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Review

Machine Learning for Wearable Devices Addressing the Sustainability of an Aging Population

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Abstract: Population aging has increased the need for continuous health monitoring, early risk identification, and accessible long-term care. Wearable devices can collect physiological, behavioral, and location data during daily activities, but these measurements require reliable analysis before they can support health-related decisions. This article presents a narrative review of machine-learning applications in wearable health monitoring for older adults. It examines wearable sensing and data-transmission systems, describes an end-to-end framework from signal preprocessing and feature representation to health-state recognition, risk prediction, personalized recommendations, and user or clinical feedback, and compares reported performance across representative applications. Existing studies show that machine learning has been applied to activity recognition, fall detection, arrhythmia classification, stress assessment, rehabilitation monitoring, and personalized health support. However, results vary across datasets, sensor modalities, target populations, and evaluation protocols. The long-term contribution of wearable systems to an aging population therefore depends not only on predictive accuracy but also on signal quality, model interpretability, privacy protection, device reliability, aging-friendly interaction, and appropriate response pathways. Current evidence remains limited by small or heterogeneous samples, cross-device differences, and insufficient longitudinal validation in real-life settings. Further work is needed on individual-baseline modeling, multimodal integration, privacy-preserving learning, cross-device evaluation, and long-term assessment in everyday settings. These developments may support continuous health management, independent living, and more targeted use of healthcare resources among older adults.

Keywords: Machine Learning; Wearable Devices; Population Aging; Health Monitoring; Personalized Healthcare

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1. Introduction

1.1. Population Aging and Continuous Healthcare Needs

Population aging has increased the demand for accessible and continuous healthcare. Older adults are more likely to experience chronic diseases, falls, cognitive decline, and limitations in daily activities, often with several conditions occurring simultaneously. These problems require long-term observation because changes in health status may develop gradually and remain unnoticed between clinical visits. Conventional examinations provide essential diagnostic information but capture a patient's condition only at selected time points, making it difficult to identify variations that occur during daily life [1].

Wearable devices provide a practical complement to periodic clinical assessment. Smartwatches, wristbands, smart textiles, biosensors, location trackers, and personal alarm systems can continuously collect heart rate, blood oxygen saturation, sleep, activity, gait, and other physiological or behavioral data with limited disruption to daily routines [2]. These data can support early warning, chronic disease management, rehabilitation, and independent living. In this article, the sustainability of an aging population refers primarily to the continuity of health management, the long-term maintenance of independent living, and the reduction of avoidable pressure on healthcare and long-term care services.

1.2. Role of Machine Learning in Wearable Healthcare

The value of wearable devices depends not only on data collection but also on the ability to interpret the resulting signals. Raw sensor data often contain noise, missing observations, motion artifacts, and variations caused by device placement or individual behavior. Machine-learning methods can process these data to recognize activities, detect abnormal physiological patterns, estimate disease risk, and support personalized health recommendations. Recent studies have demonstrated their application to fall-risk prediction and the identification of clinically relevant risk factors [3].

However, applying machine learning to older populations presents specific difficulties. Physiological baselines and movement patterns vary substantially among individuals, while multimorbidity may make a single abnormal signal difficult to interpret. Irregular device use, limited digital literacy, cost, privacy concerns, and low adherence can also reduce data completeness and long-term adoption [4]. Predictive performance alone is therefore insufficient. Wearable health systems must also consider interpretability, safety, privacy, usability, and the involvement of older adults in system design and evaluation [5].

1.3. Research Scope and Article Organization

This article presents a narrative review of machine-learning applications in wearable devices for an aging population. It addresses three questions: what physiological and behavioral data wearable devices can collect; how machine-learning methods transform these data into health-state assessments, risk predictions, and intervention information; and which technical and user-related constraints affect their contribution to sustainable aging. The following sections review wearable sensing technologies, describe the analytical process from signal acquisition to personalized support, examine representative healthcare applications, and discuss privacy, aging-friendly design, data quality, and future research needs.

2. Applications of Wearable Health Testing Devices

2.1. Main Types and Their Features

Wearable health-monitoring devices include smartwatches, wristbands, smart textiles, adhesive biosensors, GPS locators, smart badges, automatic alarm devices, and implantable sensors. Smartwatches and wristbands commonly integrate photoplethysmography, accelerometers, gyroscopes, and temperature sensors to measure heart rate, blood oxygen saturation, activity, sleep, gait, and skin temperature [6]. GPS locators and smart badges provide location and movement information, helping caregivers respond to wandering, falls, or prolonged inactivity.

Adhesive and textile sensors can record electrocardiographic, respiratory, temperature, or biochemical signals with closer skin contact. Implantable systems provide specialized measurements when surface devices are insufficient. Noninvasive wearable technologies have been investigated for monitoring heart failure through combinations of heart rate, activity, rhythm, and thoracic signals [7]. Multisensor systems can also combine wearable and nearable devices to monitor daily activities and physiological status over extended periods [8]. Table 1 compares four representative system types.

Table 1. Quantitative Characteristics of Representative Wearable Health-Monitoring Systems.

System	Signals	Signal types	Monitoring	Sample or evidence	Reported result
Smartwatch/wristband	Heart rate, SpO2, activity, sleep	4	Continuous	Older-adult monitoring studies [9]	High daily adherence, but uninterrupted multiday use remained difficult
Multimodal elderly-care system	Acceleration, bioimpedance, heart rate, respiration, activity, environmental data	6 sensor units	Two weeks	Pilot care-facility deployment [8]	Continuous daily-activity monitoring with complete multimodal records
BSN/IoT wearable	Cardiovascular, respiratory, temperature, activity, location	5 categories	Continuous	Systems reviewed in [6]	Supported multisignal transmission and automated analysis
CardioMEMS HF System	Pulmonary artery pressure	1	Daily remote	1,000 patients [10]	253 versus 289 events; HR=0.88, 95% CI 0.74–1.05

2.2. Wearable Data Acquisition and Transmission

A wearable monitoring system generally includes sensing, local processing, wireless transmission, remote storage, and feedback. Sensors convert physiological or behavioral activity into digital signals. A microcontroller then filters, synchronizes, and packages the measurements before sending them to a smartphone, home gateway, or cloud server. Body sensor networks connect several devices through Bluetooth, Zigbee, Wi-Fi, or related communication protocols, allowing cardiovascular, respiratory, movement, and environmental measurements to be analyzed together.

Local preprocessing is necessary because loose contact, body movement, interrupted connectivity, and inconsistent placement can introduce noise or missing observations. Transmitting every raw measurement also increases battery and communication demands. Some systems therefore transmit summarized measurements or event-triggered alerts. Large-scale reviews show that interoperability, security, usability, and communication reliability remain major barriers to integrating wearable data into routine telemonitoring [11].

CardioMEMS illustrates clinically targeted remote monitoring. The implanted sensor transmits pulmonary artery pressure readings, which may increase before heart-failure symptoms become evident. In GUIDE-HF, however, the overall composite of mortality and heart-failure events was not significantly reduced. A pre-COVID-19 analysis indicated a possible benefit, primarily through fewer heart-failure hospitalizations rather than lower mortality [10].

2.3. Health Needs of the Older Population

Wearable applications for older adults mainly address chronic disease monitoring, fall prevention, activity assessment, localization, and emergency assistance. Reported major health conditions among people aged 60 years and older include cardiovascular diseases (30.3%), cancer (15.1%), chronic lung diseases (9.5%), musculoskeletal disorders (7.5%), and mental and neurological disorders (6.6%) [12]. As shown in Figure 1, cardiovascular diseases account for the largest share. This distribution supports the emphasis on cardiopulmonary sensing, while the musculoskeletal and neurological categories justify gait assessment, fall detection, activity recognition, and location monitoring. These percentages cover selected disease categories and therefore do not sum to 100%.

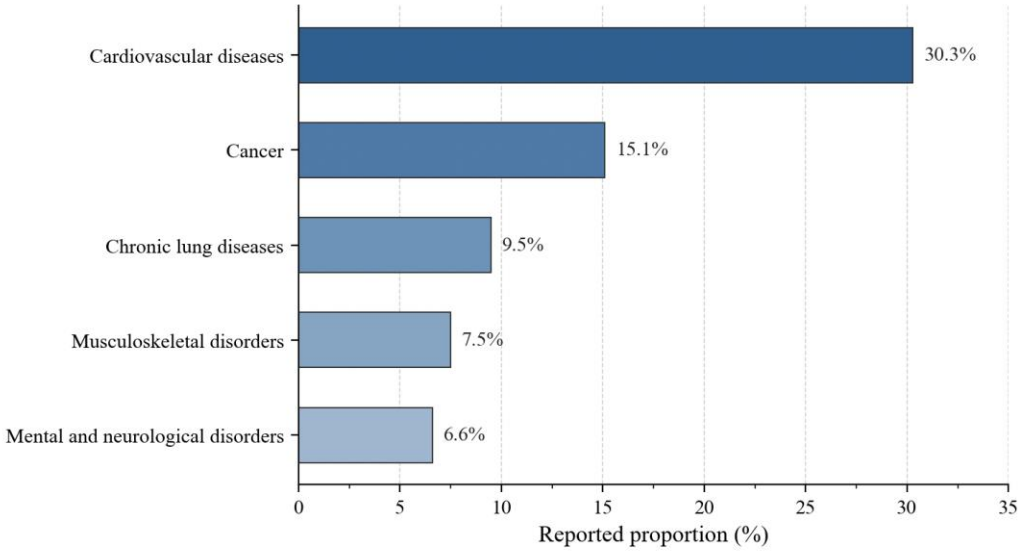

Figure 1. Distribution of Selected Major Health Conditions Affecting Adults Aged 60 Years and Older.

3. Machine-Learning Framework for Wearable Health Monitoring

3.1. End-to-End Analytical Framework

Wearable health monitoring involves more than connecting sensors to a prediction model. It requires a sequence that converts physiological and behavioral measurements into information that users, caregivers, and healthcare professionals can interpret. As shown in Figure 2, the process begins with an older adult interacting with the home or community environment. Wearable sensors then collect physiological signals, movement patterns, and contextual information. After preprocessing, the measurements are represented as synchronized features and, when several sensors are available, combined through multimodal fusion. A machine-learning model estimates the current health state or predicts a future risk, after which the system selects an appropriate recommendation, warning, or request for clinical review.

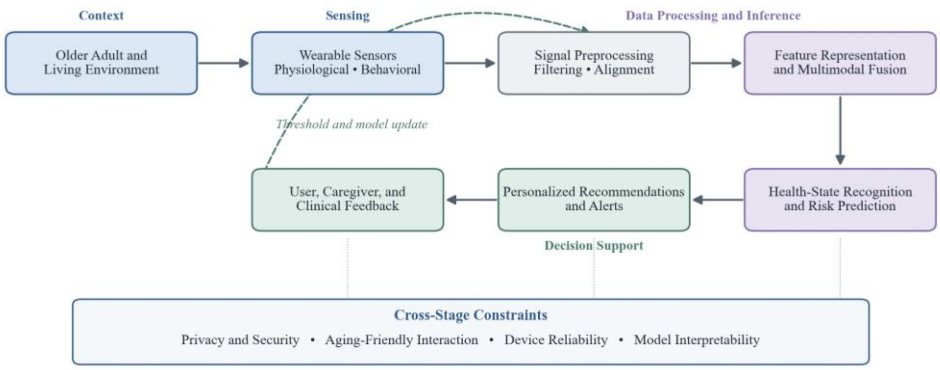

Figure 2. Machine-Learning Framework for Wearable Health Support in Older Adults.

The framework follows the sequence of older adult and living environment, wearable sensors, signal preprocessing, feature representation and multimodal fusion, health-state recognition and risk prediction, personalized recommendations and alerts, and feedback from users, caregivers, and healthcare professionals. Privacy and security, aging-friendly interaction, device reliability, and model interpretability constrain all stages.

The feedback stage is necessary because an alert may be confirmed, dismissed, or revised after additional information becomes available. This response can be used to update user-specific thresholds and reduce repeated false alarms. Recent research on machine learning for wearable sensors similarly emphasizes the connection among signal acquisition, feature learning, inference, and real-world feedback rather than treating model training as an isolated task [13].

3.2. Wearable Signal Representation

Wearable measurements are generally recorded as multivariate time series. For a monitoring window of length L, the input at time t is

$$X_t = \left\{x_{t-L+1:t}^{(1)}, x_{t-L+1:t}^{(2)}, \dots, x_{t-L+1:t}^{(M)}\right\}, \tag{1}$$

where M is the number of sensors or data modalities. The input may include heart rate, blood oxygen saturation, skin temperature, acceleration, and location.

Because these measurements have different units and ranges, the m-th signal is standardized as

$$\tilde{x}_t^{(m)} = \frac{x_t^{(m)} - \mu_m}{\sigma_m}, \tag{2}$$

where μ_m and σ_m are its mean and standard deviation. Preprocessing may also include filtering, resampling, missing-value handling, motion-artifact removal, and time alignment. The processed signals are then mapped to a feature representation:

$$z_t = f_\theta(\tilde{X}_t). \tag{3}$$

The function f_θ may use manually defined features, such as mean heart rate and gait variability, or learned temporal representations. Learned features can capture complex signal relationships but may reduce interpretability.

3.3. Health-State Recognition and Risk Prediction

Machine-learning tasks in wearable healthcare mainly include classification, regression, and clustering. Classification identifies predefined states such as normal activity, a fall, arrhythmia, or seizure. Regression estimates continuous outcomes such as blood pressure, rehabilitation progress, or future risk. Clustering identifies recurring patterns when reliable labels are unavailable.

For an event expected within a future interval Δ, the risk is represented as

$$p_{t+\Delta} = P(y_{t+\Delta} = 1 \mid X_t, u) = \sigma(f_\theta(X_t, u)), \tag{4}$$

where u contains age, chronic conditions, medication information, and the individual physiological baseline. These variables help distinguish abnormal changes from normal differences among older adults.

Applications include fall and seizure detection, arrhythmia recognition, vital-sign anomaly detection, activity recognition, and rehabilitation assessment. A recent fall-detection model, for example, combined accelerometer and gyroscope data to distinguish falls from similar daily activities [14]. However, performance obtained from controlled experiments may not transfer directly to frail older adults in unsupervised environments.

3.4. Personalized Health Recommendation

A predicted risk does not automatically determine the appropriate intervention. The same signal may require an emergency alert for one user but only continued observation for another. The intervention can be selected as

$$a_t^* = \arg\max_{a \in \mathcal{A}} [B(a \mid p_t, u) - \lambda_r R(a) - \lambda_c C(a)], \tag{5}$$

where $B(a)$ is the expected health benefit, $R(a)$ is the safety risk, and $C(a)$ is the operational, economic, or device burden. The weights λ_r and λ_c control the importance of these constraints.

Possible actions include requesting another measurement, recommending rest or exercise, notifying a caregiver, issuing an emergency alert, or requesting clinical assessment. Personalization should consider disease history, mobility, cognitive ability, user preferences, and signal reliability. Wearable systems can therefore support individualized care, but recommendations should remain subject to safety rules and professional oversight [15].

4. Machine-Learning Applications in Healthy Aging

4.1. Disease Risk Analysis and Predictive Modeling

A disease-risk model should specify the target population, predicted outcome, and prediction window. For example, a wearable system may estimate the probability of a fall within the next week among community-dwelling older adults or detect an arrhythmia from a 10-second electrocardiogram segment. Traditional statistical models generally use risk factors selected from established medical knowledge. Machine-learning models can additionally extract temporal and nonlinear patterns from high-dimensional physiological data. However, higher predictive performance does not necessarily ensure clinical usefulness. Model interpretation, calibration, false-alarm rates, and external validation remain important when predictions affect health-related decisions.

Table 2 presents results from five recent wearable studies. The results should be interpreted within their original datasets because the studies used different populations, sensors, validation strategies, and outcomes.

Table 2. Reported Performance of Machine-Learning Methods in Wearable Health Applications

Study	Application	Dataset/sample size	Sensor modality	Model	Metric	Reported result
Hossain et al. [16]	Activity recognition	6 participants; 6 activities	Eyeglass accelerometer and gyroscope	Multitasking CNN	Accuracy	95.00%
Zhang et al. [14]	Fall detection	SisFall; 38 participants	Accelerometer and gyroscope	Dual-stream CNN with attention	Accuracy	99.32%
Liu et al. [17]	Arrhythmia classification	339,648 single-lead ECG segments	Single-lead ECG	Deep CNN	Accuracy	97.31%
Fan et al. [18]	Stress prediction	159 medical workers	PPG, accelerometer, and sleep HRV	Machine-learning classifier	Accuracy	80.30%
Seo et al. [19]	Home stroke rehabilitation	9 stroke survivors; 4 tasks	Wrist-worn IMU	Dynamic time warping classifier	Accuracy/F1	92.00%/0.95

4.2. Personalized Health Programmes

Patient-centered care shifts attention from a disease category to the needs and circumstances of the individual. Wearable data contribute current information about heart rate, sleep, activity, gait, and adherence, whereas electronic health records provide diagnoses, medications, laboratory results, and previous events. Combining these sources can support individualized exercise intensity, rehabilitation targets, and monitoring frequency.

Personalization should remain clinically bounded. A recommendation based on activity data alone may be unsuitable for an older adult with cardiovascular disease, impaired balance, or multiple medications. Genetic information may further support disease stratification, but it should complement rather than replace current physiological and behavioral observations. The practical objective is to adjust monitoring and intervention to the user's baseline, functional ability, and risk profile.

4.3. Activity Recognition, Fall Detection, and Rehabilitation

Activity-recognition models distinguish behaviors such as sitting, standing, walking, running, and sleeping. Changes in their frequency or duration may indicate functional decline. Fall-detection systems use acceleration and angular velocity to distinguish falls from rapid but harmless movements. In the study shown in Table 2, the dual-stream model achieved 99.32% accuracy on SisFall [14], although performance based on simulated falls may be higher than that achieved in unsupervised elderly populations.

Wearable sensors also support rehabilitation by measuring movement repetitions, range, symmetry, and compensatory motion. Seo et al. classified the quality of upper-limb exercises performed by stroke survivors at home with 92% accuracy and an F1-score of 0.95 [19]. Stress and sleep monitoring provide additional information because poor sleep, inactivity, and psychological stress can influence recovery and independent living. Fan et al. obtained 80.3% accuracy for stress prediction from smart-device data, showing lower but more clinically realistic performance than controlled activity-recognition tasks [18] (As shown in Figure 3).

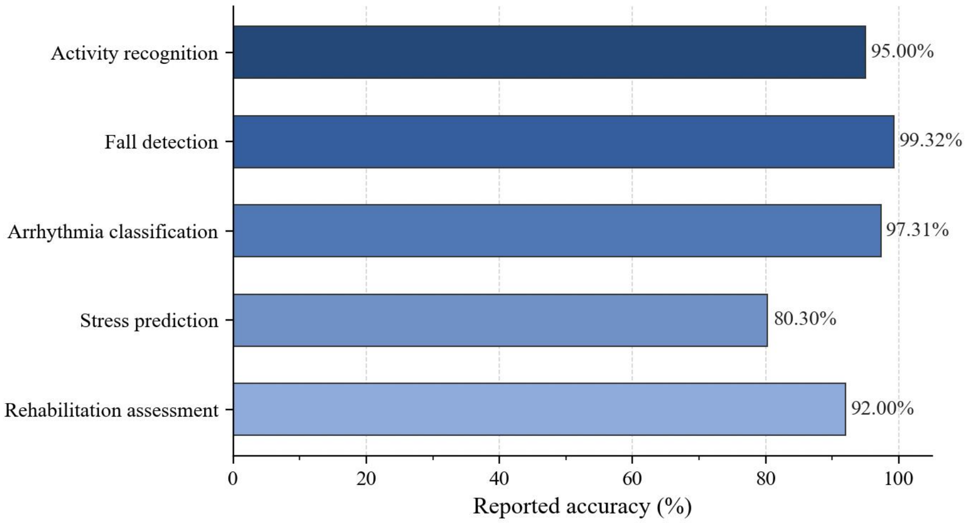

Figure 3. Reported Accuracy Across Representative Wearable Health Applications.

4.4. NLP- and CV-Assisted Interaction

Natural language processing can reduce manual operation by supporting voice commands, speech-to-text conversion, reminders, and real-time translation. These functions are useful when reduced vision, dexterity, or familiarity with touchscreen interfaces limits device use. Computer vision can assist with facial identification, emotion recognition, posture assessment, and eye-movement monitoring. For older users, NLP and CV should serve as accessible interaction channels rather than replace physiological sensing or clinical judgment. Voice and image functions must also provide clear consent controls because they can capture information about both users and nearby individuals.

5. Challenges to Sustainable Deployment

Wearable devices continuously collect sensitive physiological, behavioral, and location data. Sustainable deployment therefore requires data minimization, purpose-specific collection, and clear retention limits. Access should be assigned according to user roles so that device providers, caregivers, and healthcare professionals receive only the information needed for their responsibilities. Encryption is required during wireless transmission and storage, while security updates should continue throughout the device lifecycle. Privacy-preserving approaches, including federated learning, may support model development without centralizing all raw data. Device manufacturers, healthcare institutions, and governments share responsibility for informed consent, security auditing, incident reporting, and regulatory compliance. International standards and verified best practices can further reduce inconsistent protection across platforms.

A wearable device is effective only when older adults can operate and tolerate it over time. Interfaces should use readable text, high contrast, clear icons, and a limited number of steps. Voice interaction can reduce dependence on touchscreen operation, although visual and vibration feedback should remain available. Devices should also be lightweight, comfortable, stable during movement, and capable of operating for extended periods between charges. Automatic alerts may assist users who cannot initiate an emergency call, but excessive false alarms can produce anxiety and alert fatigue. Alert thresholds should therefore reflect individual risk and support coordinated responses from family members and healthcare professionals.

Wearable signals are affected by motion artifacts, loose contact, missing observations, and interrupted communication. Physiological baselines, movement patterns, comorbidities, and medication use also vary substantially among older adults. Models trained on small or comparatively healthy samples may consequently perform poorly among frail or clinically complex users. Differences in sensor hardware, placement, sampling frequency, and preprocessing can create additional distribution shifts. Limited interpretability makes it difficult to determine whether a warning reflects a clinically meaningful change or unreliable data. High accuracy in controlled experiments also does not establish effectiveness in long-term clinical use.

Wearable systems can contribute to sustainable aging in three practical ways. Continuous health management supports longitudinal monitoring and earlier identification of abnormal changes. Location tracking, fall alerts, and activity assessment can help older adults maintain independent living. Remote follow-up and risk-based triage may also help healthcare professionals prioritize patients requiring closer assessment. These benefits depend on reliable measurements, user adherence, and an established response pathway rather than data collection alone.

Future research should integrate physiological, behavioral, and environmental data while adapting predictions to individual baselines. Lightweight edge models may reduce transmission demands and enable faster local alerts. Privacy-preserving learning requires further evaluation under realistic device and network conditions. Particular attention is needed for interpretable warnings, long-term evaluation, cross-device validity, affordability, and support for users with limited digital access.

6. Conclusion

The reviewed evidence shows that wearable devices can continuously collect physiological, behavioral, and location data relevant to the health and independence of older adults. Smartwatches, wristbands, biosensors, inertial sensors, and location-tracking devices provide information on cardiovascular status, blood oxygen saturation, sleep, physical activity, gait, falls, and daily routines. Machine-learning methods convert these data into health-state classifications, risk estimates, and personalized recommendations. Reported applications include activity recognition, fall and arrhythmia detection, stress assessment, rehabilitation monitoring, and remote health support.

However, predictive performance alone does not determine the practical value of a wearable health system. Long-term deployment also depends on signal quality, missing-data management, model interpretability, privacy protection, device comfort, accessibility, and the ability of users or healthcare professionals to respond appropriately to alerts. Current evidence remains limited by heterogeneous study populations, differences in sensor hardware and evaluation protocols, small samples in some applications, and insufficient long-term clinical validation. Results obtained under controlled conditions may therefore not represent performance in the daily lives of frail or clinically complex older adults.

Future research should prioritize longitudinal evaluation in homes, communities, and care facilities. Models should be tested across devices and user groups, adapted to individual baselines, and evaluated for false alarms, adherence, clinical usefulness, and accessibility in addition to accuracy. Such evidence is necessary to determine whether machine-learning-enabled wearable devices can provide sustained support for health management, independent living, and efficient care in aging populations.

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