning watches to them, toggling on/off data collection, and visualizing data. The user interface allows study coordinators to design a campaign of their choice. Different configuration options corresponding

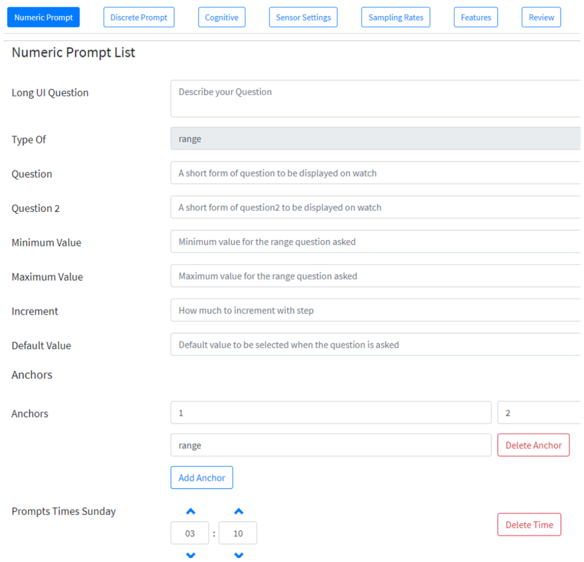

Figure 7: Figure showing a screenshot of the user interface for creating numeric prompts. Different parameters like the question to display on watch, numeric range of the response, and list of times when to prompt the question can be configured.

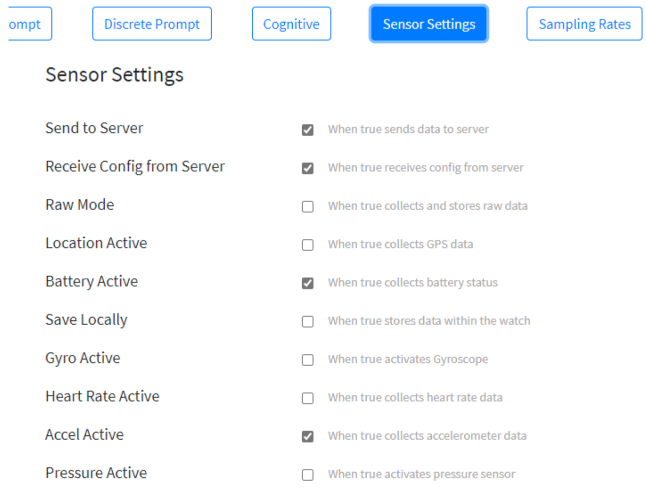

Figure 8: A screenshot of the user interface for configuring sensor-based settings. Different sensors can be configured to be turned on and off based on study requirements. The frequency of data collection can also be modified (not shown).

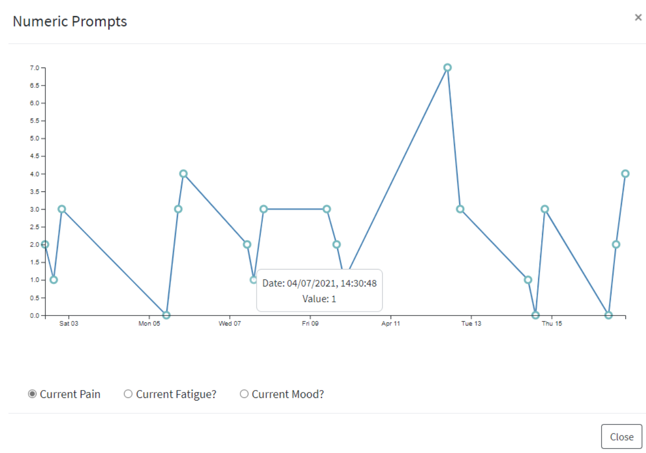

Figure 9: Figure showing a screenshot of the Web-user interface for visualizing numeric prompts data. The data from different prompts as defined in the campaign can be graphically visualized.

to the campaign (PROs, cognitive tests, sensor data) can be defined in the campaign creation interface.

Figures 7 and 8 show snapshots of this user interface. It is built using Angular, a component-based architecture, which enables the reuse of components and elements across the application. Also, the use of services in Angular assists in sharing the data across components with similar functionality. The maps that are embedded in the application are built using leaflet.js, a JavaScript library that provides interactive maps.

4 EXAMPLE CAMPAIGN

In this section, we demonstrate the effectiveness of the ROAMM platform in examining the temporal association between ecological momentary assessments (EMAs) of pain with continuous mobility tracking via the Global Positioning System (GPS) for life-space mobility ascertainment in older adults suffering from knee osteoarthritis. Mobility within the perspective of life-space can be described as the habitual movement of individuals [1, 11, 15]. Pain can adversely affect older adults’ life-space mobility. However, capturing pain is an intricate endeavor due to its variability, which makes the traditional pain surveys that are based on memory recollection unsuitable.

Utilizing EMAs allows recording pain experiences throughout the day and in the individuals’ natural environments. We developed a campaign using ROAMM for this purpose. We enrolled 19 older adults (73.1 ± 4.8 years old) with symptomatic knee osteoarthritis [10]. EMA of pain was evaluated using a valid and reliable numerical rating scale: an 11-point box scale (BS-11) of pain intensity ranging from 0 (no pain) to 10 (worst possible pain) [3, 6]. Prompts were scheduled at random times within three predefined periods (morning: 8 am – 12 pm), (afternoon: 12 – 4 pm), and (evening: 4 – 8 pm). GPS coordinates were captured continuously every 15 minutes. Then, ten life-space mobility relevant features were decomposed into the following four categories:

- Excursion features include three sub features: size, span, and total distance. The excursion size reflects the distance of the furthest coordinate away from home, while the excursion span reflects the maximum distance between any two coordinates away from home. Lastly, the total distance reflects

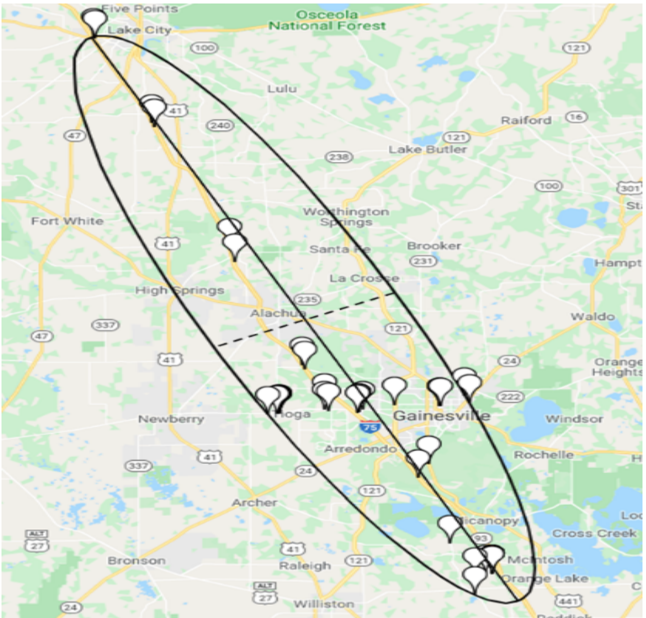

Figure 10: An ellipse encompassing all the GPS coordinates for a single participant. The dashed line represents the minor axis and the solid line represents the major axis [10].

the accumulated distance between all GPS coordinated away from home.

- Ellipsoid features include three sub features: minor axis, major axis, and area of the ellipse. These features were extracted after drawing the smallest ellipse that can encompass all the GPS coordinates. Figure 10 shows an ellipse for one of the consented participants.
- Clusters' features include two sub features: number of clusters and entropy. These features were extracted after clustering nearby coordinates by using the adaptive k-means algorithm.
- Excursion frequency features include two sub features: frequency of trips and homestay percentage. The latter provides the fraction of time spent at home.

In order to examine the relationship between pain and life-space mobility, we fit a two-level random effects model accounting for participant and day. This analysis was necessary to reveal the variability of pain within and between persons. We adjusted the model for *age*, *living alone*, and *gender* as fixed effects.

The participants wore the smartwatch for almost 2 weeks (13.16 ±2.94 days) and had an 82% compliance rate for responding to pain prompts. Additionally, the results showed that there is a negative association between pain and most of the life-space mobility features except for the *number of clusters*, *frequency of trips*, and *homestay* features. Interestingly, the intra-person variability explained more variance than the inter-person variability. The *excursion size* feature showed statistically significant and others *excursion span, total distance, and ellipse major axis* trended toward significance in this small sample. Overall, the level of increased pain intensity was associated with a 1.9-mile lower excursion size, 1.8-mile lower excursion span, 3.55-mile lower total distance travelled per day, 12.13-mile^2 smaller ellipse area, 0.29-mile lower ellipse minor axis, and 2.26-mile lower ellipse major axis. An example of life-space mobility ellipse for one of the participants is shown in Figure 10. These findings demonstrate ROAMM's ability to capture clinically meaningful symptoms that are matched to passively collected ecological data for identify new consequences of symptoms that will inform future healthcare.

5 CONCLUSIONS

In this paper, we described the ROAMM campaign system that customizes the interface to control text and on-board sensors of publicly available smartwatches across many studies in a secure environment using campaigns. We currently support both Apple and Samsung smart watches. The system is built using a cloud architecture and provides user interfaces for a study coordinator to build campaigns, manage smartwatches that are part of the campaign, and collect and analyze data collected from the campaign. We believe that our approach will aid in the more rapid adoption of smartwatches in both clinical care and research settings to take advantage of the large and growing consumer base for these devices.

In the future, we expect that there will be non-watch-based wearable sensors that will communicate with smart-watches using Bluetooth and related technologies to leverage their wireless and computation infrastructure. These sensors, such as glucose and blood pressure monitoring, will further enhance the quality and quantity of health-related information using smartwatches.

Format text is required for all articles over one page in length, and is optional for one-page articles (abstracts).

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REFERENCES

[1] Patricia S Baker, Eric V Bodner, and Richard M Allman. 2003. Measuring life-space mobility in community-dwelling older adults. *Journal of the American Geriatrics Society* 51, 11 (2003), 1610–1614.

[2] N. M. Bradburn, L. J. Rips, and S. K. Shevell. 1987. Answering autobiographical questions: the impact of memory and inference on surveys. *Science* 236, 4798 (Apr 1987), 157–161.

[3] John T Farrar, James P Young Jr, Linda LaMoreaux, John L Werth, and R Michael Poole. 2001. Clinical importance of changes in chronic pain intensity measured on an 11-point numerical pain rating scale. *Pain* 94, 2 (2001), 149–158.

[4] F. L. Fimognari, A. Pierantozzi, W. De Alfieri, B. Salani, S. M. Zuccaro, A. Arone, G. Palleschi, and L. Palleschi. 2017. The Severity of Acute Illness and Functional Trajectories in Hospitalized Older Medical Patients. *J Gerontol A Biol Sci Med Sci* 72, 1 (01 2017), 102–108.

[5] IDC. [n.d.]. IDC Forecasts Steady Double-Digit Growth for Wearables as New Capabilities and Use Cases Expand the Market Opportunities. https://www.idc.com/getdoc.jsp?containerId=prUS44930019 Last Accessed October 18, 2019.

[6] Robert N Jamison, Richard H Gracely, Stephen A Raymond, Jonathan G Levine, Barbara Marino, Timothy J Herrmann, Margaret Daly, David Fram, and Nathaniel P Katz. 2002. Comparative study of electronic vs. paper VAS ratings: a randomized, crossover trial using healthy volunteers. *Pain* 99, 1-2 (2002), 341–347.

[7] Matin Kheirkhahan, Sanjay Nair, Anis Davoudi, Parisa Rashidi, Amal A. Wanigatunga, Duane B. Corbett, Tonatiuh Mendoza, Todd M. Manini, and Sanjay

Ranka. 2019. A smartwatch-based framework for real-time and online assessment and mobility monitoring. *Journal of Biomedical Informatics* 89 (Jan 2019), 29–40. https://doi.org/10.1016/j.jbi.2018.11.003 30414474[pmid].

[8] Reed Larson and Mihaly Csikszentmihalyi. 1983. The Experience Sampling Method. *New Directions for Methodology of Social & Behavioral Science* 15 (1983), 41–56.

[9] T. M. Manini, T. Mendoza, M. Battula, A. Davoudi, M. Kheirkhahan, M. E. Young, E. Weber, R. B. Fillingim, and P. Rashidi. 2019. Perception of Older Adults Toward Smartwatch Technology for Assessing Pain and Related Patient-Reported Outcomes: Pilot Study. *JMIR Mhealth Uhealth* 7, 3 (03 2019), e10044.

[10] M. T. Mardini, S. Nerella, M. Kheirkhahan, S. Ranka, R. B. Fillingim, Y. Hu, D. B. Corbett, E. Cenko, E. Weber, P. Rashidi, and T. M. Manini. 2021. The Temporal Relationship Between Ecological Pain and Life-Space Mobility in Older Adults With Knee Osteoarthritis: A Smartwatch-Based Demonstration Study. *JMIR Mhealth Uhealth* 9, 1 (01 2021), e19609.

[11] David May, USL Nayak, and Bernard Isaacs. 1985. The life-space diary: a measure of mobility in old people at home. *International Rehabilitation Medicine* 7, 4 (1985), 182–186.

[12] D. J. Peart, C. Balsalobre-Fernández, and M. P. Shaw. 2019. Use of Mobile Applications to Collect Data in Sport, Health, and Exercise Science: A Narrative Review. *J Strength Cond Res* 33, 4 (Apr 2019), 1167–1177.

[13] Preethi R Sama, Zubin J Eapen, Kevin P Weinfurt, Bimal R Shah, and Kevin A Schulman. 2014. An Evaluation of Mobile Health Application Tools. *JMIR mHealth uHealth* 2, 2 (01 May 2014), e19. https://doi.org/10.2196/mhealth.3088

[14] Norbert Schwarz. 1999. Self-reports: How the questions shape the answers. *American Psychologist* 54, 2 (1999), 93–105. https://doi.org/10.1037/0003-066X.54.2.93

[15] Beth T Stalvey, Cynthia Owsley, Michael E Sloane, and Karlene Ball. 1999. The Life Space Questionnaire: A measure of the extent of mobility of older adults. *Journal of Applied Gerontology* 18, 4 (1999), 460–478.

[16] Theresa Weldring and Sheree M. S. Smith. 2013. Patient-Reported Outcomes (PROs) and Patient-Reported Outcome Measures (PROMs). *Health Services Insights* 6 (04 Aug 2013), 61–68. https://doi.org/10.4137/HSI.S11093 25114561[pmid].

[17] O. Zaslavsky, A. Zisberg, and E. Shadmi. 2015. Impact of functional change before and during hospitalization on functional recovery 1 month following hospitalization. *J Gerontol A Biol Sci Med Sci* 70, 3 (Mar 2015), 381–386.

[18] Anna Zisberg, Gary Sinoff, Maayan Agmon, Orly Tonkikh, Nurit Gur-Yaish, and Efrat Shadmi. 2016. Even a small change can make a big difference: the case of in-hospital cognitive decline and new IADL dependency. *Age and Ageing* 45, 4 (04 2016), 500–504. https://doi.org/10.1093/ageing/afw063 arXiv:https://academic.oup.com/ageing/article-pdf/45/4/500/11277017/afw063.pdf