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Smart Wearable Technologies for Autonomous Mental Health Monitoring in the Elderly: A Systematic Review and Design Perspectives

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Abstract

INTRODUCTION: The increasing prevalence of mental health issues among older adults has generated interest in smart wearable technologies as tools for emotion recognition and depression monitoring. However, their application in ageing populations remains underexplored, and there is no established set of design guidelines tailored to the needs and contexts of older users.

OBJECTIVES: This paper aims to review current research on wearable technologies for mental health monitoring in older adults and to identify key design considerations to inform future development.

METHODS: A systematic literature review was conducted following PRISMA 2020 guidelines. Studies from 1988 to 2025 were included if they examined the use of smart wearables for detecting emotional or depressive states in older adults, or if broader age ranges were analysed in ways that explicitly addressed ageing-related factors or design considerations.

RESULTS: The review revealed notable advances in sensor-based and contactless emotion recognition. However, most systems lacked empirical validation with older users, and usability, privacy, and ethical concerns were frequently unaddressed. Few studies adopted age-specific methodologies or considered the cognitive and physical characteristics of older adults.

CONCLUSION: While wearable technologies show potential for supporting autonomous mental health care in older adults, their effectiveness depends on user-centred and ethically responsible design. This paper identifies the absence of standardised guidelines and outlines preliminary principles to inform future interdisciplinary work. Given the limited number of eligible studies involving older adults, the findings should be considered exploratory and indicative rather than generalisable across broader ageing populations.

Keywords: Smart Wearables, Emotion Recognition, Autonomous Mental Health Monitoring, Depression Detection, Elderly Mental Health.

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1. Introduction

Mental health issues among older adults have become increasingly prevalent due to factors such as social isolation, physical decline, and age-related cognitive impairments. Depression, in particular, is one of the most common and underdiagnosed mental health conditions in the elderly population [1]. This underdiagnosis is often exacerbated by stigma, reduced self-reporting tendencies, and communication barriers, leaving many cases untreated or unrecognised [2].

In parallel, the rapid evolution of wearable technologies and ambient sensing systems offers novel opportunities for supporting mental health interventions in non-clinical,

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autonomous settings. Wearable devices, often functioning within a broader Internet of Things (IoT) ecosystem, are equipped with sensors for physiological or behavioural monitoring that can contribute to the detection of emotional distress and depressive symptoms, promoting early intervention and improved quality of life [3]. Their potential is especially relevant for older individuals living alone or with limited access to daily care, as these systems can operate passively and continuously, without relying on verbal feedback or active input [4]. Despite the growing interest in emotion-aware wearables, existing research reveals significant limitations in their application to elderly populations. Most studies focus on younger users [5], while issues of usability, acceptability, and ethical concerns remain largely unresolved [6]. Furthermore, few implementations have been validated in real-world conditions with older adults [7].

This paper presents a systematic literature review on wearable technologies for emotion recognition and mental health monitoring in aging populations. The aim is to specifically identify key trends, challenges, and research gaps, and to derive a set of design principles for future wearable systems tailored to older users. By synthesising the current state of the art, this work contributes to the interdisciplinary effort of designing inclusive and effective mental health technologies. The remainder of this paper is structured as follows.

Section 2 presents an in-depth literature review on wearable technologies for emotion recognition and mental health monitoring in older adults. It introduces key theoretical frameworks related to affective computing and outlines the role of physiological and behavioural sensing modalities, such as heart rate variability, electrodermal activity, body temperature, and motion, in the detection of emotional states. Furthermore, it examines how these technologies intersect with the unique physiological and cognitive characteristics of the elderly, highlighting both opportunities and limitations.

Section 3 describes the methodology of the systematic literature review. It details the formulation of the research questions, the databases and search terms used, the inclusion and exclusion criteria, and the process of data screening and selection. The chapter also explains the rationale for applying specific frameworks such as PRISMA and presents the quality assessment tools used for evaluating the methodological rigor of the included studies.

Section 4 presents the main findings of the review. It categorises and analyses the selected studies based on sensor types, emotion recognition methods, system objectives, and user demographics. Special emphasis is given to the extent to which these systems have been tested in real-life settings with older users, the performance and limitations of the sensing technologies, and the design gaps identified in the literature.

Section 5 discusses cross-cutting issues related to the usability, acceptability, and ethical implications of wearable emotion recognition systems in ageing populations, including perceived invasiveness, privacy concerns, age-related digital literacy, and long-term adherence. The section synthesises insights intended to guide the development of more inclusive and user-centred systems, while the Conclusions section summarises the contributions of the review, outlines its limitations, and identifies directions for future research on emotion-aware wearables for elderly mental health monitoring. Given the nascent and fragmented nature of this research area, the review adopts an exploratory stance aimed at mapping current trends and identifying emerging design considerations rather than establishing confirmatory conclusions.

2. Background and Related Work

2.1. Emotion Recognition and Mental Health in the Elderly

Emotion recognition (ER) technologies aim to detect and classify human emotions through various signals such as speech, facial expressions, physiological activity, or movement patterns. In the context of older adults, emotion recognition systems can play a vital role in identifying symptoms of depression, anxiety, and cognitive decline, conditions often underreported in this age group [8].

Age-related disorders such as dementia, Alzheimer's, and Parkinson's disease can impair emotional expression and perception, making traditional mental health assessments more difficult [9]. Moreover, studies have shown that older adults are less likely to verbalise emotional distress, either due to generational attitudes or cognitive limitations [10]. These challenges underline the value of passive, technology-supported recognition methods that do not rely on explicit user feedback [11].

2.2. Wearable Technologies and Sensing Modalities

Wearable devices offer non-invasive, continuous data collection through contact-based sensors (e.g., ECG, GSR, PPG) or remote sensing techniques (e.g., voice, gait, thermal imaging). These modalities allow for the tracking of physiological indicators associated with emotional states, such as heart rate variability, skin conductance, and movement irregularities [12].

Recent studies have explored multimodal ER systems combining several types of inputs to enhance detection accuracy. While promising, many of these systems have not been validated in real-world environments involving elderly users [13]. Usability issues, discomfort due to sensor placement, and privacy concerns remain significant obstacles to adoption [14].

2.3. Related Work and Existing Gaps

A substantial body of research exists on emotion recognition systems, but relatively few studies explicitly address the needs of users aged 60 and above. Most prototypes are tested on young or middle-aged adults in lab settings, which limits generalizability [3]. Furthermore, design frameworks often neglect factors crucial to older adults, such as cognitive load, sensory decline, and ease of use [15–17].

Some approaches rely on contactless methods, including voice modulation analysis or infrared thermography, to reduce user burden. However, these systems are still in early development stages and lack standardisation [18]. Comprehensive reviews have pointed to the need for integrated systems that prioritise user autonomy, ethical transparency, and adaptability to individual preferences [19].

3. Methodology

This study employs a systematic literature review to examine the application of wearable technologies for emotion recognition and the detection of depression in older adults. The review seeks to identify pertinent scientific contributions, assess their scope and limitations, and derive key design considerations for future systems [20].

3.1. Data Sources and Search Strategy

A systematic literature search was conducted in accordance with PRISMA 2020 guidelines [27]. The search targeted peer-reviewed journal articles and conference proceedings published in English between 1988 and 2025. The start year (1988) was selected to capture early developments in wearable and sensor-based monitoring relevant to mental health and affective computing. The following electronic databases and platforms were consulted: PubMed, Scopus, IEEE Xplore, ACM Digital Library, SpringerLink, JMIR, ScienceDirect, MedNet.gr, and institutional repositories accessible through Heal-Link (https://www.heal-link.gr).

The search strategy combined three conceptual blocks: (i) Wearable / sensor technologies, (ii) Older adults, and (iii) Emotion recognition / mental health monitoring.

Representative search strings included combinations of the following keywords and Boolean operators: ("wearable technologies" OR "smart wearables" OR "wearable sensors") AND ("elderly" OR "older adults" OR "geriatrics" OR "elderly population") AND ("emotion recognition" OR "mental health monitoring" OR "depression detection" OR "affective computing" OR "cognitive decline").

To maintain focus on mental health and emotion, exclusion terms related to unrelated domains (e.g. education, speech development) were applied where supported by database filters. In total, 218 records were retrieved across all sources before de-duplication.

3.2. Inclusion and Exclusion Criteria

To ensure the scientific rigor and thematic relevance of the review, a set of predefined inclusion and exclusion criteria was developed and applied systematically during the screening process. These criteria were intended to filter studies in a way that directly supports the research focus on wearable emotion recognition technologies for the mental health monitoring of older adults.

Inclusion criteria focused on studies that fulfilled the following conditions [21]:

(i) Relevance to wearable or sensor-based technologies: Studies were required to investigate systems that incorporate wearable devices, ambient sensors, or physiological monitoring technologies aimed at assessing mental health or detecting emotional states. These systems had to include some form of affective sensing whether through bio-signals (e.g., heart rate, skin conductance), behavioural analysis (e.g., gait, sleep patterns), or environmental/contextual cues.

(ii) Target population of older adults: Only studies that either directly involved older adults (preferably aged 60 and above) or presented insights applicable to this demographic were included. Where the age range was broader, studies were retained if subgroup analyses or design considerations explicitly addressed aging-related factors, such as sensory decline, comorbidities, or cognitive impairment.

(iii) Empirical or technical contribution: Eligible studies needed to go beyond theoretical discussion by offering technical descriptions of the system architecture, evaluation results, or data from real-world deployment. Studies were also included if they provided insights into user experience, usability testing, or acceptance measures, particularly as they pertain to elderly users. This emphasis ensured that the review would synthesise findings with practical applicability, not merely conceptual frameworks.

Exclusion criteria were used to eliminate studies that did not align with the goals of the review or lacked sufficient methodological transparency [22]:

(iv) Exclusion of purely clinical or pharmacological research: Studies focusing solely on drug-based interventions, psychotherapy, or psychiatric diagnosis without any technological integration were excluded. The focus of the review is on technology-mediated, not clinically administered, mental health interventions.

(v) Non-systematic or insufficiently detailed reviews: Secondary studies, such as literature reviews or scoping reviews, were excluded unless they clearly described their methodology, selection criteria, and data analysis process. Non-transparent reviews were omitted to preserve the quality and traceability of the evidence base.

(vi) Inapplicability to independent living contexts: Technologies that required continuous clinical supervision or were designed exclusively for hospital or institutional settings were excluded. This review emphasises solutions that support autonomous living, particularly for older adults who reside independently or in minimally assisted environments.

3.3 Screening and Analysis Process

The selection process followed the PICOS framework and the a priori inclusion and exclusion criteria described in Section 3.2.

From the initial **218** records, **11** duplicates were removed, leaving **207** unique records for screening. Titles and abstracts of these 207 records were screened manually against the PICOS-based eligibility criteria. At this stage, 178 records were excluded for at least one of the following reasons:

(i) General physical-health focus without mental-health or emotion component Studies that used wearable technologies exclusively for physical health monitoring (e.g. fall detection, cardiac rehabilitation, blood glucose tracking, gait analysis, post-operative recovery) without any explicit linkage to emotional states, depressive symptoms, anxiety, or broader mental-health outcomes were excluded. In these studies, mental health was neither a primary outcome nor analytically modelled from the sensor data [14,21]. While such research is highly relevant in the broader field of gerontechnology and aging support, these studies were excluded due to the lack of any reference to psychological or emotional parameters. The aim of this review is not to provide a generalised overview of wearable applications in older adults, but to synthesise findings related to mental health and emotional state monitoring, including conditions such as depression, anxiety, loneliness, and affective instability. Studies that omitted these dimensions or treated them as peripheral, without integrating affective data streams or mental health implications into the system's design or analysis, were deemed outside the scope. For example, a wearable system that tracks mobility to prevent falls, without any mechanism or hypothesis relating gait changes to emotional dysregulation or psychological distress, was excluded. This distinction ensures a focused and coherent evidence base aligned with the review's core objective.

(ii) Emphasis on sleep or activity tracking with no application in emotion recognition: Another subset of studies centred on quantitative metrics such as total sleep duration, sleep stage detection, step count, energy expenditure, and circadian rhythm tracking, which were often positioned as indicators of general wellness or predictors of physical frailty. Despite the acknowledged interplay between sleep patterns, physical activity, and emotional well-being, these studies were excluded when no attempt was made to analyse, correlate, or infer emotional states or mental health conditions based on the collected data. Emotion recognition implies an analytical layer that interprets raw sensor input in terms of affective meaning. For instance, identifying signs of sadness, stress, agitation, or depression from bio-signals. Therefore, wearable systems that simply tracked behaviour without contextual or algorithmic modelling of affective responses were excluded. For instance, a Fitbit-based study that recorded sleep efficiency in older adults was not included unless it explicitly linked disrupted sleep patterns to depressive symptomatology or employed the data as part of a multimodal emotion recognition framework [23,24].

(iii) Study populations composed of adults younger than 60 years of age: A considerable portion of the initially retrieved literature involved user testing or experimental validation on younger participants, typically university students, healthy adults aged 20 to 50 years old, or technology-savvy volunteers. While such studies often provide foundational insights into algorithm training, sensor performance, and usability metrics, they lack ecological validity when applied to elderly populations. Older adults face distinct physiological, psychological, and sociocultural challenges that affect both the design and reception of wearable technologies. For example, age-related declines in skin elasticity may affect the accuracy of photoplethysmography (PPG) sensors; reduced manual dexterity may hinder device manipulation; and cognitive impairment may limit user interaction or consent. Furthermore, older users often have different privacy expectations, emotional expression patterns, and trust in technology, which can significantly alter how wearable systems are used and perceived. Therefore, studies that did not involve participants aged 60 or above, or failed to simulate or account for age-specific conditions, were excluded to preserve the population-specific relevance of the review's conclusions [11,13,25,26] .

After title and abstract screening, **29** articles were deemed potentially eligible and were sought for full-text review. Full-text versions could not be obtained for 5 of these records (e.g. inaccessible proceedings or unavailable manuscripts), leaving **24** articles for full-text assessment. During full-text screening, 13 of the 24 articles were excluded for the following reasons:

- Secondary research without primary empirical data: narrative or scoping reviews and surveys that did not present original data or system implementation (e.g. Hickey et al., 2021; Gomes et al., 2023; Moore et al., 2021; Holthe et al., 2018; Peng et al., 2024; Mughal et al., 2020)[14,22,23,26–28].
- General technology or usability focus with no emotion/mental-health outcomes: studies addressing acceptance or usability of generic health wearables in older adults (e.g. Li et al., 2019; O'Sullivan et al., 2023) [7,24].
- Non-wearable or non-sensor-based emotion systems that did not incorporate wearable or ambient physiological sensing in the sense defined by the inclusion criteria.

Ultimately, eleven (**11**) studies met all inclusion criteria and were retained in the systematic review. Of these, nine (**9**) contributed quantitative data suitable for synthesis (e.g. classification performance, correlations with validated mental-health scales) [29–37], and two (**2**) were qualitative or mixed-methods studies providing in-depth insights into usability, experience and design implications in elderly populations [38,39].

These studies either involved older adult participants or were explicitly designed for ageing-related use cases, utilised wearable technologies (inertial sensors, photo-plethysmography, electrodermal activity, skin temperature, actigraphy etc.) for emotion or mental health monitoring, and provided sufficient empirical quantitative data (e.g., accuracy rates, correlation coefficients, or statistical associations) suitable for synthesis. Collectively they demonstrated the feasibility of extracting clinically meaningful indicators of depressive symptoms, emotional states, and psychological well-being.

A number of studies provided statistically robust associations between wearable-derived metrics and validated mental health scales, such as the correlations reported by [31,36] with CES-D scores. Others focused on machine learning–based emotion or depression classification using physiological signals, as seen in [29,30,33,34], each reporting quantifiable performance metrics such as F1-scores, recall rates, accuracy, or R^2 values. Additional contributions included early-stage or domain-specific implementations, such as the emotion recognition prototype presented by [35], the therapeutic IoT-integrated system by [37], and the robot-assisted emotional monitoring framework developed by [39]. Together, these studies form a coherent evidence base illustrating both the technological potential and developmental constraints of current wearable systems for psychological and emotional assessment in ageing populations.

Although the number may appear modest when compared with larger reviews, it is consistent with the specialised and interdisciplinary nature of the field, which spans wearable sensing, affective computing, and mental-health monitoring in ageing populations. Few publications meet all these criteria simultaneously, and disciplinary fragmentation - across engineering, psychology, and geriatric medicine - reduces the likelihood of retrieving all relevant studies, even when multiple databases and Heal-Link repositories are used.

Within this context, the inclusion of eleven studies - including nine with quantitative data - constitutes an appropriate evidence base for a field still in an early phase of development. The selected studies provided adequate quantitative information on sensor data, user outcomes, or statistical associations to enable quantitative synthesis [40]. Nevertheless, the present quantitative synthesis is framed as exploratory. Its purpose is to identify initial trends and assess the potential for synthesis across heterogeneous methodologies, complementing the broader qualitative analysis. The number of eligible studies also highlights the need for more rigorous, large-scale research and greater methodological standardisation in this evolving field.

The overall process of identification, screening, eligibility assessment and inclusion is summarised in the PRISMA 2020 flow diagram (Figure 1).

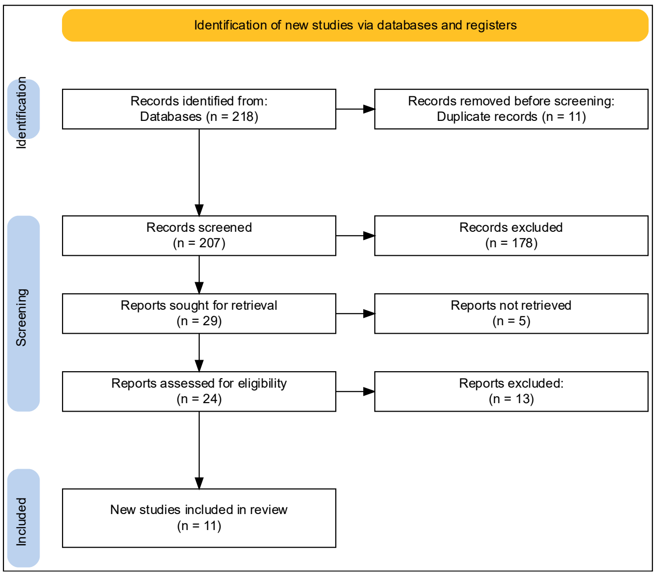

Figure 1. PRISMA 2020 flow diagram illustrating the identification, screening, eligibility, and inclusion process of studies in the systematic review.

3.4 Quality Assessment and Synthesis Approach

To assess the methodological quality and risk of bias in the selected studies, the Newcastle-Ottawa Quality Assessment Scale (NOS) was applied [41]. This tool is widely used for evaluating non-randomised and observational research and was selected to reflect the nature of the wearable-technology studies included. Depending on the study design, one of three NOS variants was applied: cross-sectional, cohort, or case-control.

Evaluation proceeded across three domains:

- Selection: adequacy of sampling procedures, clarity of participant characteristics, and representativeness of the elderly population studied.
- Comparability: control of confounding variables such as age-related comorbidities, medication use, or differences in daily living environments.
- Outcome (or Exposure) Assessment: reliability of sensor measurements, appropriateness of emotional-state labelling procedures, validity of computational or statistical methods, and clarity of reporting.

The tool was adapted to the study type (cohort, cross-sectional, or case-control) and evaluates methodological robustness through structured criteria:

Table 1a. Quality Assessment Criteria – Cross-sectional Studies.

Criterion	Explanation
Sample representativeness	Whether the study included a demographically diverse group of older adults relevant to the research aim.
Sample size	Whether the sample was sufficiently large to yield statistically meaningful findings in the context of wearable use.
Non-response rate	Whether dropouts or non-participation were reported and accounted for in the analysis.
Ascertainment of exposure	Whether the study clearly described the type of wearable used and its relevance to emotion or mental health monitoring.
Comparability of participants	Whether confounding factors like tech literacy or comorbidities were considered when comparing participant outcomes.

Table 1b. Quality Assessment Criteria – Cohort Studies

Criterion	Explanation
Cohort representativeness	Whether the cohort included older adults reflective of real-world populations using emotion-detecting wearables.
Non-exposed group selection	Whether the comparison group (not using wearables or not exposed to the intervention) was appropriately selected.
Ascertainment of exposure	Whether the nature and usage pattern of the wearable technology were accurately reported.
Baseline outcome confirmation	Whether it was confirmed that mental health symptoms or outcomes were not pre-existing at the beginning.
Comparability between cohorts	Whether control for confounding variables (age, digital skills, etc.) was adequate across groups.
Outcome evaluation	Whether the outcomes (e.g., change in emotional state) were objectively measured with appropriate tools.
Adequacy of follow-up	Whether the follow-up period was sufficient to observe the impact of wearable use on mental health.
Loss to follow-up analysis	Whether the reasons and extent of loss to follow-up were reported and analysed.

Table 1c. Quality Assessment Criteria – Case-Control Studies

Criterion	Explanation
Appropriateness of case selection	Whether the selection of cases (e.g., depressed older adults) was appropriate and clearly defined.
Sample representativeness	Whether the case group was representative of the broader elderly population with mental health conditions.
Control group selection	Whether the control group was chosen in a way that minimised bias and allowed meaningful comparison.
Control group definition	Whether the criteria defining the control group were clearly described and consistently applied.
Comparability of cases and controls	Whether adjustments for key variables were made between the case and control groups.
Ascertainment of exposure	Whether the way exposure to wearables was measured was reliable and relevant to the study's objectives.
Consistency of data collection	Whether data were collected using the same method for all participants to reduce bias.
Non-response rate	Whether the impact of non-respondents was evaluated, particularly for older adults less likely to participate.

Based on the NOS scoring rubric, each study was categorised as high, moderate, or low quality. Each study was rated based on these domains and assigned to one of three quality categories: a) High quality: 3 to 4 stars in the "Selection" domain, 1 to 2 stars in "Comparability", and 2–3 stars in "Outcome", b) Moderate quality: 2 stars in

"Selection", 1 to 2 in "Comparability", and 2 to 3 in "Outcome" and c) Low quality: 0 to 1 star in "Selection", and 0 stars in "Comparability" or "Outcome" [42]. The quality classification enables a clearer understanding of the reliability of the reviewed data and an estimation of potential bias [43].

Most studies demonstrated moderate methodological quality, reflecting both the early-stage nature of wearable emotion-recognition research and the diversity of sensing modalities (e.g., accelerometry, PPG, EDA, actigraphy, IoT ambient sensors) and analytic strategies employed.

Overall, the NOS assessment indicated that the methodological quality of the included studies was variable. Of the eleven studies, a minority achieved high-quality ratings, most were classified as moderate quality, and a small number were assessed as low quality. This distribution reflects both the emerging nature of wearable emotion-recognition research in ageing populations and the heterogeneity of study designs, sensing modalities, and evaluation procedures. These quality considerations should be taken into account when interpreting the findings of the review.

4. Results and Discussion

The eleven studies included in the review, identified through the PRISMA-based screening and eligibility process, reveal a growing interest in wearable emotion-recognition systems as tools for supporting mental health and ageing-in-place. Most of these studies demonstrate that wearable technologies offer promising avenues for capturing behavioural and physiological indicators related to emotional well-being in older adults, although practical deployment remains challenging. Before these themes are examined in detail, Table 2 provides a comparative overview of the eleven (11) included studies, summarising their sensor modalities, validation settings, and usability-related outcomes.

Table 2. Summary of the Eleven Included Studies

Study	Population / Setting	Sensor Modalities	Validation Setting	Target Outcomes
Kim et al. (2019) – Depression Prediction using EMA + Actiwatch [29]	Older adults living alone	Actigraphy (activity, sleep), EMA	Real-world, 7–14 days	Depressive symptom level prediction
Choi et al. (2022) – Depressed Mood Prediction [30]	Elderly community-dwelling adults	Wrist-worn wearable (PPG, HR, activity)	Real-world	Daily mood prediction
Mishra et al. (2021) – COVID-19 Mobility & Depression [31]	Community-dwelling older adults	Pendant wearable (mobility, posture transitions), sleep metrics	Longitudinal (pre/post pandemic)	Depressive symptoms linked to mobility decline
Chen et al. (2018) – IoT-based Behavioural Difference Warning [32]	Older adults living independently	Ambient IoT sensors (motion, smart plugs)	Real-world deployment	Detection of behavioural deviations indicative of cognitive decline or depression risk
Gutiérrez Maestro et al. (2023) – Wearable Emotion Monitoring [33]	Older adults during daily activities	Physiological + inertial sensors	Lab + semi-naturalistic tasks	Emotion recognition (valence/arousal)
Onim et al. (2025) – Physiological Emotion Detection [34]	Older adults	PPG, EDA, skin temperature, accelerometry	Laboratory (emotion elicitation protocols)	Prediction of emotional intensity
Jiang et al. (2011) – Wearable Home Healthcare System w/ Emotion Recognition [35]	Older adults (design focus)	Custom wearable (physiological sensors)	Prototype evaluation (technical)	Emotion recognition integrated into home-care system

Albites-Sanabria et al. (2025) – Motor Outcomes Informing Non-Motor Symptoms [36]	Older adults with Parkinson's disease	Wearable inertial sensors (motor performance)	Clinical setting	Links between motor patterns and non-motor symptoms (incl. depressive states)
Siddiqui et al. (2021) – IoT + Music Therapy for Anxiety/Depression [37]	Older adults (COVID-19 context)	Wearable vital-sign sensors (HR, SpO_2, temperature)	Prototype + simulated use	Anxiety and depression level estimation
Ma & Yin (2024) – EMO-Care Multimodal Emotional Interaction System [38]	Designed for elderly living alone	Conceptual multimodal sensing framework + edge intelligence	Proposed System Architecture	Emotional state monitoring to support social care
Suzuki et al. (2023) – Multimodal Emotion Estimation for Social Robots [39]	Older adult participants	Physiological sensors (EDA, HR), multimodal fusion	Lab-based evaluation	Emotion estimation to guide robot interaction

4.1. Usability and Acceptance in Older Populations

Usability is a critical factor influencing the successful adoption and sustained use of wearable emotion recognition technologies in older adults. Age-related changes in sensory perception, mobility, cognition, and emotional regulation can significantly affect how elderly users perceive and interact with such systems. When these aspects are not properly accounted for, even technically robust systems may be rejected by the intended users. Many of the reviewed studies revealed that commercial or research-grade wearable devices often assume a baseline level of digital literacy, manual dexterity, and cognitive capacity that may not align with the capabilities of older adults. Devices requiring frequent charging, tight or adhesive sensor contact, or multi-step navigation processes were frequently associated with discomfort, confusion, or abandonment of use. Moreover, users with mild cognitive impairment may struggle with remembering to wear the device or interpreting the feedback it provides. Collectively, these factors reduce adherence and diminish perceived usefulness [27].

The analysis reveals that passive operation is a primary determinant of acceptance. For example, Chen et al. [32] demonstrated that ambient IoT-based systems, which track behavioural differences through motion sensors and smart plugs, effectively mitigate the usability barriers associated with active wearable devices. By removing the need for the user to wear, charge, or manipulate a device, such systems address the "technological friction" that often leads to abandonment in older populations.

Where wearables are used, the complexity of the interaction model is a key constraint. In the design of a wearable home healthcare system, Jiang et al. [35] highlighted that system architectures must be simplified to accommodate the specific living conditions and technical literacy of older users. Devices that require multi-step navigation or frequent active input were found to be less suitable for long-term deployment. This is further supported by Suzuki et al. [39], whose work on robot-assisted emotion estimation suggests that older adults rely heavily on multi-modal interaction cues. Their findings indicate that systems attempting to estimate emotion must provide feedback that is intuitive and aligned with the user's sensory capabilities, rather than relying on complex data visualisations.

Even more, on another study, excluded but relevant for this specific case, O'Sullivan et al. [7] observed that older individuals with dementia faced challenges in understanding both the function and the benefits of a Fitbit-style wearable. The study highlighted that acceptance improves substantially when devices are passive in operation, offer minimal friction in daily use, and provide intuitive interaction through simple visuals, tactile signals, or voice feedback. Rather than imposing cognitive demands, such systems must accommodate limitations and provide clear value in the user's daily routine [44].

Furthermore, the "comfort-first" requirement for adherence is evident in longitudinal studies. Kim et al. [29] successfully collected data over a two-week period by utilising Actiwatches that required no user intervention beyond wearing the device. This contrasts with systems requiring active tagging or maintenance, suggesting that for older adults—particularly those living alone—the most usable interface is often one that is invisible. Consequently, the literature points toward a design paradigm where the technology recedes into the background, prioritising autonomous sensing over active user engagement.

The aesthetic and social dimensions of wearable technologies also influence user acceptance. Older adults often expressed hesitation about wearing devices that appear too clinical, draw unwanted attention, or imply frailty. In public settings or during social interactions, visible sensors or flashing displays can provoke embarrassment or reinforce stigmas related to aging or illness. Subtle form factors, such as wristbands resembling ordinary watches, can help normalise technology and reduce these concerns. In addition, the reviewed literature indicated that user engagement during design and testing phases was minimal. Most systems were developed without substantial input from older users, resulting in features and interfaces poorly suited to their specific needs. This top-down design approach creates a disconnect between engineering intent and practical usability. Participatory design and co-creation, where older adults are involved in iterative feedback cycles, can bridge this gap and lead to more inclusive solutions [45].

In this context, usability extends beyond ergonomics and interface design, encompassing emotional comfort, trust, autonomy, and a sense of empowerment. Older users who feel confused, surveilled, or disregarded by a technology are unlikely to incorporate it into their lives, irrespective of its potential benefits. Subtle, low-effort interactions, also known as micro-interactions, can significantly influence engagement and adherence, as for instance is demonstrated in studies related to smart packaging and medication monitoring systems [46].

Equally important in the design of medical wearable systems is the way these technologies interact with users' attention and privacy. Devices that require constant monitoring or interrupt users at inappropriate times risk causing frustration, cognitive overload (fatigue), and eventual device abandonment. This issue is especially acute for older adults, for whom usability and acceptance depends on solutions that respect their routines, pace, and cognitive preferences. Research in e-health highlights the necessity of temporal sensitivity in the design of medical wearables which should support rather than disrupt daily life of their users [47]. Researchers emphasise that the adoption of assistive technologies among older populations is closely linked to their perceived usability and the extent to which interaction aligns with users' needs for privacy, autonomy, and unobtrusive assistance. If these systems are perceived as invasive or too demanding, older users may reject them, regardless of their potential health benefits or general clinical value.

Another important design related factor with usability and acceptance is feedback transparency. Older adults often seek reassurance that the device is functioning correctly, without being overwhelmed by excessive data or unclear alerts. Offering layered feedback such as simple confirmation signals (e.g., a gentle vibration or soft LED) to more detailed insights when explicitly requested, can improve trust and better accommodate the diverse cognitive capacities within this group of people [23].

4.2. Sensing Modalities and Interpretation of Data

Emotion recognition in wearable systems relies heavily on the quality and interpretability of sensor data. Although ECG and EEG are widely used in the broader emotion-recognition literature, they did not appear in the eleven studies included in this review [26]. These modalities capture autonomic nervous system activity, which is often correlated with emotional arousal, stress levels, and mood fluctuations. However, the applicability and reliability of these sensors in older populations present specific challenges. Age-related changes, such as reduced circulation, thinner skin, or altered sweat gland activity, can affect sensor accuracy. For instance, PPG signals may be noisier due to decreased vascular elasticity, and EDA sensors may yield inconsistent readings on dry or ageing skin, particularly in low-humidity conditions.

To address the limitations of single-modality sensing, several studies adopted multimodal approaches, integrating data from sources such as motion sensors, speech analysis, facial expressions, and contextual factors like time of day or activity level [48]. These methods improved classification accuracy and robustness, especially when paired with machine learning algorithms. However, they also increased system complexity, power consumption, and computational demands, reducing feasibility for continuous real-world use.

Another emerging trend is contactless emotion sensing, including gait analysis via floor sensors or cameras, facial recognition through computer vision, and infrared thermal imaging [33]. These non-invasive methods hold promise for smart homes and assisted living settings. However, practical challenges remain, such as variable lighting, camera occlusion, privacy concerns, and inconsistent facial expressiveness among older adults. Ethical issues around consent and surveillance also become more pronounced with ambient and unobtrusive monitoring systems.

Another notable observation from the review is that few of the analysed systems were validated in ecologically valid conditions. Many studies relied on short-term lab experiments, scripted emotional stimuli, or convenience samples composed of younger adults. Only a minority involved participants aged 60 and over, and even fewer assessed system performance during daily living activities [49]. The absence of real-world validation limits the generalisability of the findings and raises questions regarding the practical feasibility of wearable emotion recognition technologies in eldercare contexts.

To enhance both validity and user relevance, future systems must balance sensing sophistication with robustness in uncontrolled environments, while also adapting signal processing techniques to the physiological profiles of aging users. Calibration routines based on personal baselines, noise-tolerant algorithms, and flexible sensor integration schemes may contribute to more effective and inclusive emotion recognition systems for older adults.

4.3. Design Challenges and Ethical Considerations

The integration of wearable technologies for emotion recognition in elderly populations is not only a technical endeavour but also an ethical and psychosocial one. The reviewed literature consistently highlights several multidimensional design challenges that must be addressed to ensure safe, effective, and acceptable deployment in real-world settings.

A key concern is data privacy and autonomy, as emotion recognition systems collect sensitive physiological and behavioural data such as heart rate, skin conductance, facial expressions, and movement patterns, which may inadvertently disclose private emotional states or mental health conditions. This raises significant issues regarding data ownership, consent, and the risk of stigmatization, especially when such data is accessed by caregivers, clinicians, or third-party platforms [50]. For older users, many of whom may already experience diminished agency in medical or institutional contexts, the idea of being constantly monitored can lead to heightened anxiety or resistance toward technological solutions.

The psychological impact of continuous surveillance is particularly acute in aging populations. While the intent of emotion recognition systems is to provide support, older adults may perceive them as intrusive or paternalistic, especially if feedback is misinterpreted or if they lack control over how their data is used. For example, a device that automatically alerts caregivers when it detects signs of distress might undermine the user's sense of independence or privacy. As such, clear consent frameworks and user-configurable sharing settings are essential components of ethical system design.

From a technical perspective, one of the most persistent challenges is balancing algorithmic accuracy with resource efficiency. Accurate emotion recognition often requires high-resolution data, continuous monitoring, and frequent data transmission, all of which increase the device’s computational load and energy demands. This can lead to short battery life, overheating, and discomfort, factors that significantly reduce usability and long-term adherence. Therefore, developers must optimise sensing frequency, employ low-power components, and implement edge-computing strategies to process data locally without compromising system responsiveness.

False positives and false negatives also present a critical limitation in real-world scenarios. A system that erroneously interprets natural restlessness as anxiety, or that fails to detect genuine depressive signals, may erode user trust or lead to inappropriate interventions. These errors are especially problematic in older adults, whose physiological signals may be influenced by comorbidities, medications, or age-related variability, making emotion classification less straightforward than in younger populations [42]. Therefore, adaptive algorithms that learn personalised baselines and take contextual factors into account are crucial for minimizing misclassification.

Another major design limitation is the lack of personalization and adaptability in many of the systems reviewed. Few studies implemented dynamic models that evolve with the user's emotional patterns over time or respond to changes in physical and cognitive health. Instead, most wearable solutions employed static detection thresholds or general-purpose emotion classifiers derived from younger, healthier populations. This leads to reduced relevance, poor engagement, and limited impact in older users, whose emotional responses may be more subtle or atypical.

Finally, user interface design often remains an afterthought. Many systems feature small screens, non-intuitive feedback mechanisms, or rely on smartphone pairing which may not be accessible or desirable for older individuals with visual, motor, or cognitive impairments. Inclusive design principles, such as voice prompts, tactile feedback, and simplified visuals, are rarely implemented but are essential for meaningful interaction and user satisfaction.

In summary, designing ethically sound and technically viable wearable systems for emotion recognition in older adults requires a holistic approach that integrates user empowerment, privacy protection, energy efficiency, and personalization. Without these considerations, even the most advanced sensing technologies may fall short in delivering real-world impact for this vulnerable population.

4.4. Design Considerations and Preliminary Guidelines

The synthesis of the included studies, supported by broader literature on gerontechnology, allows the formulation of design considerations and preliminary guidelines for wearable emotion recognition technologies intended for older adults. These should be interpreted as early observations rather than definitive guidelines, as they emerge from a small and heterogeneous body of evidence. The limited number of studies, combined with methodological variability and the scarcity of evaluations involving adults aged 60 and above, restricts the generalisability of these insights. Nevertheless, taken together, the studies outline several recurrent patterns that can inform the initial stages of systems design and act as potential design guidelines.

Minimise intrusiveness and prioritise comfort in form factors

Wearable devices should seamlessly integrate into the user’s daily life without causing discomfort or drawing attention to their function. This includes using soft materials, adjustable straps, lightweight casings, and discreet sensor placement. Older adults often report frustration or even anxiety when using bulky or rigid devices that interfere with sleep, daily routines, or clothing preferences. As noted in several research works on wearables [16,51–53], design must begin from a comfort-first perspective, ensuring that sensors do not introduce barriers to long-term adherence. Although the available studies provide only limited empirical confirmation, they consistently indicate that comfort is a prerequisite for continued use.

Support passive operation with minimal user interaction

Given that many older users experience reduced dexterity, memory decline, or limited familiarity with digital interfaces, systems should function autonomously, requiring little to no manual input. Passive data collection (e.g., continuous heart rate or skin conductance monitoring) is preferable to methods that require self-reporting or smartphone-based interaction. Automatic syncing, long battery life, and simple charging mechanisms are essential for maintaining usability across a range of physical and cognitive capacities. The following principles are to consider in designing such systems:

(i) Incorporate adaptive features that respond to behavioural patterns: Emotion recognition models should evolve with the user, recognizing that emotional expression and physiological signals are highly individualised, particularly in aging populations. Adaptive algorithms that learn from user history, contextual data, and changing health conditions can significantly improve detection accuracy and relevance. As highlighted by Calvo et al. [54], such personalisation enhances both the technical performance and the perceived value of the system, fostering user trust and engagement over time.

(ii) Ensure transparency and data control for users and caregivers: Older adults and their caregivers must clearly understand what data is being collected, how it is processed, and who has access to it. Systems should incorporate customizable privacy settings, visual explanations of detected emotional states, and mechanisms for users to review and delete their data if desired. Transparent design is not only a matter of ethics, as emphasised in Schmidt et al. [55], but also a facilitator of adoption, especially in populations sensitive to autonomy and surveillance concerns.

(iii) Foster co-creation with elderly individuals during early design phases: Perhaps the most critical insight across the reviewed studies is the need for participatory design approaches. Rather than treating older adults as passive recipients of technology, they must be included as active contributors throughout the development process, from needs assessment to prototyping and usability testing. As recommended by Lazar et al. [51], involving users in co-design improves functionality, fosters a sense of ownership, and reduces the risk of developing solutions that are technologically advanced but practically irrelevant.

These preliminary observations are further synthesised and contextualised in the concluding section.

5. Conclusion and Future Work

This paper has reviewed research on wearable technologies for emotion recognition and depression monitoring in older adults. The findings confirm the promising potential of smart wearables to enhance independent mental health care through passive, continuous, and personalised emotion tracking. Such technologies offer significant opportunities for early detection and intervention, which are crucial given the underdiagnosis and underreporting of mental health conditions among older populations. However, the available evidence remains limited, with few studies conducting ecologically valid assessments in real-life contexts or involving participants aged 60 and above. Consequently, the conclusions drawn here represent emerging tendencies rather than generalisable outcomes, and further empirical validation is required before these approaches can inform standard practice. At the same time, significant challenges persist regarding usability, ethical acceptability, data privacy, and technological maturity, all of which become more pronounced in older adults who may experience cognitive, physical, and emotional changes that influence how such technologies are adopted and used. A key implication of this review is the need to integrate age-responsive design principles from the earliest stages of development. Many existing solutions adapt general-purpose wearable systems without sufficient attention to age-related cognitive, physical, or sensory considerations. The preliminary design directions outlined in this paper highlight the importance of comfort, unobtrusiveness, passive interaction, adaptive sensing, transparent data control, and participatory development practices. Taken together, these considerations constitute an emerging set of design directions shaped by the early evidence available in this field. They should be viewed as provisional and subject to refinement as more robust empirical work becomes available. Collectively, they point toward a model of inclusive, unobtrusive, and ethically responsible design that moves beyond one-size-fits-all solutions toward context-aware systems that respect the dignity, preferences, and limitations of older adults. Their primary purpose is to guide future interdisciplinary research toward wearable technologies better aligned with the needs and lived experiences of this demographic, supporting the development of scalable and sustainable approaches to mental health monitoring that can enhance independence and quality of life in ageing populations.

Future research should prioritise longitudinal, real-world evaluations involving diverse groups of older adults to ensure ecological validity and capture the variability inherent in ageing populations. There is also a need for unobtrusive and hybrid sensing modalities that reduce user burden while maintaining signal quality. Open, representative datasets involving older adults remain scarce and should be developed to support algorithmic benchmarking and improve classification reliability. Advancing this area of research will require collaboration across engineering, psychology, gerontology, and design to ensure that technological development aligns with clinical relevance, ethical standards, and user experience. Addressing these areas will contribute to wearable systems better suited to the requirements of ageing societies and strengthen the foundations for autonomous mental health support in older adults.

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