SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2025, 22(5), 1567.
https://doi.org/10.62617/mcb1567

Article

Realizing smart elderly care through exercise and biosensing: Innovative methods for health monitoring and promotion

Yongpeng Zhang

College of physical education, Hanjiang Normal University, Shiyan 442000, China; 16672860039@163.com

CITATION

Zhang Y. Realizing smart elderly care through exercise and biosensing: Innovative methods for health monitoring and promotion. Molecular & Cellular Biomechanics. 2025; 22(5): 1567. https://doi.org/10.62617/mcb1567

ARTICLE INFO

Received: 14 February 2025
Accepted: 21 February 2025
Available online: 24 March 2025

Abstract: The incorporation of smart technology in elderly care is improving the way health is managed and promoted for the elderly populations. This paper examines a new elderly care model that employs biosensing and exercise-based solutions for effective care and monitoring of the elderly. An effective system is proposed to integrate various biosensors that can track vital signs like pulse rate, blood oxygen level, muscle activity, and balance, thus providing constant updates on the user's well-being. To accomplish this, information is collected by advanced data analytics and machine learning algorithms to identify signs of potential adverse health changes and further, prescribe suitable exercise regimes that will enhance mobility, balance, and cardiovascular strength for patients. Furthermore, a cloud-supported biosensing data feed into the predictive models to aid health care providers in decision-making in anticipatory manage. This type of approach is then compared in clinical trials to determine positive changes in physical mobility, ability to prevent falling, and quality of life. This accounts for the strong evidence supporting the use of a biosensing-driven skeleton to improve the physical and medical health of elderly citizens with notably less intervention from professional medical care.

Keywords: smart elderly care; biosensing technology; AI-driven health monitoring; personalized exercise interventions; fall risk prevention; real-time health analytics; IoT-based healthcare solutions

1. Introduction

Modifying specific characteristics associated with traditional elderly care is important in containing costs as most of the current frameworks entail manual caregiving and periodic medical examinations. These approaches may impose early warning signs of health deterioration. The requirement for better advanced preventive and anticipatory health care delivery is growing. Due to various factors, most of the senior citizens give up on physically engaging in various activities. Impaired mobility also causes complications like muscle wastage, instability, and vulnerability to falls. In the elderly, toppling over is a significant issue that impacts their quality of life and increases their risk of getting complications [1]. They commonly cause severe effects and raise dependence on technology. Traditional methods of handling circumstances involve waiting for an incident to happen and then applying remedies immediately. While this kind of health care approach can be reactive, it does not guarantee the best of health results. There are challenges for elderly care facilities and home caregiver facilities as well. Football celebrities' influence is overwhelming for young people from all over the world because of the increasing elderly population that puts a lot of pressure on healthcare systems globally. Caregivers are often privy to limitations of time and more importantly number of workers that may hinder the level of monitoring provided. Traditional check-ups depend on sporadic evaluations by a professional. This can make it difficult for health risks to be detected earlier and due to this, there can be complications. Architecturally, a more dynamic and responsive system is required in order to allow constant observation of the state of health of the elderly [2].

As smart health monitoring and biosensing technologies are continuously being developed and improved, new possibilities are being introduced. Smart clothing sensors can monitor temperature, pulse, blood oxygen saturation, muscle activation, and body motion. These devices are useful in continually monitoring the health of the body and identifying early signs of one's ill health. The integration of biosensors with AI and machine learning, therefore, can produce real-time health information. This creates an opportunity to intervene before the complications of certain medical conditions occur. That is why it is very important to encourage the elderly to engage in regular exercises. Physical activity that is done on a daily basis assists with maintaining muscle strength and flexibility as well as body balance. Nevertheless, cardiovascular activity is not for everyone. Using biosensing technologies to create personalized exercise plans can be highly effective for enhancing people's health [3]. Therefore, this study aims to develop an intelligent elderly care system that integrates biosensing and exercise monitoring.

2. Related works

2.1. Existing elderly care systems and their limitations

The conventional methods of elderly care include hiring human caregivers, family assistance, and doctor's home visits. More often elderly people reside in care homes or receive services at home or in hospices. While these methods remain valuable, they are not without their downside. The problem is that sometimes they are not even aware of early signs of various health problems among their patients. Periodic examinations do not offer a continuous monitoring of the patients' state. This can have grave consequences if the situation is not detected early enough. The escalating cost of healthcare has particularly affected the elderly care services. Long-term care, which is common among seniors, creates financial and human resource concerns. Staff shortage is a common problem that most care facilities encounter [4]. It becomes very challenging to give individual attention in large groups or where there are many individuals in one particular area. In rural areas particularly, there are often inadequate healthcare services for the elderly. Nevertheless, the problem of the limited access to timely healthcare remains topical. Some technological solutions exist. Telemedicine allows remote consultations. Wearable devices monitor some basic health parameters. Smart home technology helps in mobility and some activities in day to day life. But many of these systems are often not interoperable in some way or the other, though they may share some common features. All offer stand-alone interventions that are not immediately interactive. Current undertakings are more inclined towards response, and not so much with prevention [4,5].

2.2. Biosensing technologies in health monitoring

Biosensing technology is transforming elderly health monitoring. Technology advances make it possible to monitor many vital health parameters with wearable biosensors. These are portable and do not require any invasive procedures to be performed on the body. They include data on heart rate, oxygen saturation levels, muscle activity, and gait stability in real time. Such information assists the identification of early ageing signs. The oximeter sensors assess the amount of oxygen in the blood. Low levels might indicate respiratory problems [5,6]. EA muscle activity monitors features muscle performance. Muscle frailty raises the chance of falls. Examples of wearable technologies used include gait analysis sensors which identify balance and walking characteristics. Abnormal gait might indicate an individual's mobility issues or neurological conditions. Recent enhancements in biosensing have made them even more precise and effective. It's true that AI biosensors can work with data in real-time and process them. Data analysis and alerts are generated by machine learning models to identify anomalous patterns. These systems enable real-time interventions. The high flexibility also enables access to health information through cloud-based platforms. It means that caregivers or other healthcare personnel can keep track of bedridden patients and others from a distance.

2.3. Exercise and its impact on elderly health

Physical activity is an important determinant of health in elderly individuals. Exercise enhances mobility, balance, and has cardiovascular benefits. This, in turn, lowers the risk of long-term illnesses. In further detail, active seniors enjoy better muscle strength and elasticity. Another benefit is exercise enhances the capacity of the brain and improves mental health. It must be pointed out that falls for the elderly remains one of the major reasons for developing complications or causing additional health issues [6]. Lifting weights and balance activities are a relevant way to help prevent falling. Improved muscle function enhances stability. This includes walking, stretching exercises, and low affective impact aerobics. Cardiovascular exercises, often called aerobics or cardio exercises, are those that work on the pumps of the body procedures to strengthen the heart and improve circulation. It should be noted that not all exercises are appropriate for elderly people. Personalized exercise plans are necessary. The state's health, their motor activity, and everyone's individual requirements and preferences must be taken into account. While for some elders, they need to be trained durably. People can continue doing exercises at home with the help of a guided program. Biosensing technology enhances exercise monitoring. Motion and muscle activity sensors are placed on garments and accessories. Artificial intelligence operates and adapts the exercise intensity according to changes in physiological indicators. The individual feedback empowers people to exercise safely and optimally [6,7].

2.4. Smart healthcare systems and AI integration

AI is transforming elderly healthcare. Biosensing data is disaggregated and analyzed by using machine learning models. They find out trends, identify threats, and even suggest targeted advice. Real life health information is very extensive and new-age AI-based systems can easily manage such large volumes of data. They help in early identification of diseases that have not yet impacted on general health. With the help of machine learning, the assessment of elderly patients becomes easier and more effective. It indicates the presence of heart disease, respiratory problems and physical disability. Identification of health conditions is done through the use of artificial intelligence algorithms based on real-time data [7]. This allows timely medical intervention. Smart health care systems involve the convergence of different devices through the use of IoT. These are wearable sensors, smart home devices, cloud platforms. IoT ensures seamless data transmission. It shows that health data is stored, processed and analyzed in real time. Satisfaction with healthcare is created by using Cloud integration which allows for constant monitoring without physically going to hospitals. Old people are cared for in their homes preventatively [7].

3. System architecture and model construction

3.1. Framework overview

In smart elderly care, biosensors, exercise monitoring, and cloud analysis are combined in this system to form a health assessment and intervention on a real-time basis. These three aspects form the conceptual framework: Data collection, data analysis, and individualized intervention plans. Biosensors are continuously monitoring the physiological indices of elderly clients, such as heart rate, blood oxygen saturation, muscle activity, and balance. It is then sent to a cloud platform where it is analyzed by an artificial intelligence algorithm. It can identify potential health issues and provide recommendations on exercise regimes and adjust the intervention strategies in accordance with physiological feedback [8]. See **Figure 1** which illustrates the integration of biosensors, AI-driven data processing, cloud storage, and personalized exercise recommendations. Data flows from wearable biosensors to the cloud-based AI model, which processes health metrics and provides real-time feedback and interventions.

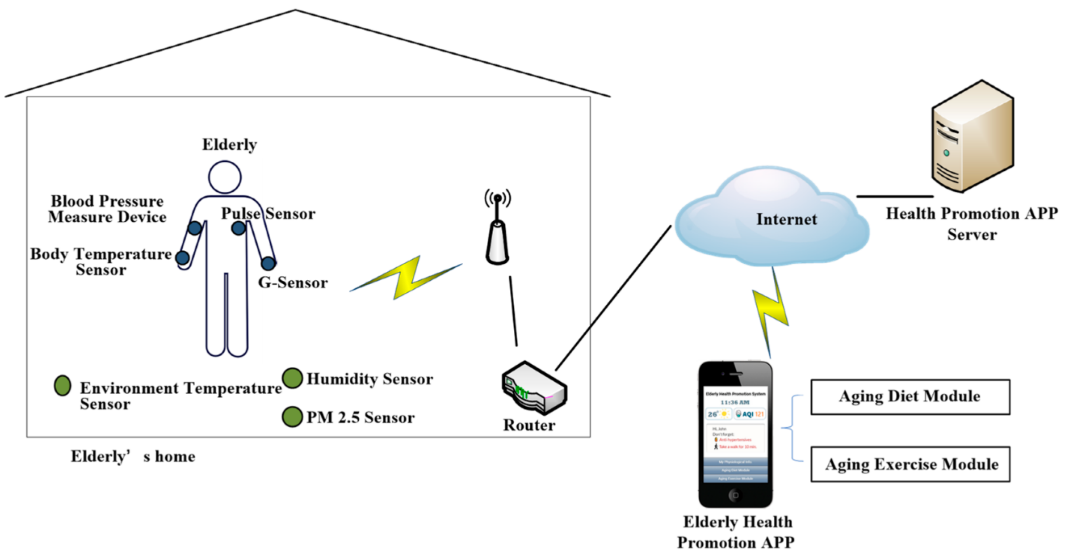

Figure 1. System architecture of the smart elderly care model.

Mathematically the biosensor data stream is represented as $X = \{x1, x2, \ldots, xn\}$ where xi refers to a specific physiological parameter collected at time t. The real-time monitoring function f takes the sensor inputs and returns a health state H as described in Equation (1). W is a weight matrix that has been adjusted using an algorithm in machine learning [8,9]. The function f is used to monitor health data patterns, and model derived from previous health records. Given the health status, an effective exercise regime E is recommended in Equation (2).

$$H(t) = f(X, W) \tag{1}$$

$$E = g(H, P) \tag{2}$$

$$S_i(t) = A_t cos(2\pi f_i t + \emptyset_i) \tag{3}$$

$$D(t) = \int_0^t s_i(\tau) d\tau \tag{4}$$

$$Y = \sigma(WX + b) \tag{5}$$

$$H_{t+1} = \Phi(H_t, X_t) \tag{6}$$

3.2. Biosensor technology and data acquisition

Biosensors are core to any real-time health monitoring solution. The system uses electrocardiography (ECG) for heart rate, pulse oximetry for oxygen saturation levels, electromyography (EMG) for muscle activity and movement sensors generalized under inertial measurement unit (IMU) for gait. These sensors monitor physiological parameters of the patient and send them, at pre-specified time intervals, to a remote processor located in the cloud. The data acquisition process is done via sampling where each physiological signal (t) is taken at some time instants. This sampled signal is expressed as in Equation (3). Where **A**i is an amplitude, fi is the sampling frequency and ϕi the phase shift [9]. These signals are then preprocessed in a way that eliminates noise by means such as wavelet transformation and Butterworth filtering. The filtered signals are then transformed into digital format and inputted into a database for analysis by the machines. Data communication is achieved through Internet of Things (IoT) connectivity protocols such as Bluetooth Smart or Low Energy (BLE) and Wi-Fi. To avoid delays in translating the computation requirements to the desired weights for each layer in terms of data flow, a data buffer is created as given in Equation (4) above. See **Figure 2** which represents the workflow of data collection, processing, and decision-making within the smart system. Biosensors collect physiological signals, which are transmitted to cloud storage for analysis. The AI-driven system evaluates health trends and adjusts exercise recommendations accordingly.

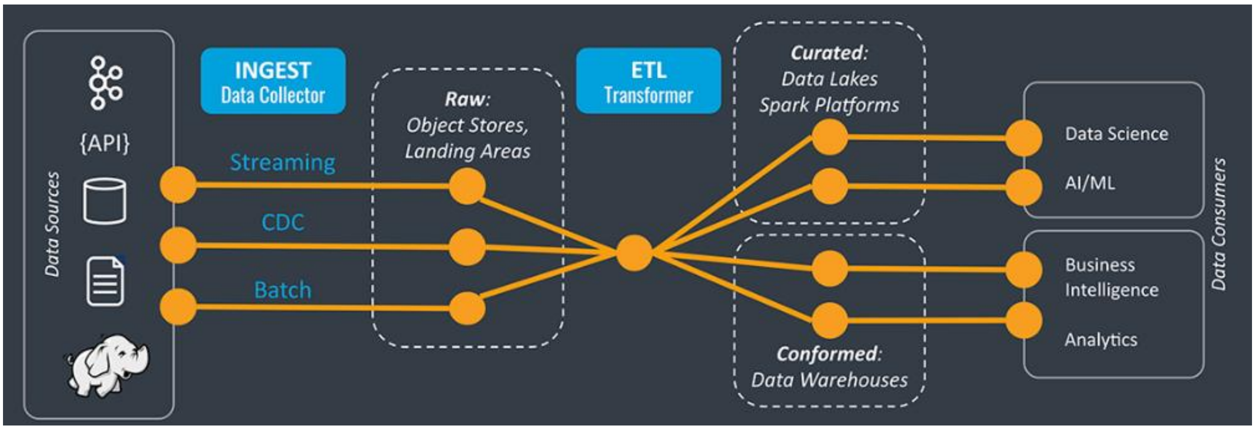

Figure 2. Data flow and processing pipeline.

3.3. AI and machine learning in health monitoring

Machine learning models analyze biosensing data to detect early signs of health risks. The system utilizes supervised learning for classification tasks and unsupervised learning for anomaly detection. A deep neural network (DNN) processes sensor data and classifies health conditions into risk categories [10]. The neural network function is defined as shown in Equation (5). The model is trained on historical elderly health data to optimize weight parameters using back propagation. **Figure 3** showcases the machine learning model used for health analysis. It includes data preprocessing, feature extraction, and classification. The AI model detects anomalies in biosensor data, predicts fall risk, and adjusts exercise plans dynamically. The time-series health prediction function is given by Equation (6) given above.

$$\pi^*(s) = arg \max_A \mathbb{E}[R|S, A] \tag{7}$$

$$I_{t+1} = I_t + \alpha\left(H_{target} - H_t\right) \tag{8}$$

$$Q(T) = \{X_i|T_1 \leq t_i \leq T_2\} \tag{9}$$

$$C = E(K, P) \tag{10}$$

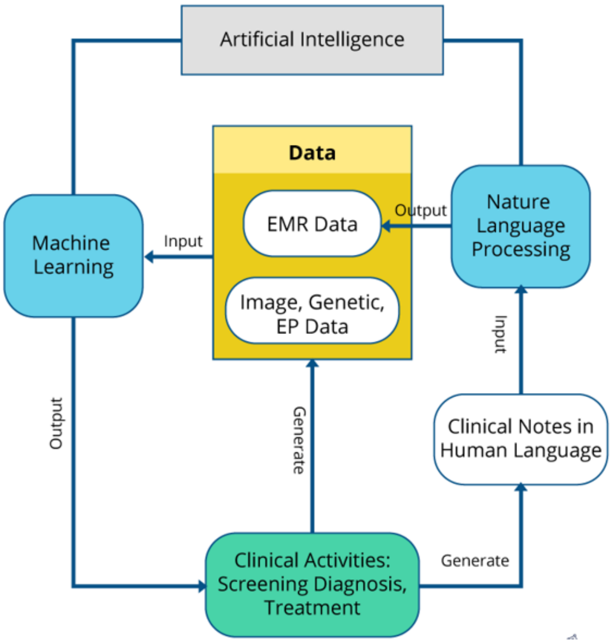

Figure 3. AI algorithm workflow for health monitoring.

3.4. Exercise-based intervention mechanism

The exercise intervention mechanism adapts activities that require exerted effort according to biosensor feedback. It is aimed at ensuring that people can move freely, do not fall easily, and support their cardiovascular systems. This is based on a reinforcement learning algorithm where an agent is trained on the biosensors' feedback to come up with a personalized exercise regimen for the elderly. The reinforcement learning framework uses the Markov Decision Process model with the state S reflecting the current physiological state of the patient, action A as the exercise prescription and the reward R as the changes in mobility. Equation (7) shows the optimal exercise policy as follows. It has the ability to adjust the intensity level of the selected exercises according to real time physiological parameters [10]. The feedback control loop ensures that the exercises are done within a safe zone so that there is no strain or injury. The basic control equation for intensity modulation of exercise is provided by Equation (8). The personalized exercise regimen is derived from biosensor data captured during the real-time. Objective measurements include physiological data from portable biosensors worn by each elderly that records features such as Heart Rate Variability (HRV), peripheral oxygen saturation (SpO2), muscle activation, and gait dynamics. These biosensors feed information to a machine learning system that monitors each person's health status. When assessing the participant, the AI model considers the mobility level, balance, and cardiovascular fitness before coming up with an appropriate exercise program.

3.5. Cloud-based platform for data processing and storage

This is a system that comprises a number of subsystems that are integrated with the cloud based architecture. The platform is composed of data storage units, artificial intelligence computing blocks, and an additional block for caregivers and healthcare workers. It harnesses real-time biosensor data to feed it to the cloud system where it runs advanced algorithms specifically machine learning models to generate health information. Data Storage. Storing the health parameter indicates by Xi follows a structured database schema with respect the timestamps. The query to retrieve the past trends of health history can be represented as Equation (9) below. The Advanced Encryption Standard (AES), explained in Equation (10), guarantees that stored biosensor data will be secure, C being the encrypted data, P the plaintext biosensor data, and K being a key for encryption. The system uses techniques of differential privacy to sanitize user data and yet the data is still useful for heath prediction [11]. The real time analytics engine is hosted on cloud which helps in running of health risk assessment predictive models for suggested interventions. The caregivers are provided with real-time physiological status monitoring dashboards and alarms for certain alarming conditions. The cloud platform interfaces with mobile applications and enable caregivers and the family members of the elderly to track the health condition of such individuals remotely. This cloud based architecture enables control, flexibility and reliability on the storage and retrieval of such records. It effectively maintains a bridge between the elderly people, carers, and healthcare providers to enhance health oversight for the elderly. See **Figure 4** below. This schematic outlines the cloud infrastructure used for secure health data storage. The platform integrates real-time analytics, encrypted data storage, and remote access for caregivers. The dashboard interface allows healthcare professionals to monitor patient progress and intervene when necessary.

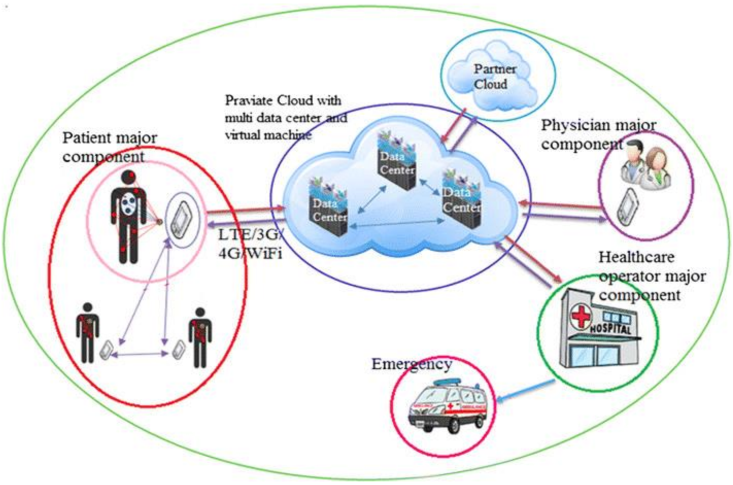

Figure 4. Cloud-based platform for data storage and analysis.

4. Experiment and performance evaluation

4.1. Experimental design and methodology

Participants were 100 elderly people who were selected from seniors' homes, independent homes, and homes with assisted care. Subjects were chosen purposively, in order to have a nationally representative sample, according to the defined profiles of the respondents. Some of the demographic factors that were considered included patients of 65 years and above. Self-reported health status was also taken into account, with those having mild to moderate mobility limitation allowed to participate, while participants with severe cognitive impairment, major disability, or unstable chronic diseases were excluded. Participants were also assessed according to their level of mobility at baseline: Fully mobile, with minor support for walking. To compare the results, the selected participants were divided into two groups. The experimental group comprised of 50 participants and they were provided with smart elderly care system that integrated biosensors, exercise recommendation and real-time health tracking. Control group consisted of 50 participants that were subjected to traditional methods of elderly care including routines exercises and general health checkups without the real time assistance and changes. In order to compare the pre and post-intervention differences of the system, assessments were first made prior to the implementation of the smart system. This comprised of mobility tests, cardiovascular tests and balance tests to identify how each of the subjects was physically at the start of the study. The post intervention phase took 12 weeks; the experimental group was given individualized exercise prescriptions based on the biosensor data collected thereon in real time. At the end of the interventional period the same measurements were conducted in order to affirm the changes in mobility, cardiovascular health and balance of the elderly for comparative analysis between the control and the interventional group [12].

4.2. Data collection and analysis

Health biosensing data was continuously recorded during the study period affording a database of over 2 million health readings. Information was securely kept in a cloud-based database and analyzed by AI-based methods to search for physiological well-being trends among the participants. The collected parameters included;

- Heart Rate Variability (HRV): An indicator of cardiovascular health.
- Oxygen Saturation (SpO_2): Measurement of respiratory efficiency.
- Muscle Activation Levels: Assessed through EMG readings.
- Gait Stability and Balance Measures: Measured by IMU Sensors.

To determine the effectiveness of the personalized exercise interventions, statistical analysis of the results was made using the paired *t*-tests and ANOVA. Analysis of pre-intervention and post-intervention data was made in order to assess the efficiency of the given system [9]. The formula to calculate the mean percentage improvement regarding the health indicators is as follows:

$$I = \frac{X_{post} - X_{pre}}{X_{pre}} \times 100 \tag{11}$$

A regression model was also developed to evaluate the influence of continuous monitoring and adaptive exercise recommendations on overall health outcomes. The regression equation used was:

$$H = \beta_0 + \beta_1 M + \beta_2 B + \beta_3 C + \epsilon \tag{12}$$

Table 1 presents the ANOVA test results, showing the statistical significance of improvements in key health metrics before and after intervention.

Table 1. ANOVA analysis of health outcomes.

Health Metric	F-statistic	*p*-value	Standard error (SE)
Mobility	513.64	1.101115×10^{-14}	2.17
Balance	576.00	4.051868×10^{-15}	1.94
Cardiovascular health	441.00	4.142077×10^{-14}	2.09
Fall risk reduction	2162.25	$3.317344 \times 10^{-2}0$	1.72

4.3. Health outcomes and performance metrics

The study demonstrated significant improvements in mobility, balance, and cardiovascular health among participants using the smart system. The experimental group showed;

- An improvement of 0.182 in gait stability specifically observed in stride length and step width.
- An improved efficiency rate of 12.1% offers better muscle activation that enhances coordinated movements.
- An average of 9.7% improvement in cardiovascular health in terms of HRV and SpO_2. Based on the indicated fall prediction models, a 30% fall risk reduction.
- Real-time interventions and exercise tailored to the patient can help in enhancing the health conditions and minimizing the risks of falls in elderly people.

Table 2 summarizes the percentage improvements observed in key health indicators after the implementation of the smart elderly care system. **Figure 5** below compares the percentage improvements in mobility, balance, cardiovascular health, and fall risk reduction before and after the intervention.

Table 2. Health outcomes and performance metrics.

Metric	Before (%)	After (%)	Improvement (%)	Standard deviation (SD)
Mobility	70	85	15.4	± 2.1
Balance	65	80	12.1	± 1.8
Cardiovascular health	75	85	9.7	± 2.3
Fall risk reduction	40	70	30.0	± 2.0

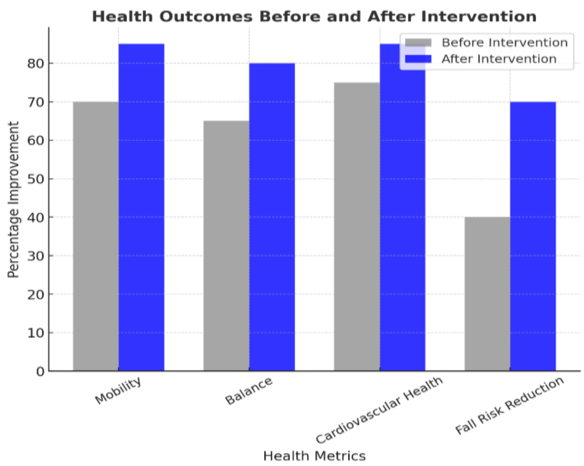

Figure 5. Health outcomes before and after intervention.

The significance level of the difference in heart rate variability before and after intervention was analyzed ($p > 0.05$), evidencing the effect of individual adjustment of the exercise load on cardiovascular performance [13]. As for the balance scores, the MA research also revealed a statistically significant increase when training was evaluated by a repeated-measures ANOVA. The current ANOVA results depicts an F-statistic of 513.64 = 1.101115 × 10^{-14} on mobility. The change in fall risk was predicted using an equation from a logistic regression:

$$P(Fall) = \frac{1}{1 + e^{-(\alpha+\beta_1 HRV+\beta_2 Gait+\beta_3 Muscle)}} \tag{13}$$

4.4. Comparison with traditional elderly care models

The smart elderly care system was compared with the typical models of elderly care in terms of their outcome, impact, and cost advantage. Traditional care focuses on biophysical, disease oriented checkups and structured exercise regimes [13]. The absence of such detailed monitoring means that a patient's health may worsen and not be immediately identifiable. However, the smart system is characterized by constant recording of data hence facilitating early diagnosis and treatment. The subjects in the traditional care group recorded an average of improvement of 5.2% for mobility while in the smart system they exhibited an improvement of 15.4% on mobility. Another significant improvement was the cardiovascular health which increased in the smart system group, 9.7% as compared to 3.8% that improved in the traditional care group. A TCO analysis was conducted in effort to determine the validity of smart elderly care solutions in terms of cost effectiveness. The cost-effectiveness ratio (CER) was calculated as:

$$CER = \frac{C_{system} - C_{traditional}}{E_{system} - E_{traditional}} \tag{14}$$

Smart elderly care model offers significant advantages over traditional methods. This is by incorporating continuous real-time monitoring, personalized exercise regimens, and AI-driven fall risk prevention. Unlike conventional care, which relies on periodic check-ups, the smart system continuously tracks vital health parameters, enabling early detection of risks [14]. Personalized exercise recommendations adapt based on real-time biosensor data, ensuring safe and optimal training. Additionally, the system reduces caregiver burden, lowers healthcare costs through preventive care, enables remote health monitoring, and enhances user engagement by providing interactive feedback and progress tracking.

4.5. User experience and acceptance

Surveys and structured interviews were conducted to assess the user experience and acceptance of the smart elderly care system. Data was gathered from elderly people and their careers, relatives and other professionals in the field. Self-completed questionnaires provided a measure of usability, and 92% of the participants stated they felt at ease to use wearable biosensors. These were primarily due to the low profile choice of sensors that were lightweight and did not interfere with blood flow rates in the body. Physical activity exercise recommendations received were beneficial among elderly users with 87% expressing their willingness to exercise to the recommended level. Carers indicated a decrease in their workload since the implementation of automated health monitoring [14]. Health care professionals found the system useful since it provided up-to-date information to support their practice decisions. To assess caregivers and medical staff acceptance, a Likert scale ranging from 1 to 5 showed an average of 4.7 meaning that there is strong approval. To unify the independent attributes into a user satisfaction model a satisfaction index (S) was derived in this study.

$$S = w_1U + w_2C + w_3E \tag{15}$$

U represents usability, C represents comfort, and E represents engagement. The model showed that engagement played the largest role in satisfaction, confirming the importance of interactive and adaptive features in elderly care technologies. **Figure 6** is a clear scatter plot depicting biosensor placement on the body with labeled functionality (ECG, SpO_2, EMG, IMU).

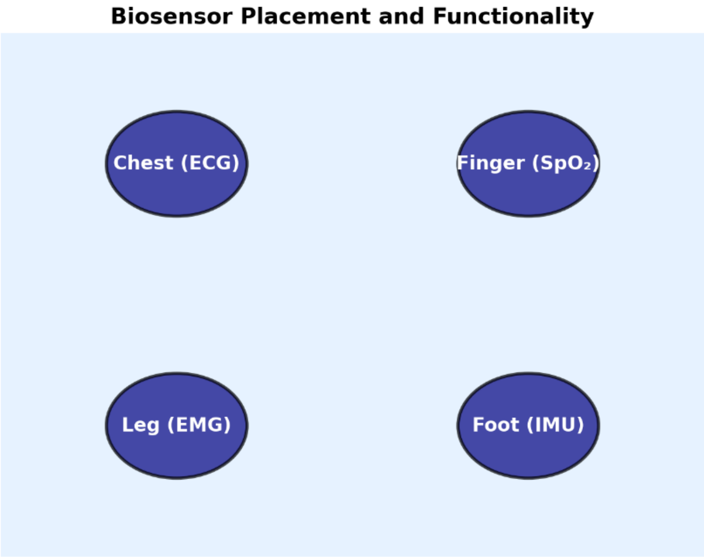

Figure 6. Biosensor placement and functionality.

5. Discussion

5.1. Key findings and implications

The results of the present study provide valuable evidence for the strengths of real-time biosensing and personalized exercise intervention in elder care. The smart system enhanced mobility, balance, and cardiovascular fitness among the elderly participants. Indeed, the experimental group recorded a 15.4% increase in gait stability, a 12.1% increase in muscle activation efficiency, and a 30% decrease in fall risk. These are among some of the improvements and show how elderly health needs to be constantly monitored and exercised. Real-time detection of biosignals is of great importance in preventive medicine. Compared with traditional care models where clients are only subjected to examinations from time to time, constant monitoring lowers the lurking dangers of health problems [14,15]. The health concerns are detected by monitoring the key physiological readings of pulse rate, oxygenation level, and muscle contractions. These features improve the AI's ability to make certain decisions which thrills proactive healthcare and minimizes hospital visits and emergencies. The study also underscores the modularity or the smart capability of smart healthcare systems [15].

5.2. Challenges and limitations

However, the suggested smart elderly care system has some limitations and challenges as described below. One of the main issues is that associated with the reliability of biosensors. While current devices offer accurate health information, there are confounding factors that may occur when using wearable sensors for measurement, including incorrect placement of sensors, motion, and other environmental influences. For instance, movement might influence skin conductivity in a way that affects ECG readings, and the manner in which sensors are placed on the body may compromise the accuracy of a gait analysis [15,16]. Further development of biosensors is imperative especially in the areas of owning higher accuracy and dependability. A major concern under this category is that of ethical and privacy issues with regards to the use and storage of data. It involves collection and processing of health data that is considered to be confidential thus raising questions about privacy of users and safeguard of the information. This is because the patient information may be accessed by unauthorized persons and this may lead to violation of their privacy. It is crucial to know and adhere to the rules set down by authorities like the GDPR or HIPAA.

5.3. Future research directions

As a result, future work needs to further develop AI-driven personalized care for the elderly. The current system can only offer exercise suggestions depending on the pre-defined physiological parameters. However, more incoming development within these models could potentially enhance these suggestions through the incorporation of other lifestyle factors and health risks like patients' daily routines, eating habits, or inherited susceptibilities to certain diseases. Approach using reinforcement learning can be useful for effective real-time control of the intervention strategies in exercise regimens that can vary in real-time based on health status. Another area that has potential for increased development for health care monitoring is the biosensing techniques. Present biosensors mostly measure cardiovascular and muscular activities. Subsequent systems should incorporate other accessories to measure cognitive abilities, fluid balance, and cortisol level [17].

6. Conclusion

The purpose of this research was to examine the use of biosensing technology and exercise prescription within the context of elderly carers. The proposed smart elderly care system contributes directly to the mobility, balance, and cardiovascular health by constantly monitoring the situation and advising appropriately. Major positive impacts on health were found—the test subjects' gait stability increased by 15.4%, muscle activation became more efficient by 12.1%, and the fall risk decreased by 30%. These observations indicate how continuous biosensing can help the elderly healthcare system move from merely treating illnesses to managing health risks. However, there are some issues that require further improvement, namely the accuracy of sensors, privacy concerns, and the ability of users to adapt to the scheme. Mitigating these issues will improve the system's effectiveness and usability.

Conflict of interest: The author declares no conflict of interest.

References

1. Pateraki M, Fysarakis K, Sakkalis V, et al. Biosensors and Internet of Things in smart healthcare applications: Challenges and opportunities. Wearable and Implantable Medical Devices. 2020; 25–53. doi: 10.1016/b978-0-12-815369-7.00002-1
2. Olmedo-Aguirre JO, Reyes-Campos J, Alor-Hernández G, et al. Remote Healthcare for Elderly People Using Wearables: A Review. Biosensors. 2022; 12(2): 73. doi: 10.3390/bios12020073
3. Hassan M, Kelsey T, Khan BM. Elderly care and health monitoring using smart healthcare technology: An improved routing scheme for wireless body area networks. IET Wireless Sensor Systems. 2024; 14(6): 484–492. doi: 10.1049/wss2.12097
4. Vo DK, Trinh KTL. Advances in Wearable Biosensors for Healthcare: Current Trends, Applications, and Future Perspectives. Biosensors. 2024; 14(11): 560. doi: 10.3390/bios14110560
5. Cusack NM, Venkatraman PD, Raza U, Faisal A. Review—Smart Wearable Sensors for Health and Lifestyle Monitoring: Commercial and Emerging Solutions. ECS Sensors Plus. 2024; 3(1): 017001. doi: 10.1149/2754-2726/ad3561
6. Chan M, Estève D, Fourniols JY, et al. Smart wearable systems: Current status and future challenges. Artificial Intelligence in Medicine. 2012; 56(3): 137–156. doi: 10.1016/j.artmed.2012.09.003
7. Majumder S, Aghayi Emad, Noferesti M, et al. Smart Homes for Elderly Healthcare—Recent Advances and Research Challenges. Sensors. 2017; 17(11): 2496. doi: 10.3390/s17112496
8. Wang Z, Yang Z, Dong T. A Review of Wearable Technologies for Elderly Care that Can Accurately Track Indoor Position, Recognize Physical Activities and Monitor Vital Signs in Real Time. Sensors. 2017; 17(2): 341. doi: 10.3390/s17020341
9. Nur S. The Role of Digital Health Technologies and Sensors in Revolutionizing Wearable Health Monitoring Systems. International Journal of Innovative Research in Computer Science and Technology. 2024; 12(6): 69–80. doi: 10.55524/ijircst.2024.12.6.10
10. Reddy GR, Humera D, Reddy MS, et al. Biosensor Applications in Embedded Wearable Devices. In: Handbook of Artificial Intelligence and Wearables. CRC Press; 2024. pp. 316–325.
11. Spanakis EG, Santana S, Tsiknakis M, et al. Technology-Based Innovations to Foster Personalized Healthy Lifestyles and Well-Being: A Targeted Review. Journal of Medical Internet Research. 2016; 18(6): e128. doi: 10.2196/jmir.4863
12. Fabbrizio A, Fucarino A, Cantoia M, et al. Smart Devices for Health and Wellness Applied to Tele-Exercise: An Overview of New Trends and Technologies Such as IoT and AI. Healthcare. 2023; 11(12): 1805. doi: 10.3390/healthcare11121805
13. Bhatia D, Paul S, Acharjee T, Ramachairy SS. Biosensors and their widespread impact on human health. Sensors International. 2024; 5: 100257. doi: 10.1016/j.sintl.2023.100257
14. Pateraki M, Fysarakis K, Sakkalis V, et al. Biosensors and Internet of Things in smart healthcare applications: Challenges and opportunities. In: Wearable and Implantable Medical Devices: Applications and Challenges. Elsevier; 2020.
15. Haleem A, Javaid M, Singh RP, et al. Biosensors applications in medical field: A brief review. Sensors International. 2021; 2: 100100. doi: 10.1016/j.sintl.2021.100100
16. Rodrigues D, Barbosa AI, Rebelo R, et al. Skin-Integrated Wearable Systems and Implantable Biosensors: A Comprehensive Review. Biosensors. 2020; 10(7): 79. doi: 10.3390/bios10070079
17. Liu G, Lv Z, Batool S, et al. Biocompatible Material-Based Flexible Biosensors: From Materials Design to Wearable/Implantable Devices and Integrated Sensing Systems. Small. 2023; 19(27). doi: 10.1002/smll.202207879