

Fitness Data Technology Stack for Wearable Devices

Data Tracking

Ramona Markoska¹[0000-0002-4594-1248], Aleksandar Markoski¹[0000-0003-0561-7758] and Darko Mircevski²

¹ Faculty of ICT, Univ. St.Kliment Ohridski, Bitola, N.Macedonia

² IWConnect, Bitola, N.Macedonia
ramona.markoska@uklo.edu.mk

Abstract. IoT fitness trackers are widely used to measure vital parameters and track sports activities of their users. Available options allow uploading data from an IoT device through a mobile application to its cloud storage. There is a limitation that only data from users with the same devices or operating systems can be collected on the same cloud. The main goal of this work is to propose a solution for tracking and collecting data from heterogeneous IoT devices for fitness tracking and storing it in a shared database. This solution is intended for use in fitness clubs where members, users of IoT fitness trackers, can share their data in the club's private cloud with regulated rights and privileges. This would enable professional fitness trainers to effectively track fitness activities and vital parameters, monitor progress, and provide individualized recommendations. Certain aspects of this solution have been fully developed and implemented, while others are presented as challenges for future resolution and improvement. The research and implemented activities, as well as the insights obtained, show that a recommended software technology stack can be based on implementing common functionalities and addressing the heterogeneity gap of devices, operating systems, working platforms, applications, and datasets. The functionality of this recommended technology stack is demonstrated with a concrete example, and its general applicability is also explained. One of the challenges addressed in this paper is how to integrate the proposed software technologies into a cohesive and functional system.

Keywords: Fitness data, wearable devices,.

1 Introduction

The monitoring and analysis of personal vital parameters and physical activities for the purpose of improving one's own health has become a global trend over the last decade. This can be achieved through the use of affordable and high-quality wearable IoT solutions, such as wristband trackers and smartwatches, designed for daily personal use. These wearable devices connect to smartphones via standardized connection methods, mainly Bluetooth. Wristband trackers and smartwatch owners have the option to select from a variety of mobile applications that are compatible with their

device. Additionally, they can choose which parameters and markers from their personal profiles they want to share as data for synchronization, analysis, and cross-processing. Users who have installed the same mobile application and whose profiles are synchronized in its cloud, often have the possibility of mutual communication and data sharing.

Various studies and scientific papers have developed different methods for acquiring and processing data from IoT fitness trackers. The following variants have been identified:

1. Collection of data from different users, using a single application's cloud.
2. Collection of data for different users of different IoT fitness trackers, running on the same operating system, using a single application's cloud.

This type of processing holds statistical significance and can provide generalized health observations and recommendations. However, the approach lacks individualization for the users, which is a notable disadvantage.

Several surveys and questionnaires conducted in the fields of social habits, behaviour, fitness, and health impact have resulted in the development of a typical average user profile for IoT fitness trackers. The user expectations are in terms of personal benefits and improved quality of life.

Research shows that a considerable number of users who use IoT fitness trackers exercise at fitness clubs. Based on the shared data, fitness trainers create personalized exercise recommendations.

Without adequate software support, the fitness trainer at the fitness club would need to individually review and analyze the IoT fitness tracker data with each user. This would require the user to show the data from their mobile app to the trainer.

The focus of this paper is to design and propose a solution that addresses the following challenges:

1. Managing device and connectivity heterogeneity - the fitness clubs utilize a range of IoT fitness trackers that connect to various operating systems, mobile applications, and cloud storage systems.
2. Managing data heterogeneity - Even within the same application, different IoT fitness trackers measure distinct sets of parameters, and the data is structured and organized differently.
3. Preserving and organizing heterogeneous data for effective search and analysis.
4. Ensuring the sustainability and adaptability of the solution to accommodate new IoT devices.
5. Developing a concept for integrating and digitizing other services and devices in the fitness club to create an integrated whole of services, information, and instructions.

A viable solution would include regulated data rights and privileges, where each user has access to their own data and the trainer has access to all users' data as needed and selected.

2 Research background

The convergence of cloud computing, wearable technology, and the Internet of Things (IoT) has opened up new possibilities for various applications, including healthcare, physical activity monitoring, and data analysis. Several research papers have explored different aspects of wearable devices, access control frameworks, data collection, and the impact of wearable activity trackers on physical activity and health.

In recent years, numerous studies have analyzed the challenges associated with collecting and processing data from wrist-worn devices in diverse and multi-user environments. These works provide a comprehensive overview of existing development platforms, types of data that can be collected, and methods of monitoring and visualizing the data for various applications [1]. In order to overcome the problem of heterogeneity of data from different IoT devices, there is an agreement that it is necessary to organize them through semantic models [2] and various studies and work activities have been carried out in order for semantic models to help develop an ontology for physical activity [2, 3], but those efforts are still far from any generally acceptable and widely applicable format. Also, wearable tracking devices can have a significant impact on increasing physical activity, especially among women and those with high Body Mass Index (BMI), [4], [5] who tend to be less active.

In [6] an access control framework for cloud-enabled wearable IoT devices is presented, aimed to ensure secure access to sensitive data collected by wearable devices, addressing privacy and security concerns. Comprehensive literature review on gamified wearable fitness trackers for physical activity is presented in [7]. Authors explored the effectiveness of gamification in promoting physical activity and discussed various features and design elements that can enhance user engagement and motivation. In [8], [9] and [10] were conducted a systematic reviews and meta-analyses to evaluate the effectiveness of wearable activity trackers in increasing physical activity and improving health and promoting physical activity. Their analysis revealed significant positive effects on physical activity levels, indicating the potential of these devices in behavior change interventions.

The impact of the COVID-19 pandemic on global cloud-based wearable tracking devices is investigated in [11]. The study highlighted the increased adoption and importance of such devices for remote monitoring and health management during the pandemic. [12] examined the status and needs of different actors in mobile health monitoring systems involving wearable sensors. The study emphasized the importance of data exchange and collaboration among stakeholders to enable effective and comprehensive monitoring solutions.

In [13] is proposed a standards-based approach for integrating data from wearable activity trackers to health information systems, with a specific focus on supporting independent living among the elderly population, and [14] discussed the intersection of wearables, the cloud, and the IoT, highlighting considerations for developers. The paper explored the challenges and opportunities in designing wearable devices that effectively leverage cloud services and IoT infrastructure.

Nowadays, the ICT solutions are already integrated into various workout machines in the form of measuring basic vital parameters and determining the target heart rate zone, depending on the user's age and planned effect, such as improving performance, fat burning weight, aerobic, anaerobic training, etc. In several fitness clubs, QR-code integrated explanations for each fitness machine are now available, providing instructions for proper exercise and clarification of the effects of the exercises. Currently, there are a large number of fitness devices and smart watches widely used, which allow tracking of data from each user. The values of the measured parameters are largely comparable with measurements from fitness machines, making these IoT fitness trackers relevant for tracking parameters and making conclusions.

3 Concept of the solution

The common characteristic of different available IoT fitness trackers is the connectivity to a mobile phone through Bluetooth connection. Depending on the device manufacturers and the operating systems of the IoT tracking device and the mobile phone, there are various available mobile applications that collect data generated during fitness activities. The challenge is how to dealing with the different data formats that can be obtained from IoT trackers, which requires an individualized approach. This would mean that in practice, data profiles are needed for all types of devices used by fitness club members, and the creation of individual profiles of a precisely defined type. For example, a group of users may use Xiaomi Mi Band, another group Samsung Galaxy Watch, or Huawei Watch, or devices from another manufacturer. Some of them may use the same mobile application, but in any case, these working and functional aspects must be taken into account when creating the database.

3.1 Practical implementation

The practical implementation of the proposed idea is achieved through the combination of multiple software technologies. Applied software technologies are based on semantic data organization and acquisition from members of the particular fitness club, using NoSQL database, as well as experience from open source and accessibility solutions, such as Wearable Data Layer API, Google Fit API and similar solutions. Briefly described, this paper presents a working functional version of the connection between an IoT fitness tracker and a MongoDB database using Google Fit tools and application realized in Mule Soft. The remaining challenge for the development of this concept is to connect multiple different fitness tracking devices with different sets of measured vital parameters. Tracking of steps in a given time interval by an IoT device, connected to a mobile phone via Bluetooth connection, is elaborated. The integration of Google Fit and MongoDB has been facilitated by the utilization of moderated connections and the Rest APIs provided by Google Fit. Submissions are securely hosted and stored in MongoDB, allowing for convenient local searching and updating capabilities. This integration solution, developed at MuleSoft, is still in its conceptual stage and has the potential for further improvement. The semantic data model and ontology may vary based on the device and its corresponding data set.

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3.2 Fitness Technology Stack – components

Below follows a description of the applied software technologies:

Google Fit is a health and fitness tracking platform that allows users to track their physical activity, nutrition and other wellness metrics using their smartphones, smartwatches and other wearable devices.

MuleSoft provides a unified platform for connecting different applications and systems, both on-premises and in the cloud, through a range of prebuilt connectors and APIs, in this case, for Google Fit and MongoDB.

MongoDB is an open-source document-oriented NoSQL database that uses a flexible JSON-like format to store data. It is designed to scale horizontally across multiple servers and provides features such as automatic sharing and replication.

OAuth 2.0. is an open standard protocol that allows users to grant access to their resources to third-party applications or services without sharing their login credentials.

There are two types of activity and interactions: working settings which means oft configuration and communication settings (which are displayed on screens with a black background in Fig.1 and Fig.2, such as those from Mule Soft), and data exchange (which are displayed on screens with a white background in Fig.1 and Fig.2, such as those from Google Fit and MongoDB). However, in practice, there is no strict separation between these activities, and they are often performed in combination.

3.3 Fitness Technology Stack – Data Flow explanation

Data Flow components for the Fitness Technology Stack are:

1. **HTTP Listener** that "listens" on a certain port and a certain path for calls that would start the execution of the set flow.

2. **SetInputRequest** - generates a transformation message called "InputReq", with a data set, containing: "dataSourceId", the ID to which the request refers, (provided by Google Fit), "bucketByTime", the time interval that will serve as the base (In the example- 86400000 milliseconds or 24 hours) and the working range of the interval within those 24 hours "startTimeMillis" and "endTimeMillis"

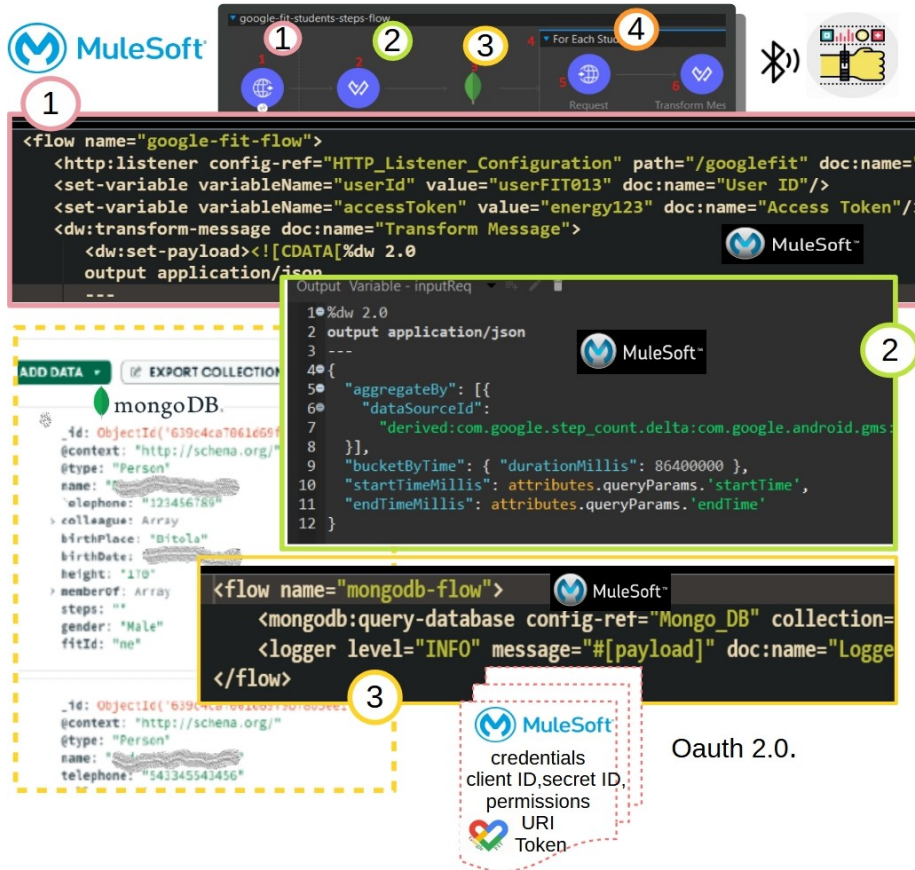


Fig. 1. Working Settings and Data Flow components (1-3) of the Fitness Technology Stack

3. GetUsers - A MongoDB database document is used to store data for each user (i.e. FIT.users). The document includes the fitID, which is taken from Google Fit, and the code indicates that the measurement range for steps is initially empty (i.e., steps = " ")

4. ForEach - allows iteratively replenishing the data in the collections by updating the measurement data from the Google Fit API, at different time intervals and for different users.

5. Set Responce -The obtained measurement data from Google Fit is transferred to MuleSoft using an HTTP connector (on the screen, steps in a time interval during the day i.e., on the begin steps: " ", after steps:"8348"). Mapping the retrieved data into the desired format (JSON-LD) and preparing it for further integration into MongoDB collections.

6. Update Documents - The "insert-collection" configuration allows mapping data to be stored in MongoDB, which can then be selectively accessed as needed.

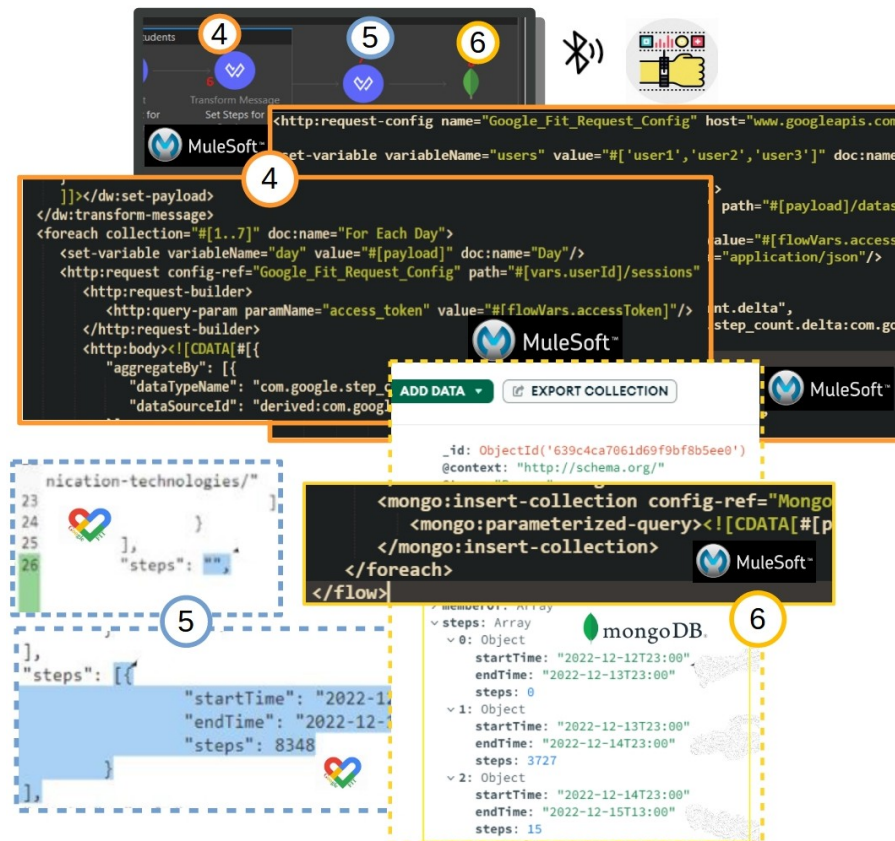


Fig. 2. Working Settings and Data Flow components (4-6) of the Fitness Technology Stack.

The communication, interaction, and data exchange steps between Google Fit, the MuleSoft application, and MongoDB are enabled and supported by OAuth 2.0. This protocol uses parameters such as client ID, secret ID, MuleSoft application URI, credentials, and token to ensure availability, proper order, and appropriate rights and privileges.

4 Conclusion

The significance of this study can be examined at two levels. At the first level, the development of a Fitness Data technology stack for each individual fitness club would enhance the user experience, with workouts being focused and based on personalized experiences, which serves as an additional incentive for healthy exercising. At the second level, the collected data from various fitness centers across different time intervals and countries with varying lifestyles and habits would complement the datasets obtained from targeted focused research encompassing a specific region and duration.

This way, comprehensive real-world data would be obtained regarding the impact of fitness activities on the health of a specific population at both global and local levels. These data could be correlated with age, gender, local components, lifespan, and other lifestyle habits. Over a certain observation period, these collected data could serve as an additional parameter in health statistics, correlating with other factors such as geolocation, nutrition, lifestyle, lifespan, and drawing conclusions for improving healthy habits, as well as the devices and procedures used to monitor those habits.

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