Wearable Sensor Systems to Detect Biomarkers of Personality Traits for Healthy Aging: A Review

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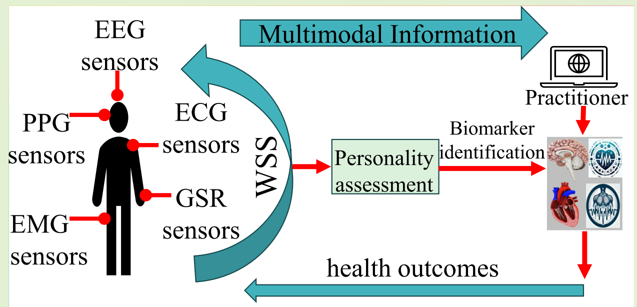
***Abstract*—Wearable sensor systems (WSS) have garnered substantial attention as they showcase their versatility not only in the development of automated healthcare systems and shaping smart cities but also in extending their applications into fields such as personalized fitness monitoring and seamless human–computer interaction. Wearable technologies have evolved into more sophisticated forms, significantly improving their capacity to capture multimodal physiological signals from individuals. The recorded physiological signals, including electroencephalography (EEG), electrocardiogram (ECG), galvanic skin response (GSR), photoplethysmography (PPG), and electromyogram (EMG), contain significant and compelling information about the health conditions of individuals. This information has the potential to contribute to and enhance longevity and subjective well-being, aspects that remain mostly unexplored to date. This review delves into the contemporary landscape of research, aiming to unravel the multifaceted interplay among personality traits, physiological signals, and biomarkers that collectively contribute to active and healthy aging. Specifically, we focus on sensing methods and techniques to identify particular personality traits and their connection with health outcomes. The review also outlines key studies that involve the physiological parameters used for health control and age-related diseases. The work also highlights the various kinds of physiological signals containing different useful identifiable bioindicators for healthy aging across five personality dimensions. Finally, we address technical challenges observed in wearable sensor systems, encompassing data integration, sample size limitations, and privacy concerns, while also presenting a roadmap for future research directions and opportunities.**



***Index Terms*— Biomarkers, electrocardiogram (ECG), electroencephalography (EEG), electromyogram (EMG), galvanic skin response (GSR), healthy aging, personality traits, photoplethysmography (PPG), physiological signals, wearable sensors system (WSS).**

I. Introduction

PERSONALITY refers to the unique set of enduring patterns of thoughts, feelings, and behaviors that characterize an individual. It encompasses the relatively stable and consistent ways in which people perceive, interpret, and interact with the world around them. Personality traits, on the other hand, are specific dimensions or characteristics that describe different aspects of an individual's personality. These traits are relatively enduring and influence an individual's behavior across various situations [1]. Personality trait recognition is important for self-awareness, understanding others, building strong relationships, making informed career decisions, personal growth, and resolving conflicts. It enhances our ability to navigate social interactions, adapt to different situations, and make choices that align with our personal strengths and values. Psychological and medical researcher's goal is to explore the individual differences in performing daily activities in order to build a realistic model for personalized healthcare system [2]. At present, various personality trait theories have been developed to categorize and interpret human personality. For example, Cattle 16 personality factor (IPF6) [3], extroversion and neuroticism (PEN) [4], Myers-Briggs Type indicator (MBTI) [5], and Big Five [6] have been presented to understand human personality. Big Five, also known as the five-factor model (FFM), is the most widely recognized and extensively studied model. The Big Five personality traits include as follows.

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Fig. 1. Big Five personality trait model.

1) *"Openness to Experience (O)":* This trait reflects a person's willingness to embrace new ideas, imagination, and intellectual curiosity.
2) *"Conscientiousness (C)":* This trait relates to a person's level of organization, responsibility, dependability, and self-discipline.
3) *"Extroversion (E)":* Extroversion refers to a person's sociability, "assertiveness," and preference for external stimulation.
4) *"Agreeableness (A)":* This trait involves a person's tendency to be cooperative, compassionate, and considerate toward others.
5) *"Neuroticism (N)":* Neuroticism refers to the degree of emotional instability, anxiety, moodiness, and vulnerability to stress.

The detailed model of the Big Five personality traits is depicted in Fig. 1.

Wearable sensor systems (WSS) integrate various tiny, portable, and flexible sensors intended to be worn on or attached to the human body. These systems deliver valuable information regarding daily routine activities and personal well-being to both end-users and caregivers [7]. In the past, numerous studies have been conducted to recognize Big Five personality traits that include questionnaires or laboratory assessment, and wearable sensor-based approaches have found applications across various fields, including emotional studies [8], social interactions [9], recommendation systems [10], education [11], and biomarkers for health status [12]. There is ever-increasing research across research communities to record and monitor physiological signals, such as electroencephalography (EEG), galvanic skin response (GSR), photoplethysmography (PPG), electrocardiogram (ECG), and electromyogram (EMG) to support diverse applications. Amidst numerous objectives, personality trait classification using physiological signals has been the major aim for psychophysiological researchers. For example, in [13], heart rate was used for personality trait recognition during different training sessions. In [11], ECG, GSR, and fEMG signals have been acquired to explore the relationship between personality traits and online teaching. In [14], EEG, GSR, ECG, and facial activity have been used to recognize personality traits during affective video clips. In [15], [16], and [17], EEG signals have been employed to explore the personality traits. The existing literature depicts that various aspects of human personality can be assessed through wearable devices more accurately than their assessment based on subjective approaches.

To investigate how the Big Five personality traits affect individuals' health, this review study aims to enhance quality of life by combining physiological and psychological data. It is observed that age-related diseases are uncommon and highly nonlinear; even within the same family, some individuals are more susceptible to diseases, while others remain active throughout their lives. With this in mind, our primary objectives are given as follows:

1) to examine the influence of the Big Five personality traits on active and healthy aging;
2) to investigate the use of machine learning and deep learning techniques in wearable technologies for promoting healthy aging;

3) to identify common methodologies used to explore the dynamic relationship between physiological biomarkers, personality traits, and health status.

Based on these objectives, we have developed research questions to evaluate the significance of individual personality traits on lifestyle and health behaviors through the use of smart wearable technologies.

A. Concept of Active and Healthy Aging

Aging is a natural process, and according to a report published by the World Health Organization (WHO) in 2015, the aging population is one of the main causes of social and economic challenges [18]. Normal aging is a process that results from a variety of cellular or molecular accumulation at the biological level over time, and this results in a gradual decline into physiological reserves, cognitive deterioration, and quality of life, which is reduced. This decline is the main cause of various types of chronic diseases, such as cardiovascular and neurodegenerative diseases [19] and ultimately mortality.

In contrast to typical aging, active and healthy aging involves the ongoing effort to preserve a higher quality of life throughout one's lifespan. This concept entails relishing a life characterized by a reduced likelihood of age-related illnesses, strong mental and physical capabilities, and active participation in various aspects of life, as mentioned in [20]. According to [21], achieving or maintaining active and healthy aging is attainable through appropriate physical activity, social engagement, proper dietary habits, genetic factors, and overall environmental conditions. There are several factors that help explain how certain individuals experience a quicker rate of biological aging, making them more susceptible to diseases, while in other individuals, the decline is slower, leading to longer and healthier lives. In [22], it is emphasized that the key to healthy aging lies in individual decisions and behaviors, as the effects of aging are not uniform and follow a nonlinear pattern. Consequently, it is imperative to tackle these challenges and seek answers to questions such as who currently enjoys a high quality of life and who will in the future.

B. WSS for Active and Healthy Aging

WSS has emerged as an integral tool having the capability to capture the diversity of physiological signals simultaneously. Integration of wearable sensors provides a dynamic approach to detect and monitor health parameters. Consistently tracking physiological parameters allows for personalized interventions, facilitating the early detection of age-related diseases. Incorporating noninvasive sensors and computing and communication capabilities allow a wearable device to proficiently manage, facilitate transmission, manipulate, and interpret the individual's health status. For example, in [23], a sensor is designed for remote monitoring of blood pressure (BP), heart rate (HR), and blood oxygen level (SpO_2). In [24], a discreet wearable biofeedback system has been introduced for the personalized management of emotional states. EEG, ECG, and respiratory signals have been monitored to provide information related to personalized health, fitness, and diseases [25].

Active and healthy aging has been widely explored, and today research related to the aging process is attracting increasing interest. As individuals aspire to live actively and healthily, the focus is on promoting sustained well-being and vitality. Several studies illustrated the association between the quality of life and personality traits. Since individuals of the same chronological age have different paces of biological aging, biomarkers are the potential indicators for measuring physiological aging, life expectancy, assessing the degree of active and healthy aging, and maintaining active life span [26]. Biological aging of individuals measured at chromosomal level [27], physiological attributes [28], and behavioral representation is affected by human behaviors, lifestyles, daily routine activities, and attitudes to the world. Given that a person's past experiences, educational background, and dietary choices [29] influence the dynamics of biomarkers associated with healthy aging, there is a potential correlation with their unique individual typological traits. Biological aging has been determined by either phenotypic biomarkers such as blood pressure, body mass index (BMI), cholesterol level, gene expression patterns, or specific protein markers. These biomarkers are the valuable measurable characteristics or traits that can be observed in an individual that reflects health status, disease risk, or response to treatments and are ultimately helpful for developing personalized healthcare applications. Various researches have aligned aging biomarkers with individual personality traits and behaviors, particularly negative habits and addictions. These factors not only impact the frailty index but also influence an individual's immunological age, leading to compromised immunity and hastened aging [30].

C. Biomarkers for Active and Healthy Aging

Many chronic diseases often manifest with symptoms that are frequently overlooked, either by the individuals affected or sometimes even by healthcare professionals. Recently, there has been a growing focus within the research community on identifying suitable markers for assessing active and healthy aging. For instance, Jiang et al. [31] investigated prolonged social sensing for mental well-being by creating and deploying a wearable device that incorporates various sensors, including an audio sensor, environmental sensor, behavioral monitoring, and physiological sensing. In another study [32], the concept of BrainAGE was employed as a biomarker to gauge the difference between the biological and chronological ages of the brain function. Similarly, in a separate study [33], the concept of inflaming-aging was explored through the analysis of potential inflammatory biomarkers.

As aforementioned, medical professionals frequently overlook the symptoms of chronic diseases such as neurological disorders, cardiovascular diseases, diabetes, cancer, arthritis, and chronic respiratory conditions. These symptoms can manifest at an early stage in life, and by addressing them, more severe forms of these diseases can be prevented in later years. Furthermore, these types of diseases are nonlinear, varying not only across countries but also across individuals. For example, within the same family, there can be varying rates of biological aging, with some family members being more susceptible to diseases and aging faster than others. Therefore, there is a compelling need to extensively investigate this concept and adopt a more personalized approach to studying it.

1) Relevance of Personality Traits and Active and Healthy Aging: Association between psychological factors including personality traits and the aging process has been largely identified in recent years. In [34], it has been clearly stated that active or healthy aging is dependent upon personality traits and especially conscientiousness. In [35], it is stated that people having higher vital personality scores (calculated from the FMM model) have lower rates of aging, decreased mortality risk, and healthier lifestyles. In [36], the personality-informed interventions have been discussed in detail. Social or behavioral outcomes related to the personality variables have been determined and investigated to determine how diseases are manifested across those personality traits that result in premature death.

While numerous studies have explored the connections between aging, personality, and biological indicators, to the best of our knowledge, the influence of personality traits on healthy aging through physiological signals has not been thoroughly studied. Therefore, discussion and more work are needed to understand how a specific personality trait is associated with active and healthy aging and who is enjoying a good quality of life and who will in the future.

To gain a profound comprehension of the concept of active and healthy aging, this section embarks on an exploration of how personality dimensions are intertwined with and exert influence on this process. Traditionally, an individual's health status has been gauged primarily through the assessment of physiological signals. However, recent years have seen a notable shift toward a broader perspective, one that not only encompasses physiological parameters but also considers social and psychological factors in the context of active and healthy aging. Among these psychological facets, personality traits have risen to prominence as significant determinants in shaping the aging experience, impacting not only health-related outcomes but also an individual's overall sense of well-being. Research has unequivocally demonstrated that personality traits wield a substantial influence over an individual's health and their adoption of healthy behaviors throughout the entirety of their life [37].

D. Objectives

The objective of this review is to highlight the significance of individual characteristics or personality traits in fostering a healthier lifestyle and enhancing overall life quality. Several state-of-the-art studies have been conducted for identifying personality traits using physiological signals (e.g., EEG, ECG, GSR, PPG, and EMG) and facial expressions either in response to various stimuli or even in resting states. A large amount of data has been investigated that documents the link between traits and age parameters. Our study explores the impact of personal factors with a particular focus on Big Five personality traits recognized using wearable sensing technologies or subjective approaches to active and healthy aging. Our analysis also explores the difficulties and contradictions associated with the connection between biomarkers for healthy aging and individual traits, addressing the research questions outlined in Table I.

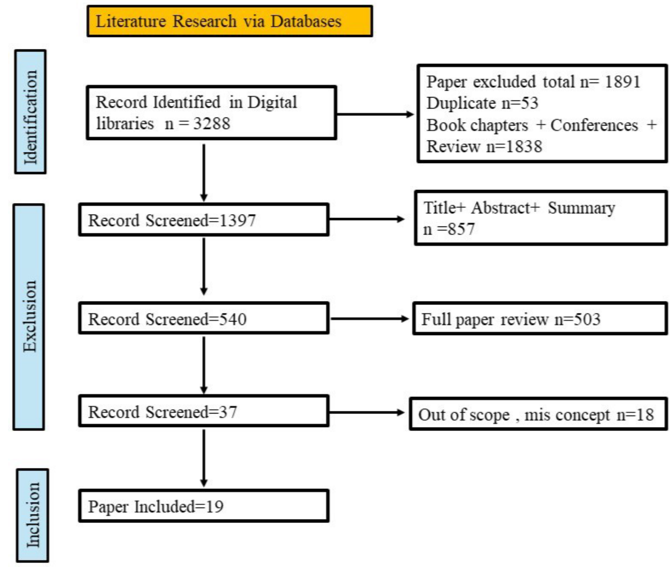

Fig. 2. Flowchart of studies identification, screening, and inclusion process.

E. Research Strategy

Different criteria have been used to develop an appropriate searching strategy. The main aim is to design a searching strategy that should be able to address the questions listed in Table I. The articles were searched from IEEE Xplore, ScienceDirect, and Scopus digital libraries. We used the following string of keywords: *("Personality traits" OR "Five factors model") AND ("Physiological indicators" OR Biomarkers OR "Physiological signals" OR "Wearable sensors") AND ("Healthy aging" OR "Active living").*

F. Selection Criteria

The selection process has been identified based on the main objective of our review. Two selection criteria were used, i.e., inclusion and exclusion, as shown in Table II. The assessment of each paper was performed on the selection criteria and categorized as "included" or "excluded." Three inclusion criteria were used. As per identified keywords, there were about 3288 studies in the abovementioned digital libraries, and we eventually selected 19 journal articles for detailed analysis. A comprehensive flowchart has been created to elaborate on the methodology discussed in the article, outlining the steps involved in identifying, screening, and ultimately selecting the studies reviewed in this research. Fig. 2 illustrates the completes process adopted for selecting the studies form different digital libraries.

G. Data Analysis

To begin, the literature review is constructed by examining systems and frameworks for recognizing personality traits. Such personality traits are identified in various contexts, such as daily routines, academic settings, work schedules, social interactions, eating habits, sleep patterns, and exercise

TABLE I
RESEARCH QUESTIONS

ID	Mapping Questions	Motivation
RQ1	Which personality traits have been most commonly linked with healthy aging?	To investigate the publications in the field of personality trait and aging. To understand that through which mechanism these types of traits impact aging outcomes
RQ2	How wearable sensors have been used to monitor and measures the physiological signals to assess the health related parameters in adults?	To determine the the mostly recorded physiological signals to measure and monitor the health status of various individuals.
RQ3	Which type of physiological indicators or biomarkers have been explored in the existing literature as predictor of active and healthy aging?	To explore the different predictors or bio-indicators of successful life or good quality of live and active living
RQ4	What is the correlation among personality traits and physiological indicators of active and healthy aging?	To gain the thorough knowledge about the biomarkers of healthy aging from the recorded biological responses and to explore the relationship with Big Five personality traits
RQ5	Which methodologies are commonly employed to study the interplay between personality traits, wearable technologies and biomarkers for health?	To thoroughly understand the contributions of existing wearable technologies in assessing personality traits and how they are essentials for successful aging.

TABLE II
INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	**Description**
IC1	Studies containing the keywords personality and wearable sensors or physiological sensors in the title, keywords or in the summary and abstract
IC2	Studies published from 2010 to 2024 are included
IC3	Studies published at various journals within the scope of this study.
Exclusion Criteria	**Description**
EC1	Studies not exclusively dedicated to the problem personality traits and healthy aging
EC2	Studies such as reviews or surveys related to personality traits, wearables and biomarkers for aging process
EC3	Book chapters, workshops and conferences on personality trait recognition

regimens. The analysis comprises two main sections. The first section focuses on the identification of personality traits through subjective methods, and the second one is about the identification of personality traits using objective approaches, such as the utilization of wearable sensors to record physiological signals (i.e., EEG, GSR, PPG, ECG, and EMG) in response to stimuli, during resting periods, or in specific situations. The discussion also delves into the detailed evaluation of classification performance across various machine learning algorithms, accompanied by a thorough statistical analysis.

Finally, the study delves into the aspects of aging while maintaining an active and healthy lifestyle, taking into account the diverse range of individuals and their behaviors. Within this scope, the research conducts an analysis of a range of bioindicators associated with active and healthy aging, utilizing physiological data collected.

The reminder of the article is organized as follows. Section II concentrates on the theoretical approaches and the methodologies used in recognizing personality traits. Section III addresses previous studies related to active and healthy aging, discussing the influence of different personality traits on this topic. Section IV provides a comprehensive discussion of challenges. Finally, Section V offers concluding remarks along with potential avenues for future research.

II. PERSONALITY TRAIT RECOGNITION FRAMEWORK

Researchers have noted that the assessment of core personality traits can be approached through two distinct methods. The first method is subjective, involving the evaluation of various personality traits through questionnaires and surveys. The second method is objective, where physiological responses are recorded during various activities, and personality traits are predicted based on extracted features using techniques, such as machine learning, deep learning, or manually designed algorithms.

A. Audio-, Video-, Text-, and Image-Based Personality Assessment

This section provides an overview of the assessment of personality traits using subjective methods. It involves the evaluation of five dimensions for individuals in different conditions. For instance, in [38], individuals completed the big five questionnaires, and the connection between behaviors and personalities was examined using acoustic features and support vector machine (SVM) classifiers. Xue et al. [39] discussed the use of a neural network enhanced with semantics to recognize Big Five labeled personalities from atomic text features. Sidorov et al. [40] presented a model for automatic personality trait recognition based on features extracted from audio and video data. Mohammadi and Vinciarelli [41] focus on automatic personality trait recognition using prosodic features extracted from speech signals. Mairesse et al. [42] employed linguistic cues for automatic personality trait recognition. Similarly, in [43] and [44], text-based recognition of Big Five personalities was explored. In [45], a fusion of linguistic, psycholinguistic, and acoustic features was used to automatically identify the speaker's personality traits. Zhao et al. [46] present a novel framework for integrating audio and video modalities for personality trait recognition via a hybrid deep learning model. Multimodal self-assessed personality

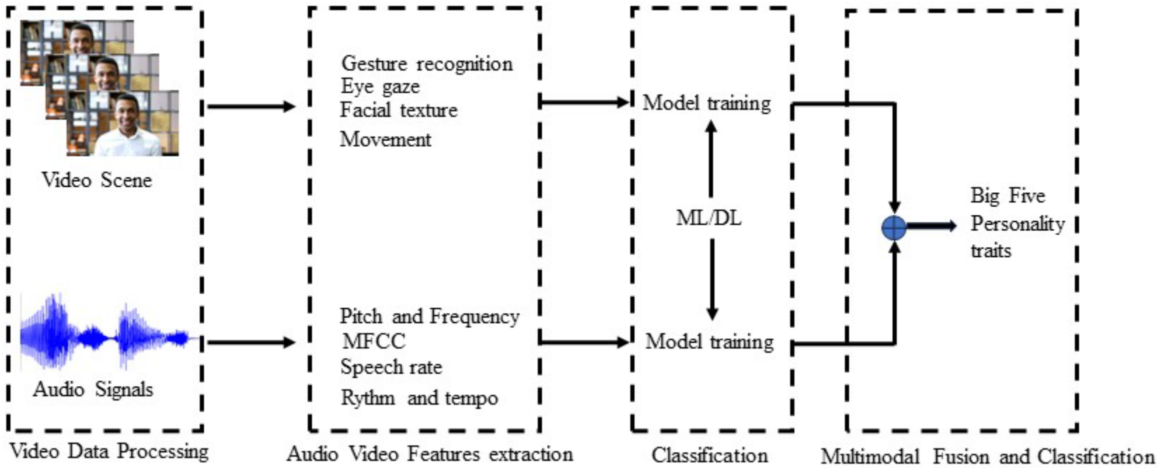

Fig. 3. Flowchart for multimodal personality trait recognition method combining the audio and visual features.

estimation framework [47] is followed using two types of sensors i.e., camera and wearable. A basic flowchart for personality trait recognition using audio and video clues as combined is shown in Fig. 3.

B. Wearable Sensor-Based Personality Trait Recognition

Physiological responses to emotional stimuli have a strong correlation with individual personality traits, and numerous studies have explored this connection. A variety of biomedical signals, such as EEG, GSR, PPG, ECG, and EMG, have been employed to capture human responses to audio–visual stimuli, offering valuable insights for research in medical and cognitive psychology. These signals are sometimes utilized individually or in combination to enhance the accuracy and depth of understanding regarding human behavior in different situations. For instance, to recognize the Big Five personality traits in response to emotional videos, an EEG dataset is developed and analyzed [15], [48]. Similarly, prior studies [15], [16], [17] have utilized EEG to investigate personality traits. Researchers have also employed electrodermal activity (EDA) signals to assess drivers' personalities using the Big Five inventory and state-trait anxiety inventory (STAI) traits, as seen in [49]. In studies involving individuals watching emotional video clips, EEG, GSR, and EMG measurements were collected to characterize their personality traits [50], [51]. Furthermore, in [11], the relationship between online teaching and teachers' personality traits was explored through ECG, GSR, and FEMG measurements. Personality traits have even been assessed in response to videos and images using eye tracking and GSR sensors, as presented in [52].

The framework used to identify Big Five personality traits during various activities by utilizing physiological signals is illustrated in Fig. 4.

In brief, the integration of personality trait recognition with physiological signals improves knowledge and delivers more valuable information to understand and characterize human personal factors and behaviors in response to audio–visual stimuli and other situations. As wearable technologies are still evolving and more smart sensors are being launched in the market, the synergy between the personality traits and physiological signals is likely to provide more profound, and depth insights into human nature and behavior, and human behavior modeling under diverse contexts will be possible.

TABLE III
SECTIONWISE REFERENCES OF SELECTED STUDIES

Section	Research Questions	References
Section III-B	RQ1 &RQ2 & RQ3	[53]–[62]
Section III-C	RQ4 & RQ5	[13], [14], [63]–[69]

III. WEARABLE SENSORS, PERSONALITY TRAITS, AND HEALTHY AGING

The assessment and analysis of physiological parameters are of substantial significance within both healthcare and psychological domains.

It is crucial to acknowledge the continuous global population growth, which amplifies the focus on exploring and devising healthcare strategies. These strategies aim not only to elongate individual lifespans but also to uphold optimal physical and cognitive well-being throughout the entire lifespan. In this context, the examination of how personality traits impact and how wearable sensors can utilize physiological signals becomes pivotal in the quest to enhance overall quality of life during the aging process.

In this section, we reveal the key findings from our systematic literature review, highlighting the intricate relationship between the Big Five personality traits, physiological responses, and biomarkers in the context of active and healthy aging. Table III presents the summary of references selected to answer the research questions relevant to this review work.

A. Physiological Signals for Active and Healthy Aging

Amidst the multifaceted landscape for active and healthy aging, physiological signals have been notified as prominent

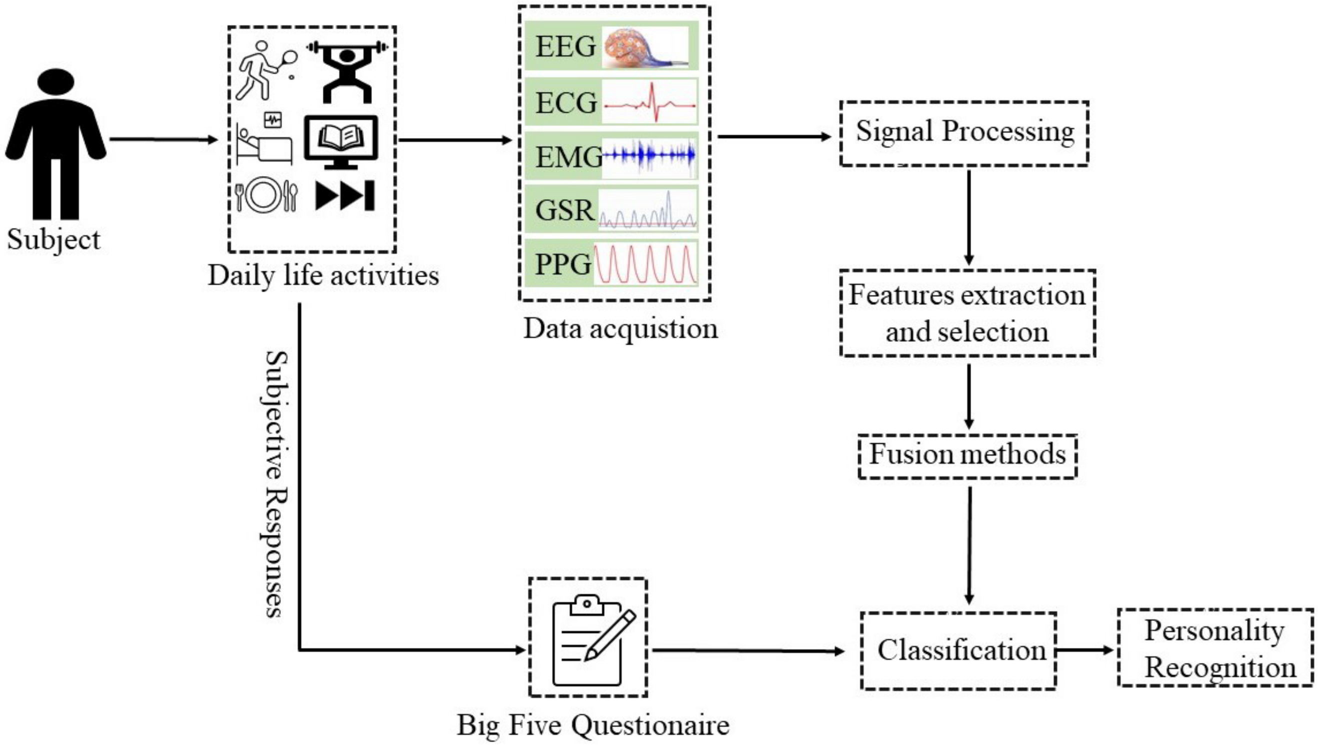

Fig. 4. Flowchart for multimodal personality trait recognition method through WSS.

determinants for measuring the health status and subject wellbeing. These biomedical responses recorded from subjects provide important cues to successfully understand, regulate, and control the aging process in order to improve overall quality of life. With this aim, this section refers to the RQ1, RQ2, and RQ3, while detailed summary of the existing studies in this context is given in Table IV.

Lassi et al. [53] indicate that the early detection of Alzheimer's disease (AD) is feasible through EEG recordings. This study employed various biomarkers across different participant groups, including those with subjective cognitive decline (SCD) and mild cognitive impairment (MCI). The findings strongly imply that the deterioration of cortical regions is closely linked to the progression of dementia. The study [61] examined the relationship between resting EEG measures and late-age risk factors, such as cognitive impairment and dementia. The findings indicated that individuals with a greater cardiometabolic burden exhibited reduced alpha peak frequencies and diminished beta peak power. In addition, APOE-ϵ4 carriers demonstrated lower beta peak frequencies. In [54], respiration monitoring using ECG and wrist-worn motion signals has been examined. Context classification was carried out for inertial measurement unit (IMU) motion sensor-based features to predict current physical activity context, while for ECG, R-height, R-width, T-height, T-width, and R-R interval were used for respiratory analysis. According to [55], the identification of individuals at earlier stages of the AD disease is possible through the use of blood plasma protein. This study utilized the data from the AD neuroimaging initiative (ADNI) database.

A recent work [56] discusses the association between HRV and perceived stress by conducting a follow-up study. Major depressive disorder (MDD) can be identified by analyzing biomarkers in the brain default mode network (DMN) using wavelet coherence (WCOH). The main finding is that this approach, combined with a 2-D convolutional neural network (2D-CNN) network, achieves high classification accuracy, sensitivity, and specificity in distinguishing MDD patients from healthy controls, validating the effectiveness of DMN-based WCOH as a potential biomarker for MDD diagnosis [57]. In [58], behavioral examination and EEG resting microstates are shown as potential biomarkers in predicting and even preventing the onset of schizophrenia. When analyzing magnetic resonance imaging (MRI) data from three datasets, namely, ANSI, OASIS, and PAC-2019, it became evident that assessing the disparity between an individual's chronological age and their brain age holds promise as a potential biomarker for accurate prediction and classification of cognitive decline [59]. In [60], ECG signals of 171 patients from New York Heart Association (NYHA) were analyzed to explore the QT interval and sudden cardiac death association. The QT interval is the biomarker that can be obtained from the ECG signals, and it tells about the polarization of the heart's ventricles. An integrated overview of key concepts, methodologies, and health conditions is illustrated in Fig. 5. The findings from various health and cognitive studies are discussed, establishing a link between physiological biomarkers and predicted diseases or health outcomes. For example, EEG microstates, blood plasma proteins, respiratory rate, and HRV have been used to identify mental health conditions, such as AD, depression, and schizophrenia through wearable biosensors.

TABLE IV
SUMMARY OF REVIEWED STUDIES ON PHYSIOLOGICAL SIGNALS FOR ACTIVE AND HEALTHY AGING

Ref	Year	Subjects	Sensor	Health Indicators	Key Findings
[53]	2023	103 patients	EEG, 64 channels Galilo NT system	PSD, microstate, connectivity, CSF	AD disease was predicted by change in the cortical activity detected through microstate analysis
[61]	2023	86	EEG signals	APOE-ϵ4 carriage, cardiometabolic burden, PSD	High cardiometabolic have lower alpha peak frequency, APOE-ϵ4 carrier have lower beta peak frequencies
[54]	2023	15(6/9)	Shimmer3 ECG, IMU	Ventricular depolarization, re-polarization, heart rhythm	Respiratory biomarkers from wearable are helpful in designing preventive measures during exercise sessions
[55]	2021	54,136,108	blood samples	A2M, ApoE, BNP, Eot3, RAGE, SGOT are key protein profiles	Identification of persons with the earliest stage of AD is possible
[56]	2022	657	Wearable fitness tracker	16 HRV features	A weak but significant association was found between HRV and perceived stress
[57]	2022	30+30	EEG 19 channel	WCOH of brain's DMN regions	WCOH is a potential biomarker for the diagnosis of MDD
[58]	2020	65	EEG	Behavioral examination and EEG microstates	Combined biomarkers can predict and prevent schizophrenia
[59]	2021	3 public datasets	T1-weighted MRI data	BrainAGE	Gap between chronological age and brain age is an effective biomarker for AD, dementia classification
[60]	2022	171 patients from NYHA	ECG data	QT interval	A novel technique for analyzing ECG has been found to effectively identify the risk of sudden cardiac death in patients suffering from chronic heart failure and atrial fibrillation
[62]	2017	15(8/7)	EEG, EDA, HRV	wearable sensors and Salivary cortisol analysis	A stress detection system has been developed by identifying a strong correlation between cortisol, a potential stress biomarker, and certain physiological parameters

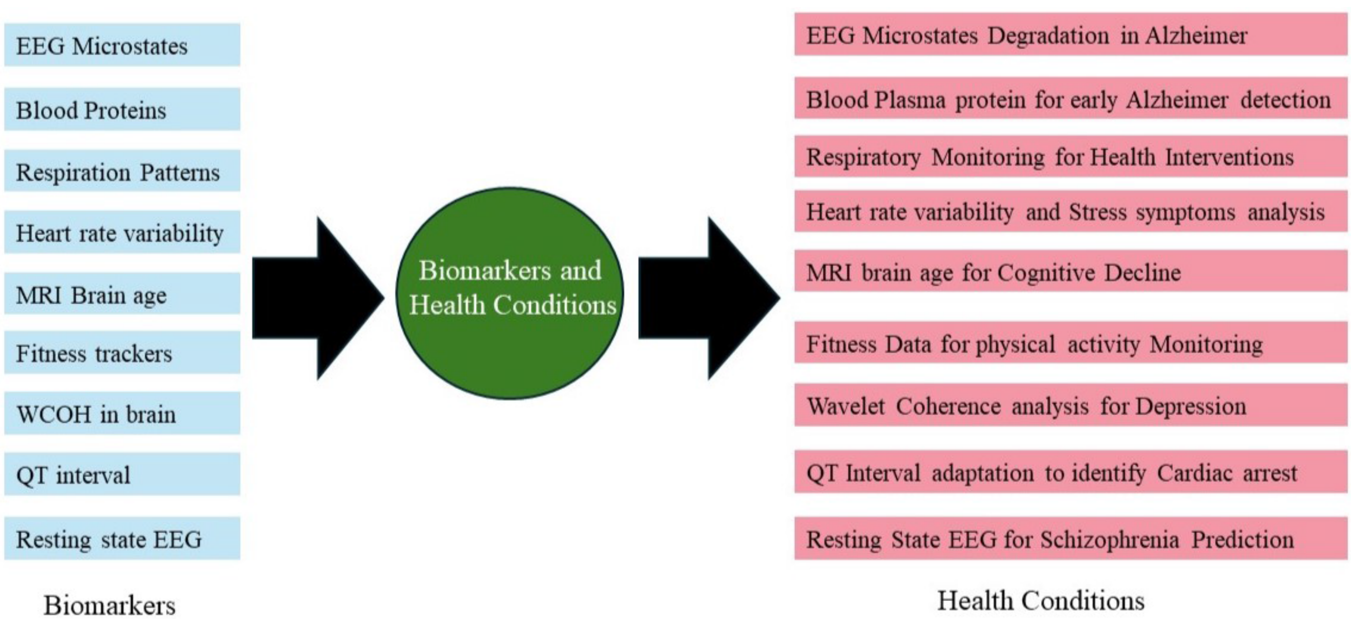

Fig. 5. Identified biomarkers and respective health outcomes observed in a different physiological and cognitive research.

B. Dynamic Interplay Among Personality Traits, Wearable Sensors, and Biomarkers in the Pursuit of Active and Healthy Aging

In the quest to find the network of factors that affect the process of active and healthy aging, the dynamic relationship between personality traits, physiological responses, and health indicators has emerged more compelling and appealing area of investigation. This multifaceted investigation delves into how individuals' unique disposition, their underlying bodily responses or physiological records, and intrinsic biomolecular

TABLE V
SUMMARY OF FINDINGS—PERSONALITY TRAITS, PHYSIOLOGICAL SIGNALS, AND BIOMARKERS IN THE PURSUIT OF ACTIVE AND HEALTHY AGING

Ref	Year	Subjects	Personality Traits	Physiological Signals	Biomarkers Studied	Key Findings
[63]	2015	92 healthy older	N, E, O, C, A	Neuroimaging (PET)	Brain Amyloid-beta	SCC and N may reflect psychological distress that results in AD during aging
[64]	2012	88(45/43)	E	EEG	Cortical sources of EEG activity	Agentic extroverts exhibit heightened theta activity in the default mode
[65]	2016	160	N, E	Saliva was centrifuged at 3000rpm	Cortisol awakening response	HPA is connected with HPA functioning, highlighting health outcome changes
[66]	2015	122 students	N, E, O, C, A	SC, TMP, HR	biofeedback and muscle relxation	During PMR, BAR HR decreases for HN, HE
[67]	2011	31(15/16)	N	SCL, fMRI, pain level	..	HN is associated with greater activity in limbic areas of the brain during the anticipation of visceral pain
[68]	2021	28(13/15)	N, E, O, C, A	EEG, GSR, PPG	T-F domain features	In multimodal classification, agreeableness had the highest accuracy for public speaking
[14]	2016	58	N, E, O, C, A	EEG, GSR, ECG, EMO	T-F domain features	Traits are recognized during affective clips. Emotions and personality are physiologically correlated
[13]	2023	80	N, E, O, C, A	Heart rate	Statistical features	Multi-situations HR measures showed a strong connection with personality traits
[69]	2020	125	RST-PQ	EEG	PSD bands	Delta-beta coupling in the brain serve as indicator of anxiety levels and effect of relaxation

indicators are integrated in order to accurately and effectively shape the path way of the aging trajectory. As the global population continues to surge, and in tandem, the factors influencing health and aging evolve, we turn our attention to addressing RQ4 and RQ5. In this section, we merge the psychological and physiological characteristics of individuals to elucidate the outcomes of health. A comprehensive summary is provided in Table V.

A study on EEG signals established the connection between the personality traits and the biomarkers of the AD [63] and predicted that high neuroticism individuals experienced the prediction of high complaint-high amyloid-β association. According to [64], agentic extroverts exhibit heightened theta activity in the DMN's posterior hub and diminished theta activity in the orbitofrontal cortex (OFC), reflecting a distinctive pattern of OFC elevation and DMN reduction compared to introverts. The key findings of this study are the identification of distinct EEG spectral power gradients associated with agentic extraversion, revealing higher theta activity in the DMN's posterior hub and lower theta activity in the OFC. In [65], it was found that neuroticism, but not extroversion, exhibited a connection with hypothalamic pituitary adrenal-axis (HPA-axis) functioning in older individuals, underscoring its potential significance in understanding health changes linked to HPA-axis activity. These results highlight the potential influence of personality traits on physiological stress responses in aging populations. Shui et al. [13] discuss the results of personality trait recognition using heart rate features acquired through bracelets during morning exercises and class sessions of the daily life of 80 college students. Peciuliene et al. [66] demonstrated that students characterized by high levels of neuroticism and extroversion exhibited a reduction in their heart rate when participating in progressive muscle relaxation (PMR) and biofeedback-assisted relaxation (BAR) sessions. Physiological variables such as heart rate and skin conductance levels can be effectively reduced using both PMR and BAR techniques. However, the success of these methods is influenced by individual personality traits, indicating that the impact of relaxation techniques varies among people based on their unique psychological characteristics. According to [67], there is no connection between neuroticism and the skin conductance level and pain ratings, but neuroticism and brain activity are positively correlated during anticipation of visceral pain. EEG, GSR, and PPG signal-based features have been fused to recognize the big five personality traits in response to public speaking activity, and results showed that the fusion of modalities gives better classification performance [68]. Subramanian et al. [14] discuss the findings that explore the correlation between emotion and personality, distinct from the connection between personality traits and user affective ratings in response to affective video clips. In [69], it was found that resting anxiety leads to an increase in EEG delta–beta correlation, which has implications for understanding personality traits according to the reinforcement sensitivity theory-personality questionnaire (RST-PQ).

IV. Discussion, Challenges, and Future Direction

The investigation of WSS for identifying bioindicators associated with active and healthy aging, particularly in relation to personality traits, presents a hopeful path within the healthcare system. The application of this technology enhances the comprehension of researchers and medical practitioners, enabling them to collaboratively utilize physiological and personal factors linked with personality traits as individuals undergo the aging process. In [69], occupational health is monitored using wearable flexible sensors. In [70], compressed sensing approaches for EEG, ECG, EMG, and EDA have been explored to improve the health status of individuals. Likewise, the studies explore techniques for tracking individuals and detecting stress by integrating data captured from wearable sensors [71], [72].

With a deep understanding of the factors that shape successful aging, both psychologically and physiologically, our review paper not only provides valuable insights into the process of healthy aging but also reveals new possibilities for the development of a modern healthcare system. Through our exploration, we navigate the intricate landscape of aging, uncovering a wealth of knowledge and complexities that can contribute to the advancement of healthcare practices. With the advent of novel wearable technologies and advancements in psychological concepts, it is certainly possible to improve the healthcare industry and enhance the overall quality of life. Taking a more rigorous approach to quantifying the connections among personality traits, physiological signals, and biomarkers for active and healthy aging, machine learning and deep learning methods can offer valuable insights. These advanced techniques, somewhat underexplored in prior research, hold the potential to shed new light on this complex relationship. Keeping our focus on this section, we delve into the challenges that we have encountered, present recommendations for the future, and outline exciting new research directions.

Referring to the RQ1, RQ2, and RQ3, Section III-A provided a detailed discussion of physiological signals that can be effectively collected by means of wearable sensors and the active and healthy aging. Diseases or symptoms of various chronic diseases such as AD, respiratory biomarkers, HR, HRV, MDD, Schizophrenia, and cardiovascular diseases have been assessed through the help of different wearable sensors. For example, EEG signals for AD assessment, resting stare EEG across middle to late life, and association with age [53] have been explored to discuss various health outcomes. Similarly, wearable fitness trackers have been employed for measuring the relationship between HRV and perceived stress [56], ECG signals have been monitored for respiratory biomarkers [54], EEG signals to analyze MDD [57], brain age and chronic age gap through MRI [59]. Furthermore, QT intervals have been extracted from ECG signals to study sudden cardiac death [60].

It is crucial to emphasize that all the analyzed studies are centered on physiological signals and elucidate how an individual's health status can be tracked through biomedical indicators. However, it is important to acknowledge that the datasets used in these studies are relatively limited in size, which may hinder a comprehensive assessment of health conditions. Furthermore, each study in this context primarily concentrates on a unimodal or singular type of physiological response to delineate specific diseases. To enhance the accuracy and effectiveness of health monitoring for active and healthy aging, it is imperative to consider the integration of multiple modalities. Combining data collected from various wearable sensors has the potential to provide a more comprehensive and precise understanding of an individual's health status. Most important human vital signs such as body temperature, pulse, and blood oxygen saturation can be obtained either using wearable sensors or nonwearable or environmental sensors, such as cameras that remotely provide valuable health-related insights to caregivers and health entities.

As mentioned earlier in the context of dataset limitations, another challenge pertains to the age-related constraints, particularly when investigating cognitive decline. For instance, Lassi et al. [53] do not account for age factors when examining the degradation of EEG in individuals with SCD and MCI. Similarly, identifying a larger number of biomarkers from the acquired physiological samples can effectively characterize the onset of age-related diseases; a larger number of APOE-ϵ4 carriers can accurately characterize the subtle differences in resting states' EEG power measures [61].

Addressing the crucial challenge of handling diverse physiological data from various wearable sensors involves surmounting technical barriers. This challenge arises from the need to integrate data that often arrive in different formats and may not be adequately synchronized. In addition, the inherent sensitivity of physiological data, coupled with the presence of noise and potential artifacts, poses the risk of yielding less accurate health-related outcomes. The fusion of physiological parameters such as heart rate, accelerometer data, and sleep trackers acquired in response to various types of activities can provide a more comprehensive view of individual health. In the future, focus on machine learning and AI-based methodologies can support the development of methodologies to efficiently monitor the aging process of human beings.

In response to RQ4 and RQ5, Section III-B offers a comprehensive exploration of the interplay between personality traits, physiological signals, and the pursuit of active and healthy aging. Within this context, several notable studies are examined, shedding light on how distinct personality traits exert influence on age-related health outcomes. Differing from Section III-A, which primarily delineates the relationship between personality and health status, this section delves deeper, incorporating personality traits alongside distinctive biomarkers identified through diverse physiological recordings as pivotal elements in the journey toward active and healthy aging. Positron emission tomography (PET) neuroimaging technology was employed to identify amyloid-beta biomarkers. The research revealed a significant association between neuroticism and psychological distress, which, in turn, is linked to the development of AD during the aging process [63]. Extroverts were found to exhibit the enhanced theta activity of brain signals [64]. Puig-Perez et al. [65] show the relationship between extroversion and neuroticism and morning cortisol concentration that is essential for health and wellbeing. Physiological parameters, i.e., SC, TMP, and HR, are measures for Big Five personality traits, and students with high neuroticism and high extroversion have been found to experience a decrease in the HR and BAR during PMR sessions [66]. SCL and fMRI are used to explore the relationship between neuroticism and activity in various brain areas during the visceral pain [67]. Results of personality trait recognition using wearable sensors in response to public speaking [68] and affective clips [14] are explained.

It is important to remark that all the presented studies did not involve a large number of participants to generalize which personality trait is particularly related to diseases that progress with chronic age. Some studies showed potential concern about the sparse nature of physiological signals, for example, in the case of EEG [64]. One significant challenge in exploring the connection between personality traits and active living through physiological monitoring is the lack of research on data integration. This issue remains relatively unexplored by researchers from diverse fields, including computer science, medicine, and psychology. With the advancements in wearable technologies for health purposes, the numbers of health-related physiological and psychological indicators have been increased. The integration of additional psychophysiological elements and the adoption of advanced data analytics, machine learning, and artificial intelligence approaches can assume greater significance in tackling the challenges associated with health monitoring and the precise management of the aging process in adults.

A. Application of WSS in Real-World Settings

WSS is regarded as uniquely important for enhancing health conditions cost-effectively though its market penetration and user adoption remain poorly understood. Various biosensors, each with their own designs and principles, facilitate human–computer interaction. These biosensors have been widely employed in sports, environmental monitoring, and medical fields, significantly impacting individuals' lives. For instance, wearable sensors have played a crucial role in medical monitoring by tracking heart rate, respiratory rate, temperature, humidity, and blood oxygen saturation [73]. Remote and continuous monitoring of ECG with EMG with additional sensors to record thoracic and abdominal signals linked with movement and respiration date have been shown [74].

Similarly, in [53], EEG-based wearable sensors have been practically used to monitor the onset of dementia disease among the healthy group and subjects with initial symptoms of cognitive decline. In addition to this, there are mobile phone applications specially designed for wearable sensors. During the last decade, tremendous development has been observed in creating wireless low-cost communication devices that transfer the data from sensors integrated into the body to the remote server for example recently developed ultrawideband (UWB) impulse radio-based IEEE 802.15.4a standard [75]. Various types of wearables have been used to monitor glucose levels, heart rate, body temperature, and cognitive functions during everyday activities, such as walking, exercising, social interactions, sleeping, and eating. These devices collect biological information and send it directly to a cloud server. On this server, different neural networks are trained [76], which then prompt medical specialists to recommend treatments and medical care based on the condition of the individuals being monitored, as illustrated in Fig. 6.

B. Comparison of Wearable Technologies in Terms of Sensitivity, Specificity, and Practicality

Different sensor technologies each have their own specifications, ease of use, and compatibility with real-world applications. These sensors include temperature sensors, electrochemical sensors, mechanical sensors, biosensors, and optical sensors, all of which are used to maintain or achieve healthy lifestyles. For instance, electrochemical sensors are utilized for monitoring glucose or electrolytes due to their high sensitivity from directly measuring specific compounds, making them practical for continuous biomarker measurement. Similarly, optical sensors are employed to monitor heart rate and oxygen saturation with high sensitivity though they are primarily designed for laboratory settings. In contrast, mechanical sensors are more reliable for tracking blood pressure, heart rate, and physical activity but are also sensitive to noise, necessitating careful tracking. Electrical sensors, such as those measuring EEG, EMG, and ECG, are highly sensitive and specific to target physiological signals, accurately recording electrical activity.

The choice of sensors depends on the objectives of using these technologies, considering ease of use, sensitivity, and specificity in real-world settings.

C. Current Challenges

Despite the significant potential and positive impact of wearable sensors in shaping smart healthcare systems, their adoption and implementation face several real-world challenges. Understanding and addressing these challenges is crucial to fully leverage the benefits of smart wearable sensors. Our state-of-the-art analysis highlighted that literature studies show limitations and some major challenges in terms of the small sample sizes, potential biases of health situations, and use of wearable technologies in real-world settings. Some of the key challenges are summarized in the following.

1) Data Privacy and Security Concerns: The use of wearable sensors across various information and communication protocols requires data acquisition, transmission, storage, and standards that are not yet fully optimized or encrypted. In the reviewed studies, none have implemented proper encryption techniques to ensure the privacy and security of transmitted data. Healthcare organizations must establish regulations that guarantee robust data security against unauthorized access, cyberattacks, and breaches. However, these security measures should not impose additional burdens or complexities on the involved parties.

2) Interconnectivity and Data Integration: Ensuring seamless and compatible data across healthcare systems is challenging due to the variety of wearable sensors used to monitor

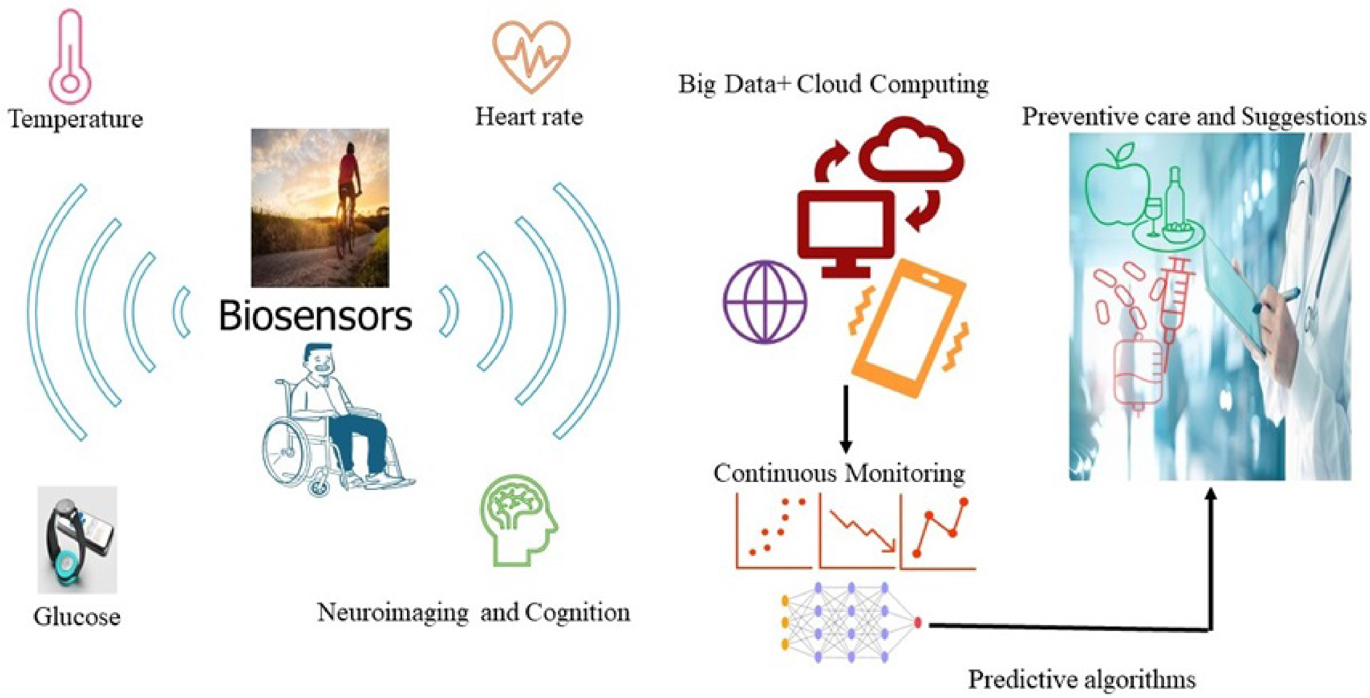

Fig. 6. Interconnected wearable sensors transmit data to a remote hub via information and communication channels, where it is accessed by caregivers to provide feedback to users.

individual health. Integrating and synchronizing these diverse data for smooth transmission and interpretation across different applications are complex. For instance, as discussed in [77], using Fitbit data to detect COVID-19 symptoms proved difficult. Elevated heart rates, which could indicate respiratory illnesses such as seasonal flu or COVID-19, led to inaccurate predictions and overestimation based on wearable sensors alone. Various types of wearable sensors provide nonlinear or inconsistent data, which sometimes results in delays or improper interventions. In summary, issues with interconnection and data integration result in less accurate and effective digital healthcare systems. These problems lead to delays and improper interventions, undermining the overall design and functionality of digital health solutions.

3) Sample Size and Data Reliability: The reliability of information gathered through wearable sensors is directly influenced by sample sizes, which are often small and dispersed. These limited sample sizes affect the generalizability and accuracy of the outcomes. For instance, in [78], it is noted that a major challenge in developing robust and generalized fall detection models is the limited sample size. Furthermore, studies reviewed have observed fewer moderators, such as age, gender, socioeconomic status, and employment, especially among the active and healthy aging population. In addition, obtaining more information, including psychological and physiological health indicators, requires homogeneity among various factors, making the dataset challenging to analyze and interpret. As a result, this complexity limits the scalability of the system and reduces the accuracy of more personalized healthcare solutions.

4) Key Technical Issues: Among the various hurdles in adopting wearable sensors for health purposes, significant technical obstacles include battery life and noise artifacts, which can compromise signal accuracy. Developing a robust and fully automated personalized healthcare system requires continuous, noise-free health monitoring. However, this is frequently disrupted by limited battery capacities and noise interference [79].

D. Future Research Directions

1) Integrating AI and Machine Learning Techniques: With the advent of emerging AI, the Internet of Things (IoT), and continuously evolving machine learning and deep learning algorithms, the development of smart healthcare systems must be updated accordingly. These advancements present opportunities to enhance patient health conditions and deliver more effective relief across medical communities. For example, integrating AI and machine learning algorithms can improve predictive analysis, ultimately enhancing the quality of life for patients.

2) Uninterrupted Health Monitoring in Digital Environment: Digital health platforms offer opportunities for actively engaging patients in adopting and utilizing modern wearable technologies. By creating a seamless and persistent digital environment, these platforms enable patients to participate directly in shared decision-making. User-friendly application programming interfaces (APIs), smart applications, and the Internet of Medical Things (IoMT) can significantly enhance individuals' overall quality of life.

3) Utilization of Ambient-Assisted Technologies in Shaping Personalized Healthcare Designs: In recent years, ambient-assisted technologies have been widely employed to offer tailored suggestions and preventive measures to patients based on their specific needs and preferences. These technologies also provide excellent opportunities for monitoring behavioral responses, habits, and routines, delivering appropriate preventive measures and alerts. For example, ambient-assisted technologies can detect falls, track daily physical activities, and monitor vital signs. By accurately capturing these data, these technologies can help generate personalized recommendations that improve health outcomes and allow for necessary lifestyle adjustments [80].

4) Inter Disciplinary Research and Collaboration: Collaborations spanning multiple disciplines pave the way for groundbreaking advancements and usher in a new era of innovation in wearable technology. By fostering partnerships that unite experts from diverse fields such as computer science, behavioral science, mechanical and electrical engineering, and medical science, we can shape the future landscape of WSS. This integration allows for the implementation of specialized knowledge: blockchain technology enhances data security, and IoT applications facilitate seamless data collection, while machine learning and AI refine predictive analysis. In addition, advancements in electrical engineering contribute to the development of smarter, more user-friendly wearable biosensors.

Addressing the challenges and embracing these future recommendations could lead to significant innovations in developing personalized digital healthcare systems.

E. Ethical and Privacy Considerations

Wearable technologies have seamlessly integrated into healthcare systems, an area fraught with ethical and privacy concerns. It is imperative to acknowledge and address these considerations, as their significance cannot be overstated. While individuals may provide informed consent, it is crucial that certain sensitive information remains accessible only to them, guarding against potential exploitation or misuse [81]. In [82], it is emphasized that the ethical benefits of wearables in assessing user stress levels are prominent yet underscore the persistent privacy challenges. For instance, when dealing with stress-related data, ensuring data security and privacy throughout the development and transmission processes, including cloud storage, is paramount. This necessitates comprehensive and robust security measures, affirming the commitment to patient privacy.

Moreover, there are additional ethical considerations to bear in mind, particularly when dealing with multidimensional data. Furthermore, if a third party expresses interest in any dataset, it is imperative to ensure that a signed agreement is in place, and accountability protocols are established. Nevertheless, individuals should always retain access to their own data and maintain ownership rights over it. By carefully addressing ethical concerns and implementing robust privacy measures, developers of wearable sensors can fully leverage the advantages of these emerging technologies, fostering a healthier and more active lifestyle for individuals across diverse cultures.

V. Conclusion

Our literature review work presented a comprehensive overview of the intricate interplay between personality traits, wearable sensors, and biomarkers in pursuit of healthy aging. First, this article attempted to explore the relationship between the Big Five personality traits and healthy aging through statistical approaches and surveyed significant studies in this context. Second, we highlighted the health outcomes of the individuals by analyzing the physiological signals and tried to identify some prominent health-related biomarkers from the physiological responses of healthy and unhealthy population samples. Finally, we elucidated the connection between healthy aging and personality traits by employing physiological signals. The development and execution of WSS have been investigated for the evaluation of increasingly individualized healthcare methods. It delves into the methodologies employed to identify personality traits through wearable sensors across various real-life situations and the resultant impacts on health outcomes.

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