Lively Ageing: an integrated system of services and technologies to enhance the well-being of elderly*

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Abstract

The aging population presents a growing challenge to healthcare systems, necessitating innovative approaches to support the well-being and independence of elderly individuals. The Lively Ageing project, based in Emilia-Romagna, Italy, aims to address this challenge by integrating wearable devices, home automation, robotics, and telemedicine to improve elderly care in residential and co-housing environments. This paper focuses on introducing the use of wearable technologies to monitor and enhance the health of older adults. Specifically, it examines the criteria for selecting suitable wearable devices, explores key health metrics that can be monitored, and investigates the potential of integrating wearable data with clinical indicators, such as cardiovascular risk factors, diabetes, and hypertension. A preliminary analysis of open data will assess the ability of wearable devices to infer psychological traits, while in the future, we intend to analyze direct correlations between wearable data and clinical indicators such as cardiovascular disease, diabetes, or hypertension.

Keywords

Wearable Technologies, Elderly Care, Health, Vital Signs Monitoring, Data Science

1. Introduction

The aging population poses significant challenges to healthcare systems worldwide. According to the European Commission, by 2050, more than 30% of the European population will be 65 or older, requiring innovative solutions to ensure the well-being and autonomy of elderly individuals. These solutions must address both the clinical and social aspects of aging, integrating technological advances into healthcare practice.

Lively Ageing, an integrated project running in Emilia-Romagna, Italy, seeks to create a network of services and technologies designed to enhance the well-being of the elderly. The project leverages wearable devices, home automation, robotics, and telemedicine to support older adults in residential care or co-housing environments. Specifically, it aims to:

- Develop living spaces that preserve autonomy and safety;
- Prevent cognitive decline and improve elderly health outcomes, particularly regarding cardiovascular risk factors;
- Promote an integrated network of social and healthcare services trained to use new technologies effectively.

Wearable devices play a pivotal role in the project's vision by enabling continuous monitoring of vital signs and physical activity, thus offering real-time insights into an individual's health status.

This paper represents a preliminary step in the broader **Lively Ageing** project, focusing data analysis supported by AI on data coming from wearable devices as a cornerstone for enhancing eldercare.

The integration of wearable devices and artificial intelligence (AI) in geriatric medicine is rapidly advancing, offering the potential to significantly enhance elderly healthcare by enabling continuous monitoring, early detection of health issues, and personalized interventions [1]. Wearable IoT systems equipped with advanced biometric sensors can collect real-time physiological data, such as heart rate,

Ital-IA 2025: 5th National Conference on Artificial Intelligence, organized by CINI, June 23-24, 2025, Trieste, Italy

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temperature, blood oxygen, and activity levels. These data, when analyzed by AI algorithms, provide valuable insights for both preventive and proactive care management. These technologies facilitate remote monitoring, allowing healthcare professionals and caregivers to respond promptly to changes in an older adult's health status, ultimately improving outcomes and supporting independent living [2, 3].

However, challenges remain, such as the need for more randomized controlled trials, addressing AI bias that may worsen health inequities, ensuring external validation for older populations, protecting privacy and autonomy, increasing model transparency, and safeguarding against errors [4]. This preliminary study lays the groundwork for future developments within the project, including integrating wearable data with clinical systems and exploring its potential to enhance care quality and decision-making.

2. The Lively Ageing Project

The Lively Ageing project[1] aims to create an integrated network of services and technologies to enhance the well-being of elderly individuals through an innovative care model based on advanced technologies. The project will be implemented in residential facilities and day centers in Modena, Carpi, Reggio Emilia, and Parma, involving universities, healthcare companies and social services. The goal is to create a scalable model that can be expanded nationwide.

Wearable Devices: The evaluation started with a preliminary study that assessed multiple wearable sensors, focusing on their cost, compliance with European regulations, and the type of data they collect. Our selection criteria required the ability to monitor vital signs such as heart rate and oxygen saturation, a price below 300 euros, extended battery life, and the option to ensure that data is stored within EU borders to comply with GDPR regulations. This approach allowed us to narrow the selection to six sensors, which were then analyzed in greater detail:

- **Fitbit Sense 2**. A comprehensive health smartwatch offering ECG, heart rate, sleep, stress, SpO_2, skin temperature, body composition, and hydration tracking.
- **Fitbit Inspire 3**. An affordable tracker focused on steps, distance, calories, heart rate, and sleep monitoring.
- **Fitbit Versa 4**. A fitness-oriented smartwatch featuring heart rate, sleep, stress, SpO_2, hydration, and menstrual health tracking.
- **Garmin Venu Sq 2**. A multi-purpose health tracker with heart rate, sleep, stress, SpO_2, and hydration monitoring.
- **Garmin Forerunner 55**. A GPS-enabled watch for runners, including heart rate, sleep, SpO_2, and hydration tracking.
- **Samsung Galaxy Watch 4**. An advanced health tracker with ECG, heart rate, sleep, stress, SpO_2, body composition, blood pressure, and hydration monitoring.

Wearable devices offer valuable health monitoring for the elderly, aiding in chronic disease management through continuous data collection and early anomaly detection. This data might support informed medical decisions and personalized treatment plans. However, data may be noisy or incomplete, which affects accuracy. Furthermore, older adults may struggle with device usability due to technological complexity, physical limitations, and unfamiliarity with digital interfaces.

Data Flow and Creation of an Integrated Database: The project aims to develop an integrated database that collects and unifies information from heterogeneous data sources, including wearable devices, medical devices, electronic health records, and environmental sensors monitoring the guest's living space. The goal is to build a data infrastructure capable of managing both real-time data streams and historical records, while ensuring high data quality and integrity. This process requires seamless integration of different data formats and source systems while guaranteeing the protection and privacy of sensitive data, particularly medical information. The data flow and the stakeholders involved (ASP,

[1] https://www.livelyageing.unimore.it/

municipalities, local health authorities, universities) have been defined, and a system for sending pseudonymized data has been established.

A **Digital Twin** for elderly care would be a virtual replica of an individual, continuously updated with real-time health and wellness data from various sources [5, 6]. This technology enables continuous, unobtrusive monitoring of an older adult's daily activities, physiological parameters, and living environment, supporting personalized health management and early detection of anomalies or potential health risks.

Planned Data Analysis: The primary objectives of the analysis are to identify significant health patterns, evaluate the overall well-being of elderly users, and assess the effectiveness of wearable devices in monitoring and predicting health outcomes:

- **Preprocessing Strategies:** We will perform data standardization and cleaning to handle missing values, outliers, and ensure consistency across datasets. Feature engineering techniques will be applied to extract meaningful attributes from raw data, such as: Heart rate variability (HRV) trends, Sleep quality indices, Physical activity classifications (e.g., sedentary vs. active behavior), Deviation from individual baselines (useful for detecting anomalies). These processed features will enable for a more accurate representation of each individual within the Digital Twin model.
- **AI Methods:** We will employ predictive modeling techniques, including regression analysis and classification algorithms (e.g., LightGBM, Random Forests) to: forecast health outcomes, identify early risk factors for conditions such as cardiovascular disease or cognitive decline. Furthermore, clustering methods (e.g., K-means, hierarchical clustering) will be used to segment users based on health profiles and activity patterns, facilitating personalized health interventions.

Expected Benefits: By integrating and managing all data related to the daily life, routines and medical information of the elderly, our goal is to improve their well-being through proactive health monitoring, enabling early detection of chronic diseases and personalized healthcare plans based on real-time conditions. This approach is expected to improve autonomy and safety, reducing hospitalization risks through preventive care, while also optimizing healthcare resources by ensuring efficient allocation of personnel and home assistance.

3. Preliminary Results on Open Datasets

Due to delays in obtaining authorization from the ethics committee to start the experiments, we began our analysis using publicly available datasets. Here, we present the application of LightGBM for classification to predict personality traits after preprocessing and the use of SMOTE [7] to address class imbalance. The analysis was carried out on 50 time series from different participants.

Dataset: The dataset used is derived from the LifeSnaps dataset[2], an open-access resource containing anonymized wearable data from 71 participants. However, only 50 participants completed the associated personality test, reducing the sample size for this component. The dataset includes features categorized into general information, demographic details, health variables, physical activity metrics, and personality traits. It tracks physiological data, heart rate zones, time spent in different locations, and physical activity goals. The personality traits—*extraversion*, *agreeableness*, *conscientiousness*, *stability*, and *intellect*—are derived from a survey and offer insights into participants' psychological profiles.

Statistical Analysis: For each user, we compute the mean, standard deviation, minimum, maximum, median, and skewness for each numerical feature. Categorical features are encoded using label encoding. These features form the final feature vector, resulting in a dataset of 50 entries, each with the augmented features described above. The target variables correspond to the five personality traits predicted in the analysis.

LightGBM: Understanding personality traits through sensor data can enhance personalized recommendations in health and wellness applications. This study applies LightGBM [8] to predict the five

[2]https://zenodo.org/record/7229547

personality traits, *extraversion*, *agreeableness*, *conscientiousness*, *stability*, and *intellect*, each categorized as low, medium, or high. To address class imbalance, we use SMOTE to generate synthetic samples for underrepresented classes. SMOTE works by selecting examples from the minority class, identifying their k-nearest neighbors, and creating new synthetic instances along the line segments connecting the examples and their neighbors. The LightGBM classifier is trained on extracted features with *multiclass classification*, using a learning rate of 0.01, max depth of 5, and class weight set to 'balanced'. The dataset is split 70% for training and 30% for testing.

Trait	Accuracy	Macro F1-score	Weighted F1-score
midrule Extraversion	0.80	0.84	0.80
Agreeableness	0.60	0.58	0.57
Conscientiousness	0.87	0.87	0.87
Stability	0.73	0.66	0.72
Intellect	0.93	0.93	0.94

Table 1
Performance of LightGBM for Personality Trait Classification

Results: Table 1 shows the LightGBM model's performance in classifying personality traits, with the highest accuracy for *intellect* and *conscientiousness*, while *agreeableness* remains harder to predict. This suggests that smart sensor data may be insufficient for some traits but more reliable for others. Performance variability indicates room for improvement through better feature engineering and addressing class imbalances. Despite the limited sample size, these results highlight the potential of wearable data for inferring personality traits.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT in order to: Grammar and spelling check, Paraphrase and reword. After using these tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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