ADVANCED ELECTRONIC MATERIALS Open Access
www.advelectronicmat.de

Smart Textile Systems for Loneliness Monitoring in Older People Care: A Review of Sensing and Design Innovations

*Yi Zhou, John Ratcliffe, Erika Molteni, Ashay Patel, Jingqi Liu, Nikitia Mexia, Jessica Rees, Faith Matcham, Michela Antonelli, Anthea Tinker, Yu Shi, Sebastien Ourselin, and Wei Liu**

Loneliness is a critical issue among older people and poses a significant risk factor for various physical and mental health conditions. While recent wearable technologies can monitor behavioral and physiological changes associated with loneliness, existing solutions such as accelerometers and inclinometers often lack comfort and flexibility for long-term monitoring. Smart textile systems offer a viable solution for continuous monitoring by integrating sensors and conductive materials into textiles. However, there remains a critical technological gap that no existing solution integrates multimodal textile-based sensing specifically for loneliness detection. This review addresses that gap by providing a comprehensive review of smart textile technologies for monitoring loneliness in older people, highlighting sensing and design innovations to meet the needs of older users. Key behavioral patterns and physiological symptoms associated with loneliness are explored and suitable wearable sensing technologies, focusing on textile-based solutions that combine comfort, flexibility, and monitoring accuracy, are reviewed. In addition, current advances in data collection, transmission, and analysis are examined for smart textile systems, exploring their potential and challenges in the field of elderly care. By identifying specific design requirements and challenges for monitoring loneliness in older people, this review lays the foundation for future research and development of proactive loneliness detection and intervention.

1. Introduction

Loneliness in older people is a multifaceted issue and it is influenced by various social, psychological, and physical factors.[1,2] As people age, they may engage in fewer social activities due to many reasons such as reduced mobility, retirement, or loss of loved ones, which can lead to social isolation.[3] This sense of isolation can exacerbate loneliness, an emotional state distinct from just being alone.[4] In the UK, ≈1.4 million older people report feeling lonely, and globally, nearly 50% of people aged over 60 are at risk of social isolation.[3] Since the COVID-19 pandemic, social isolation and loneliness among older people have become serious long-term problems. Studies have indicated that social isolation and loneliness are closely related to worsening physical and mental health conditions, increasing the risk of frailty and mortality.[5–7] Chronic loneliness can lead to depression, anxiety, and cognitive decline and it is associated with an increased risk of cardiovascular disease, weakened immune responses, and increased mortality rates.[8,9] Additionally, loneliness can affect sleep quality, exacerbate stress, and even impair brain function.[8]

Given the impact of loneliness on the physical and mental health of older people, it is important to detect loneliness in a timely way. Many new technologies such as fitness trackers have been developed for the continuous monitoring of loneliness in older people, aiming to detect symptoms

Y. Zhou, J. Ratcliffe, W. Liu
Department of Engineering
King's College London
London WC2R 2LS, UK
E-mail: wei.liu@kcl.ac.uk

The ORCID identification number(s) for the author(s) of this article can be found under https://doi.org/10.1002/aelm.202500300

DOI: 10.1002/aelm.202500300

E. Molteni, A. Patel, M. Antonelli, S. Ourselin
School of Biomedical Engineering and Imaging Sciences
King's College London
London WC2R 2LS, UK

J. Liu, N. Mexia, Y. Shi
School of Design
University of Leeds
Leeds LS2 9JT, UK

J. Rees, A. Tinker
Department of Global Health and Social Medicine
King's College London
London WC2R 2LS, UK

F. Matcham
School of Psychology
University of Sussex
Brighton BN1 9RH, UK

early and prevent from further deterioration.[10] As older people may be reluctant to express their feelings openly, it would be helpful to develop reliable monitoring systems for proactive detection and intervention.[11] Technologies for monitoring mental well-being have advanced considerably, particularly in the domain of wearable and remote sensing systems.[12–14] Traditionally, mental health assessments were conducted through self-reported questionnaires and clinical evaluations, but recent innovations have introduced digital systems that can track behavioural and physiological indicators related to well-being.[13] Wearable devices now play a vital role in monitoring psychological states through biosensors that can detect stress levels, heart rate variability (HRV), sleep patterns, and even subtle changes in social behaviours. Such data are analysed to infer the mental well-being of the individual over time.[12,15,16] While loneliness monitoring via wearable sensing remains a conceptual and emerging application, the behavioral and physiological correlates of loneliness are well documented in the psychological literature.[9,17] Current reliance on self-report methods in loneliness research introduces recall and social desirability biases, which underscores the need for objective and continuous sensing approaches.

Commercial sensing technologies, such as camera-based motion capture systems (applied for tracking human motions visually), accelerometers (which measure changes in acceleration to monitor physical activity levels like steps), and inclinometers (used for monitoring human posture), have been widely applied to monitor loneliness or social isolation in older populations.[18–20] However, camera-based technologies often require extensive camera setups, making them not suitable for daily monitoring and raising privacy concerns. Additionally, the rigid nature of accelerometers and inclinometers impacts the flexibility and comfort of wearables, reducing acceptance among older users.[14,21] Furthermore, existing wearables often lack ergonomic design and fail to provide the comfort and fit required for long-term data collection.[22] Insights from focus groups and interviews, such as those reported by Freya et al.,[23] have highlighted comfort as a critical factor influencing the adoption of wearable technologies among older people. Building on this feedback, textile-based smart wearables integrated with microelectronics can offer a comfortable and effective solution for long-term monitoring.

Textile-based wearable technologies embed sensors and conductive materials into the fabric, enabling clothing to detect physiological markers associated with stress, emotional arousal, and overall mental health.[16,24,25] The integration of textile with sensing functionality is key to developing wearable solutions that are both effective and user-friendly.[26] The design must prioritize comfort, flexibility, and aesthetics, ensuring that older users are willing to wear the garments regularly. At the same time, the embedded sensors must be discreet and durable to withstand regular use and maintenance, while also providing accurate data collection.[27] Despite advances in smart textiles for health monitoring, there is currently no textile-based multimodal sensing system specifically developed for loneliness detection. There are individual studies that investigate the correlation between certain behavior or physiological parameter and loneliness in older people, but no cohesive system integrates multiple physiological and behavioral parameters within a single textile platform. Recent literature further confirms this research gap. A co-design study published in 2024 noted that no existing systems have applied smart textiles for the direct detection or systematic assessment of loneliness, identifying only one early-stage prototype using a textile band without loneliness-specific validation.[16,27] Additionally, a scoping review analyzed over 40 000 studies and found only 29 related to passive sensing for loneliness detection, none of which applied textile-based systems and all were based on a single behavioral or physiological indicator.[17] Furthermore, few studies address the integration and importance of user centered design in development of such garments to ensure comfort, wearability and user acceptance among older people. Current review studies on smart textile systems also solely focus on evaluating sensing systems performance for general health monitoring and lifestyle advice, without specifically focus on loneliness monitoring in older people.[22] Therefore, there is a critical technological gap that requires a comprehensive framework capable of integrating multiple physiological and behavioral signals through textile-based sensing systems to support loneliness detection in older people.

To address the research gap, this review aims to present the current state of smart textile technologies and propose a multi-parameter fusion monitoring framework for loneliness. Section 2 introduces the behavioral patterns and physiological symptoms associated with loneliness in older individuals, incorporating findings from our previous qualitative studies.[10] Since there are no sensing technologies have been specifically developed for loneliness detection, this section discusses existing wearable sensing technologies and smart textiles for monitoring symptoms that are directly related to loneliness. Section 3 focuses on textile-based sensing technologies, discussing various textile sensors, sensing materials, and fabrication methods for integration into smart wearable systems. Section 4 reviews the key developments in integrated textile monitoring systems, including wearable sensing interfaces, signal processing and analysis, and provides key design considerations for older people. Section 5 addresses challenges and future perspectives on potential innovations and research directions. Finally, Section 6 concludes the paper by summarizing the findings and emphasizing their implications for older people care.

2. Wearable Technologies for Loneliness Monitoring

Wearable sensing technology involves placing sensors directly on the body to collect data, which is crucial for accurately monitoring loneliness. In this section, we first explore the behavioral patterns and physiological symptoms associated with loneliness in older individuals and the existing wearable sensing technologies that have been applied to monitor these symptoms. Additionally, we examine the advancements in smart textiles, comparing smart textile systems with traditional wearable technologies.

2.1. Loneliness Indicators and Wearable Sensors

Loneliness is a common mental health issue among older individuals which significantly affect their psychiatric and

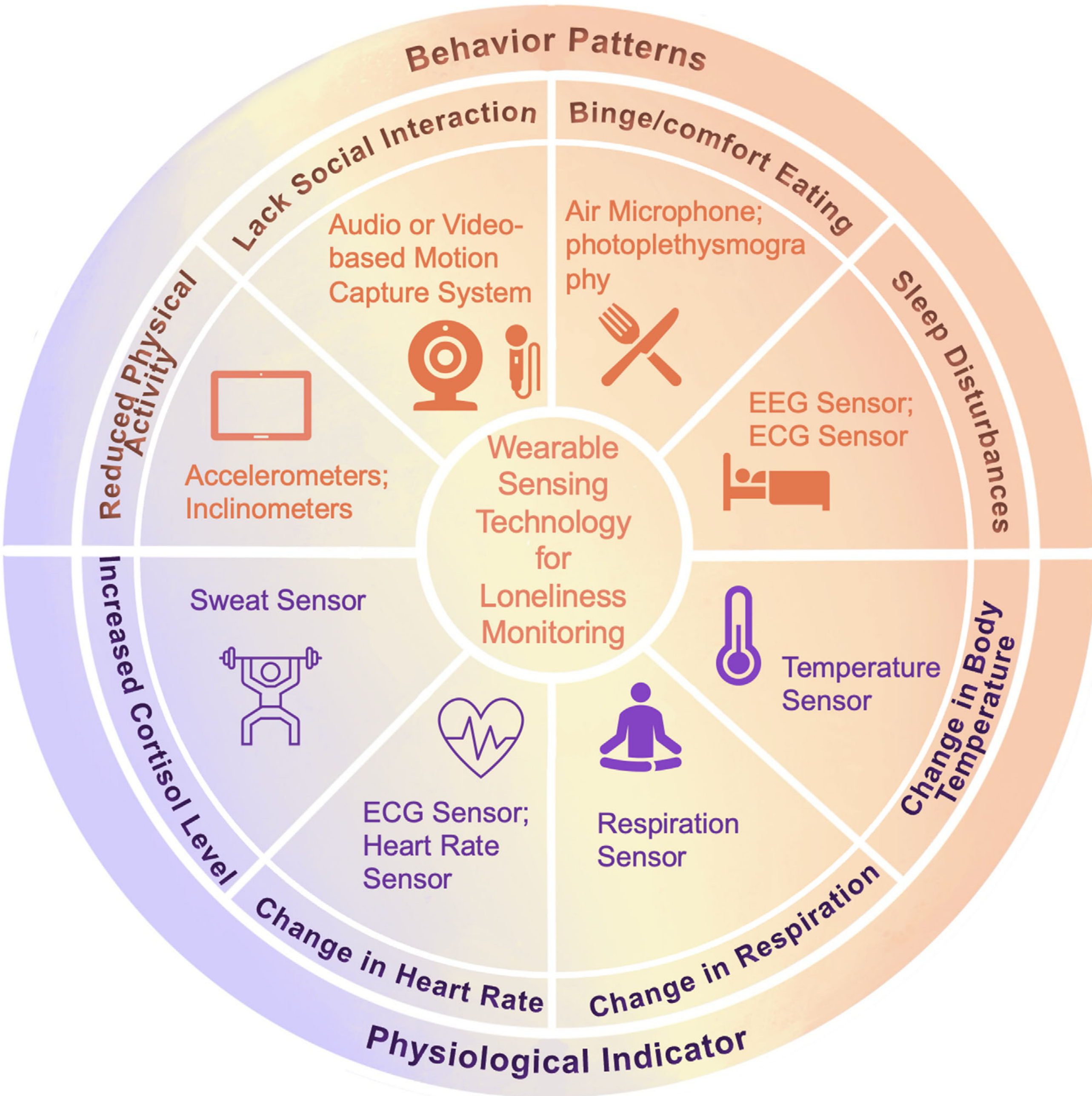


Figure 1. Overview of wearable technologies for monitoring behavioral and physiological indicators of loneliness in older people.

physiological well-being.[5,28,29] Loneliness in older people can be characterized by changes in behavioral patterns and physiological indicators, such as reduced physical activity,[5,30] sleep disturbances,[28] social isolation,[28,31] binge/comfort eating,[6] elevated blood pressure,[4] and increased average salivary cortisol levels.[15,32] Therefore, many existing studies have applied wearable sensors to monitor physical activities and physiological parameters to estimate loneliness levels in the older people. **Figure 1** is developed based on a comprehensive review of the literature and informed by findings from qualitative interviews conducted in our previous studies.[10,33]

One of the most prevalent correlation of loneliness in older people is reduction in their physical activities, which often involves lack of movement such as prolonged sitting or lying down.[30] Many published studies have used smartphones (including Global Positioning Systwem (GPS) locations) and wearable technologies including accelerometers or inclinometers to collect posture data from older people to monitor activity levels and subsequently estimate their loneliness levels.[17] For instance, Schrempft et al.[5] used wrist-worn accelerometers on 267 older people, with an average age of 66, and applied linear regression to analyze the association between social isolation,

ADVANCED ELECTRONIC MATERIALS Open Access
www.advelectronicmat.de

loneliness, and activity levels. They found that individuals who were socially isolated exhibited lower overall activity counts (p = 0.003) and spent more time in sedentary behavior (β = 0.143, p = 0.013), while engaging in less light, moderate and vigorous physical activity throughout the day. Similarly, Kalisch et al.[19] applied accelerometers and inclinometers on the waist and thigh to measure overall sedentary behavior in older people, finding that wearable accelerometers could accurately estimate daily total sedentary time.

Many older people often live alone with limited social networks. Social isolation or lack of social interactions is another key indicator of loneliness.[34,35] Most studies focusing on social interaction monitoring have employed audio-based systems, such as microphones to record daily conversations or video-based motion capture systems (cameras) to monitor mouth movements.[18,36] For example, a study by Petersen et al.[37] installed telephone monitoring devices in the homes of 26 independent older adults (mean age = 86) over an average period of 174 days, and found that higher loneliness scores were significantly associated with fewer total phone calls per day (IRR = 0.99, p < 0.05), particularly fewer incoming calls (IRR = 0.98, p < 0.01). However, the usage of these voice- and video-based detection methods raised privacy concerns not only to the wearer but also to surrounding personnel.[31] There are also issues regarding the portability of such systems which often require the wearer to carry cumbersome equipment that may interfere their ability to socialize and confound the results.[31] Therefore, some researchers have been exploring more discreet and portable wearable solutions. For example, Ejupi et al.[16] integrated resistive stretch sensors into wearable elastic bands to be worn on the chest and abdomen to assess social interaction by monitoring breathing patterns during normal speech and respiration.

Stress and anxiety are also common symptoms in older people suffering from loneliness.[12] These conditions can directly affect physiological systems such as the cardiovascular system and the respiratory system, leading to increased heart rate, faster and deeper breathing, along with decreased body temperature.[38,39] Therefore, various wearable sensors have been reported to assess these physiological responses through non-invasive monitoring systems. For example, Nath et al.[40] developed a wristband sensor that detects anxiety in older people by monitoring electrodermal activity (EDA) and photoplethysmography (PPG). Their study involved 41 older participants, and they trained multiple machine learning models to classify anxious and non-anxious states. The best-performing model, a Random Forest classifier, achieved an accuracy improvement of 3.37% (EDA) and 6.41% (PPG) when combining physiological signals with contextual information.

Also, in order to cope with emotions such as anxiety and sadness, older people may engage in binge/comfort eating.[10,41] Previous research has led to the development of dietary wearable monitoring system, which combines an air microphone and photoplethysmography sensors to monitor and record eating behaviors.[42,43] Chun's research group also proposed a discreet and lightweight dietary monitoring necklace, capable of tracking users' eating behavior by capturing head and jawbone movements.[44]

Moreover, sleep disturbances are often associated with loneliness in older people.[17] Many factors can contribute to the decline in sleep quality, particularly polypharmacy and presence of mental health or physical health disorders.[28] Various commercial wearable sleep monitoring devices have already been developed, which provide continuous and long-term sleep tracking. For instance, the Zeo device collects EEG and electromyogram (EMG) signals from the head to differentiate between different stages of sleep.[45] Other research studies have used smartphone sensors to monitor sleep patterns, with electrocardiogram (ECG) sensors placed on the chest to track total sleep time and sleep quality.[46,47] Additionally, some researchers have employed accelerometers integrated into smartphones and smartwatches to monitor body movements during various sleep stages and assess sleep quality.[20,48] For example, Benson et al.[28] applied smart watch as wrist actigraphy to monitor sleeping quality of older people. They analyzed objective sleep metrics such as wake after sleep onset(WASO), percent sleep, and total sleep time among older adults and investigated their associations with loneliness scores derived from the UCLA Loneliness Scale. Results showed that greater loneliness was significantly associated with more disrupted sleep, as reflected by increased WASO (β = 0.08, p = 0.02) and lower percent sleep (β = - 0.07, p = 0.03), even after adjusting for demographic covariates.

The existing care technologies for monitoring loneliness in older people care have been summarized in **Table 1**. Most human behavior technologies for monitoring loneliness rely on video and audio-based methods, raising concerns about privacy and portability in everyday use.[31] Wearable devices that rely on accelerometers and inclinometers are also widely used to track older people's behavioral patterns, but these rigid sensors often lack flexibility and comfort, making them less ideal for long-term use. Furthermore, most monitoring systems function independently and have yet to offer multimodal approaches to loneliness detection.[13,49] To address these challenges, the integration of sensing technology directly into textiles presents a promising solution. By developing smart textile wearables embedded with flexible sensors, it is possible to create a more comfortable, flexible, and unobtrusive monitoring system that can seamlessly track physiological and behavioral indicators of loneliness in older people. However, several key technical challenges remain unaddressed. First, existing systems lack robust multimodal data fusion methods that can integrate diverse sensor signals such as motion, respiration and heart rate to produce reliable loneliness indicators.[50] Also, there is limited validation of long-term stability, including durability under repeated washing, signal consistency over time, and usability in real-life settings. Addressing these issues is essential for the practical implementation of textile-based loneliness monitoring systems.

2.2. Existing Smart Textile Wearable Applications

Textiles and clothing are ubiquitous in everyday human life. With advancements in textile and electronic engineering, smart textiles have become a new area of research, receiving extensive attention. Smart textiles can easily interact with the human body, allowing for the monitoring of various physiological data, such as humidity,[52] body temperature,[53] pulse rate,[24] and movement.[26,54] Due to their softness, breathability, and biocompatibility, smart textiles are suitable for long-term monitoring and provide a comfortable experience to the users.[55] In addition,

Table 1. Reported sensing technologies for monitoring loneliness in older people.

Detection categories	Parameter obtained	Sensor	Position	Refs.	Advantages	Disadvantages
Behaviour patterns	Detection of activity levels	Accelerometers	Wrist	[5]	Low cost; privacy protection	Lack flexibility
	Detection of sedentary behavior	Accelerometers; inclinometers	Waist; thigh	[19]	Low cost and easy to apply	Discomfort during long-term use
	Detection of talking	Video camera	NA	[18]	Extract valuable user information	Privacy concerns
	Detection of talking	Microphone	Home setting	[36]	Extract valuable user information	Privacy concerns
	Detection of eating	Inertial, optical and acoustic sensor	Head	[42]	Easy to apply	System stability is unclear
	Detection of eating	Air microphone and PPG sensor	Ear	[43]	Accurate detection	Privacy concerns
	Detection of sleeping	EEG sensor and EMG sensor	Head	[45]	Easy to apply; Privacy	May cause discomfort during long-term wear
	Detection of sleeping	EEG sensor	Chest	[46]	Easy to apply; Privacy	May cause discomfort during long-term wear
	Detection of activity levels	Smartphones (including GPS locations)	NA	[17]	Portable and easy to apply	Privacy concerns
	Detection of individual behavior	In-home sensors (motion and contact sensors)	Home setting	[51]	Extract valuable user information	Privacy concerns
Physiological indicators	Detection of anxiety	EDA and PPG sensor	Wrist	[40]	Easy to apply	System stability is unclear
	Detection of resting heart rate	ECG sensor	Chest	[38]	Accurate detection	Not portable
	Detection of respiration	Resistive stretch sensor	Chest; abdomen	[16]	Flexible and easy to integrate	System stability is unclear
	Detection of stress level	Sweat sensor	NA	[15]	Portable and easy to apply	Lack durability
	Detection of body temperature	Temperature sensor	NA	[39]	Accurate detection	Lack flexibility

connectors, actuators and power sources can also be integrated into wearable devices through various textile technologies, forming a complete smart sensing wearable system.[56]

With the development of smart textiles and wearable electronics platforms, smart textile system has gained significant attention in both academic and industrial settings. Smart textile wearable integrates multiple sensors, combining advanced nanomaterials with textile technologies, often maintaining the appearance of regular garments. This provides a non-invasive, comfortable, and reliable monitoring solution, distinguishing it from traditional wearable technologies.[22]

As discussed in Section 2.1, loneliness in older people can be identified through changes in behavioral patterns and physiological indicators. Smart textile wearable, capable of integrating various sensors with different functionalities, has already been widely applied in multiple health monitoring fields (**Figure 2**). For example, Huang et al.[57] developed smart ECG clothing by preparing flexible nanofiber carbon membrane electrodes through electrospinning, which can monitor ECG and EMG signals. Mo et al.[58] used electrochemical textile sensors, produced via electro-assisted core-spun yarn technology, sew into clothing and enabling the analysis of health conditions through sweat monitoring. Furthermore, commercially available smart monitoring garments have been developed to capture biological signals, equipped with typical software systems that analyze the physiological information and health status of the user. For instance, Hexoskin smart clothing integrates sensors into textiles which able to offer comprehensive monitoring of cardiac, respiratory, sleep, and activity conditions. Their product can provide real-time insights into the user's physiological states.[59] Although Hexoskin has not yet been directly validated for loneliness detection, recent studies have demonstrated its capability in detecting physiological markers of emotional stress. In one study involving individuals with autism spectrum disorder (ASD), Hexoskin was used to collect physiological signals such as heart rate and heart rate variability during emotional stimulus exposure and throughout daily life.[60] The collected data were then processed using a Long Short-Term Memory algorithm to predict behaviors associated with stress. The system demonstrated the ability to detect stress-related changes with 70% predictive accuracy based on heart rate signal analysis. This approach highlights the potential of wearable physiological monitoring systems to detect stress related behavioral changes, which are also highly relevant in the context of loneliness. Another example is the LifeShirt system, which enables wireless patient monitoring in medical environments. Originally developed for clinical applications such as post-operative monitoring and high-risk medical environments, LifeShirt has demonstrated the ability to accurately record vital signs, including respiration rate, ECG and posture over extended periods. In early validation studies, the system achieved high correlation coefficients ($r = 0.95$) with gold-standard reference systems for respiratory and cardiac measures, indicating high measurement reliability.[61] Advances in smart clothing technology have also introduced haptic feedback mechanisms, allowing wearable devices to provide tactile responses to users. This integration can create intuitive user interfaces which enhance both functionality and user engagement in health monitoring applications.[62]

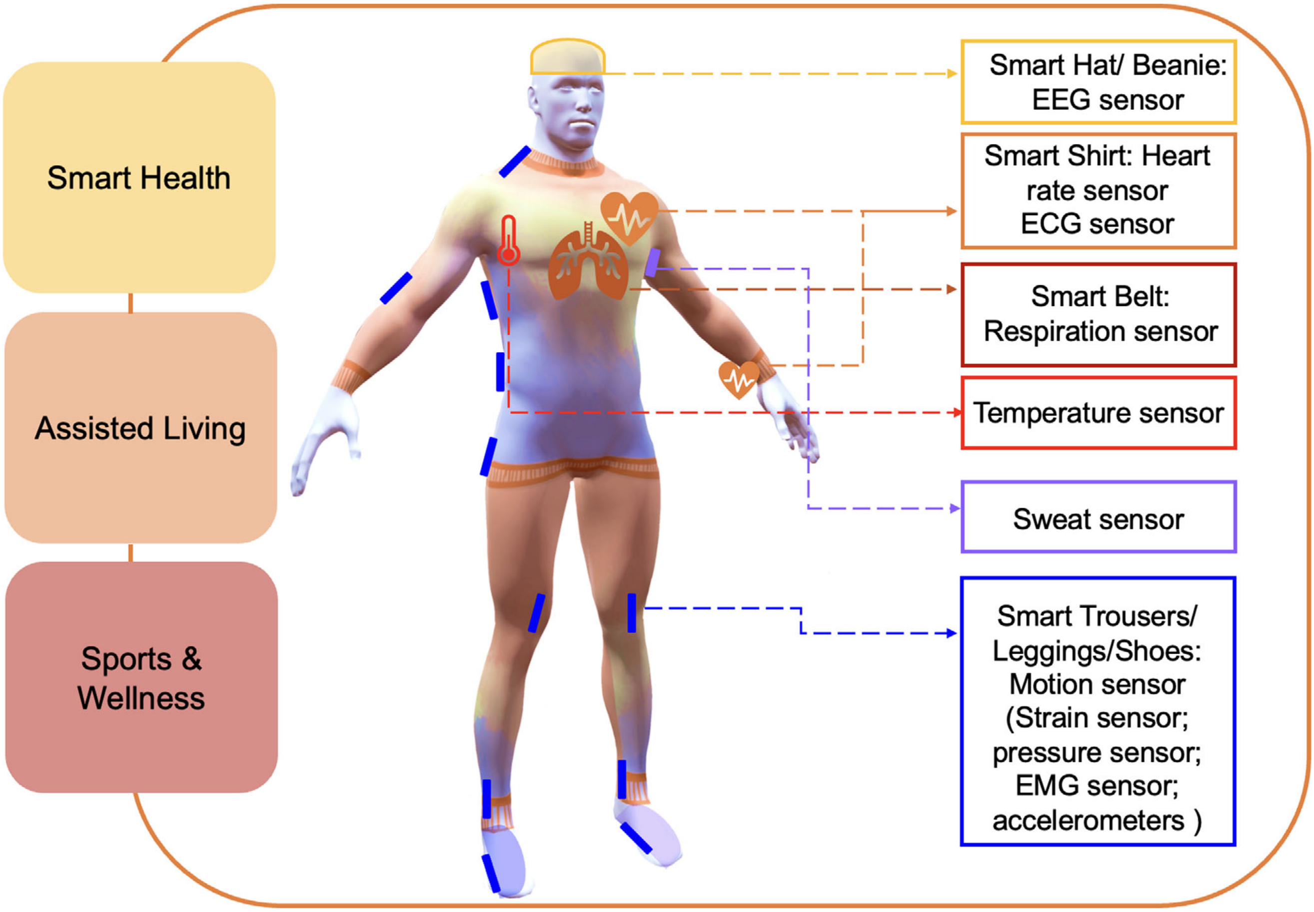


Figure 2. Smart textile wearables that integrates various sensors with different functions for health monitoring.

In the context of loneliness monitoring for older people, textile-based sensors have become an ideal solution compared to traditional wearable monitoring technologies due to their being lightweight, flexible, and comfortable. For instance, the Lilypad platform integrates accelerometers that can be easily sewn into garments to identify user behavioral patterns.[63] Textile strain sensor-based goniometers have also been widely applied to knee flexion monitoring in various activities, aiding in the identification of different activities.[26,64] These studies suggest that smart textile sensors can be well integrated into clothing and provide higher levels of comfort for the wearer.

Although numerous studies demonstrate the capabilities of smart textile systems for physiological and activity monitoring, few have directly explored its application in loneliness monitoring for older people (**Table 2**). The development of smart textile wearables for older people care must account for the specific

Table 2. Examples of the existing smart textile wearables applied in different health monitoring fields.

Categories	Technology	Sensor	Parameter obtained	Refs.
Smart health	Smart mask	Textile humidity sensor	Breathing rate	[52]
	Sensing knee/elbow sleeve; sensing glove	Textile strain sensor	Human motion	[54]
	Sensing shirt	Textile antenna	Respiration	[65]
	Sensory baby vest	ECG, moisture and Temperature sensor	Heart rate; temperature; humidity and sweat	[53]
Assisted living	Sensing knee sleeve	Textile strain sensor	Human motion	[26]
	Sensing elbow sleeve	Textile strain sensor	Human motion	[64]
	Sensing Vest	ECG and EMG sensor	ECG and EMG signals	[57]
Sports and wellness	2M Smart Clothing	Pressure sensor; accelerator	Breathing rate; human motion	[62]
	Hexoskin smart garment	ECG sensor; plethysmography sensor	ECG; heart rate	[59]
	Lifeshirt	Strain sensor; ECG sensor and accelerator	Respiration; ECG; activity and posture	[61]
	Sensing vest	Textile sweat sensor	K+ signals in human sweat	[58]

Table 3. Textile-based sensors with different sensing element for measuring different behavioral indicators.

Sensor type	Sensing material	Parameter obtained	Performance	Relevance to loneliness monitoring	Refs.
Textile capacitive sensor	Nickel metal	Human motions	High elasticity and excellent capacitance characteristics under different compression frequencies and strains	Identifies reduced physical activity, a behavioral sign of social withdrawal	[71]
Textile capacitive sensor	Graphene	Human motion and muscle activation	Sensitivity of 0.0136 kPa^{-1} (under 75 kPa) and 0.0063 kPa^{-1} (above 75 kPa)	Tracks subtle movement changes linking to inactivity or isolation	[72]
Textile capacitive sensor	MXene	Human motions	High sensitivity of 1.11 under 100% sensing range, 13.02 kPa^{-1} under pressure of 200 kPa	Detects activity levels to identify sedentary behavior	[73]
Textile capacitive sensor	Silver	Knee joint motion	Fast response time and high linearity	Track joint movement frequency, which can reveal changes in physical activity patterns	[66]
Textile capacitive sensor	PEDOT:PSS	Human activity level; body posture	$\Delta C/C = 1.37$ pF under average foot pressure	Evaluates activity and posture changes, which can correlate with social withdrawal	[76]
Textile piezoresistive sensor	Silver	Human motions	GF = 2.31, 70% sensing range	Captures physical inactivity, a behavioral symptom of loneliness	[91]
Textile piezoresistive sensor	CNTs	Human joint movement	Fast response, large sensing range (~100%)	Detects reduced movement frequency, linked to emotional and social isolation	[92]
Textile piezoresistive sensor	Carbon black	Body posture	High sensitivity of 1.25k/mm	Identifies sedentary behavior or posture changes	[93]

needs and personalized characteristics of older people. Therefore, understanding the practical usability and reliability of smart textile systems for loneliness monitoring in older people care is crucial.

3. Textile-based Sensing Technologies for Loneliness Monitoring

Although various wearable devices have been reported to monitor loneliness in older people, few previous reviews have directly investigated the development and application of textile-based sensing technologies for this purpose. Textile sensors offer advantages in terms of comfort, flexibility, and integration into daily life, making them highly suitable for long-term monitoring in older people care. As discussed earlier, loneliness in older people is mainly characterized by changes in behavioral patterns and physiological indicators. Therefore, this section examines the critical aspects of textile-based sensing technologies for loneliness-related behavioral and physiological monitoring. It explores different types of textile sensors, the selection of sensing materials and fabrication process, and the role of textile substrates in enabling seamless integration into wearable systems.

3.1. Textile Sensors for Behavioral Monitoring

Textile-based sensors have been integrated with wearable technologies and played a prominent role in human behavior monitoring. Various types of textile-based sensors have been developed for tracking human motion, with capacitive and piezoresistive sensors being the most widely applied (**Table 3**).[66]

3.1.1. Textile Capacitive Sensors

Textile-based capacitive sensors are often applied in pressure and tactile sensing, and operate on the principle of capacitance changes caused by variations in physical contact or deformation.[67] These sensors typically consist of two electrodes separated by a dielectric layer. External pressure causes deformation in the dielectric layer which in return affects its thickness and the effective surface area of the electrodes, leading to changes in capacitance.[68] This mechanism enables the detection of sensor deformation by the human body, such as joint bending, twisting or shifting any postures. Through this detection mechanism, capacitive sensors are thus especially suitable for monitoring behavioral patterns. In the care of older people, where prolonged sedentary behavior or reduced physical activity can indicate loneliness or social isolation, capacitive sensors offer a potential solution for continuous monitoring of these indicators.

Many studies have currently fabricated textile-based capacitive sensors through embedding conductive fiber into the fabric structures or coating the fabric surface with conductive materials.[69] This integration ensures the sensors remain lightweight, flexible, and comfortable for long-term use, allowing them to be easily integrated into everyday clothing. Common materials used for flexible textile-based capacitive sensors include metals, carbon-based materials, and conductive polymers.[69,70] Metallic materials are widely applied due to their excellent conductivity and ductility, but their rigidity can limit their application in wearable devices.[71] Carbon-based materials offer advantages such as high electrical conductivity, large active surface areas, and high electrochemical activity, but their fabrication pro-

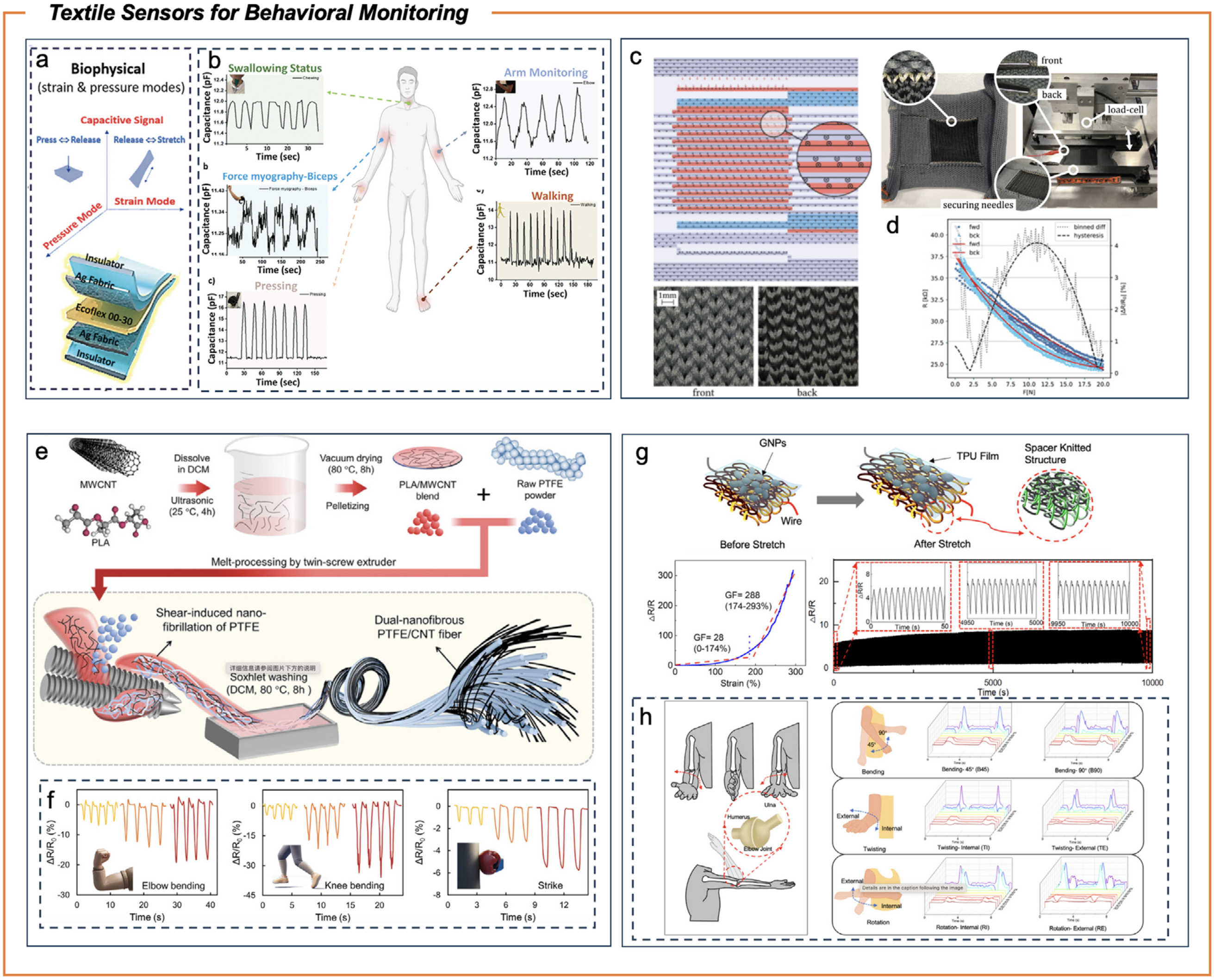


Figure 3. Examples of textile-based sensors for behavioral monitoring. a) Embedding conductive knitted fabric in polymeric composite dielectric layers to fabricate strain and pressure sensor. b) Multimodal sensor for human motion monitoring. Reproduced with permission.[74] Copyright 2024, John Wiley and Sons. c) Knitting conductive yarns into fabrics to fabricate textile strain sensors. d) The knitted sensor can achieve effective detection of both strain and pressure. Reproduced with permission.[85] Copyright 2024, IEEE. e) Using in situ fibrillation method to developing textile strain sensors for real-time human motion monitoring. f) Textile sensor can monitor various human motions, including elbow bending, knee bending, and striking. Reproduced with permission.[86] Copyright 2024, John Wiley and Sons. g) Developing a knitted strain sensor based on TPU and graphene. h) The knitted sensor can be integrated into a knee and elbow sleeves, enabling monitoring of interactive postures. Reproduced with permission.[26] Copyright 2024, John Wiley and Sons.

cesses are often complex and costly.[72] Additionally, conductive polymers have attracted the attention of researchers due to their superior flexibility, but challenges remain in improving their stability, conductivity, and manufacturing capability for practical applications.[73]

Textile-based capacitive sensors have been applied in various monitoring systems to detect posture, activity transitions, and capture subtle physiological signals linked to behavioral patterns. For instance, Tchantchane et al.[74] proposed the development of a capacitive textile sensor for monitoring body movements, using conductive knitted fabric embedded in a polymeric composite dielectric layer (**Figure 3a**). Their sensor operates in both pressure mode and strain mode, allowing it to detect applied pressure and fabric deformation due to body movements (Figure 3b). Similarly, Yang et al.[75] developed capacitive textile sensors using silver-plated fabric and foam pads for detecting thoracic and abdominal respiration, parameters directly linked to emotional states and stress. Some studies have demonstrated innovative fabrication techniques for integrating conductive fibers into textile substrates. Takamatsu et al.[76] designed a large-scale capacitive fabric pressure sensor for monitoring human positioning on the floor. This sensor consisted of two layers of fabric woven with conductive polymer-coated fibers, with capacitance changes measured between the top and bottom electrodes under applied pressure.

Flexible capacitive pressure sensors can be fabricated through knitting or weaving techniques to retain the original textile structure, offering improved adaptability to 3D body surfaces. This flexibility makes them ideal for integration into wearable electronics, providing enhanced comfort and seamless functionality. However, compared to other sensing technologies such as piezoelectric or resistive sensors, capacitive textile sensors often demonstrate lower sensitivity and are more susceptible to motion artifacts in dynamic conditions. For example, in a comparative study, a capacitive sensor-based on carbon nanotube-embedded compliant electrodes, exhibited a sensitivity of 0.44, whereas the corresponding resistive sensor achieved a higher sensitivity of 1.16.[77] While the capacitive sensor demonstrated better linearity and repeatability over prolonged use, its signal anti-inference capability, and response to mechanical deformation were inferior under complex motions, highlighting practical limitations for real-time human motion monitoring. Furthermore, capacitive sensors tend to show performance degradation after repeated mechanical deformation and washing cycles. While some studies report less than 10% capacitance loss after 3–5 washing cycles, others indicate instability in capacitance baseline due to moisture absorption and dielectric layer deformation.[78–80] Moreover, most capacitive sensors require complex measurement equipment and often lack performance validation under long-term usage scenarios. These limitations need to be addressed to enable practical and effective use in real-world scenarios, particularly for monitoring loneliness in older people.[81]

3.1.2. Textile Piezoresistive Sensors

Textile piezoresistive sensors detect changes in electrical resistance within conductive structures when subjected to strain or pressure. When strain/pressure is applied, the geometry of the conductive network within textiles changes, leading to alterations in the conductive pathways and the resistance.[82] The conductive structures are typically fabricated by incorporating conductive materials such as metallic or carbon-based materials into yarns or fabric surfaces.[83] For instance, the textile research lab of Thuringia–Vogtland successfully developed conductive threads by coating Nylon 66 with silver, which were seamlessly integrated into fabrics to create wearable strain sensors.[84] Similarly, companies like Elektrisola Feindraht AG in Switzerland produce metal monofilaments, including copper, aluminum, and silver, which can be blended into yarns and directly woven or knitted into fabrics to fabricate strain sensors.[84] Aigner et al.[85] used a Dubied knitting machine to knit various metal and carbon-based yarns into textile strain sensors, achieving effective detection of both strain and pressure with improved sensitivity and consistency. (Figure 3c,d). While metallic materials offer significant benefits, such as high electrical conductivity and excellent integration flexibility, their cost particularly for precious metals like gold and silver poses a challenge for large-scale production.

In recent years, many carbon-based materials such as carbon black, carbon nanotubes (CNTs) and graphene, have been widely applied in manufacturing wearable sensors due to their excellent chemical stability and cost-effectiveness. For instance, Chai et al.[86] applied a novel continuous in situ fibrillation method to integrate CNTs into woven fabric, developing textile strain sensors for real-time human motion monitoring (Figure 3e). The CNT coating not only improved the fabric's mechanical properties but also imparted excellent electrical conductivity. Their proposed sensor demonstrates fast response times and outstanding stability, making it effective in monitoring a variety of human motions, including elbow bending, knee bending, and striking (Figure 3f). Zhou et al.[26] developed a knitted strain sensor based on thermoplastic polyurethane (TPU) and graphene, which can measure large body motions with high sensitivity and durability (Figure 3g). Their sensor can be easily integrated into a knee and elbow sleeve, enabling precise monitoring of interactive postures (Figure 3h).

For loneliness monitoring, piezoresistive textile sensors can play a critical role in monitoring physical parameters associated with behavioral patterns. These sensors can detect a broad range of human motions, from large-scale human activities to subtle motor signals.[54,87] Beyond motion monitoring, piezoresistive textile sensors have been extensively applied in capturing subtle physiological signals, such as respiration and heartbeats. Zhou et al.[54] created a piezoresistive textile strain sensor based on graphene nanoplatelets (GNPs) to monitor abdominal respiration and carotid pulse waves. Since loneliness has been linked to altered physical activity patterns, irregular breathing, and elevated HRV, integrating piezoresistive sensors into smart clothing provides an opportunity to continuously monitor these indicators.[88–90] The data obtained can offer valuable insights into behavioral and physiological changes, enabling early detection of loneliness and timely interventions in older people care.

3.2. Textile Sensors for Physiological Monitoring

With advancements in material science, numerous textile-based sensors have been developed to gather health data by analyzing physiological parameters such as electrical signals, mechanical signals, chemical signals from sweat, and body temperature (**Table 4**).

3.2.1. Textile Electrodes

Textile electrodes can conduct electrical currents while maintaining the inherent flexibility and comfort of textiles, therefore have be integrated into garments or accessories for monitoring physiological signals such as ECG and EMG.[94] These electrodes can be embedded into clothing using techniques like weaving, knitting, felting, or embroidery. Alternatively, they can be fabricated by applying conductive coatings directly onto fabrics or garments, ensuring optimal skin contact for signal acquisition.[95,96]

The most common application of textile electrodes is ECG monitoring, which measures the electrical activity of the heart through the skin surface. Each heartbeat generates ionic movement across the myocardium, creating an electrical gradient.[97] Textile ECG monitoring systems typically consist of multiple textile electrodes to capture comprehensive cardiac signals.[98] For example, Li et al.[99] developed a textile-integrated multi-electrode system using a spray-coated liquid metal nanoparticles suspension, which demonstrates high sensitivity and accuracy in detecting various ECG features (**Figure 4a**). Their results demonstrate comparable performance to commercial wet electrodes while improving comfort and wearability (Figure 4b). Silva et al.[100] applied stainless steel yarns in various knitted structures to fabricate textile electrodes, which were further integrated

Table 4. Textile-based sensors with different sensing element for physiological monitoring.

Sensor type	Sensing material	Parameter obtained	Performance	Relevance to loneliness monitoring	Refs.
Textile electrodes	Sliver/carbon	ECG signals	Able to measure ECG on the waist and able to detect R-peaks from noisy data	Detects HRV, a physiological marker for stress and emotional states	[145]
Textile electrodes	Sliver	ECG signals	Measured well-defined QRS signals with electrodes producing a better signal in wet conditions	Tracks irregular heart rhythms linking to emotional stress or social isolation	[100]
Textile electrodes	Single-walled Carbon nanotube and sliver nanowire	ECG signals	Low resistance ($\sim 10\ \Omega\ cm^{-1}$) and showing similar ECG morphology comparing to traditional electrodes	Monitors stress-related changes in heart activity	[101]
Textile electrodes	Poly-3,4- ethylenedioxythiophene/Poly (styrene sulfonate)	EMG signals	High similarity in noise amplitude, electrode-skin impedance and EMG morphology comparing to conventional electrodes	Provides insights into muscle fatigue or stress levels	[146]
Textile electrodes	Silver/carbon	EMG signals	Comparable performance to Ag/AgCl electrodes	Tracks variations in muscle activity caused by emotional states	[107]
Textile optoelectronic sensor	FBG/Silicone rubber	Respiratory rate and heart rate	Able to measure respiratory rate and heart rate with similar results to commercial devices	Monitors changes in breathing and heart patterns associated with stress or loneliness	[114]
Textile optoelectronic sensor	FBG	Respiratory rate	Can measure inspiratory and expiratory phases with similar results to optoelectronic plethysmography system	Captures irregular breathing patterns that correlate with emotional distress	[147]
Textile optoelectronic sensor	FBG/fibre-optic interferometer	Respiratory rate and heart rate	Comparable results to conventional methods with higher accuracy in interferometric sensor (RR: FOI 95.66% and FBG 95.53%; HR: FOI 96.22% and FBG 95.23%)	Tracks subtle physiological signals like heart rate and breathing irregularities	[116]
Textile thermoelectric sensor	Titanium/gold and polyimide	Temperature	Thermal time constants under 10 s, sensitivity at $2.5 \times 10^{-4}\ °C^{-1}$, $3.6 \times 10^{-4}\ °C^{-1}$, and $7 \times 10^{-5}\ °C^{-1}$	Tracks changes in skin temperature linked to emotional arousal	[123]
Textile thermoelectric sensor	Silver/polyimide	Temperature	Sensitivity at $2.23 \times 10^{-3}\ °C^{-1}$	Measures temperature variations indicative of emotional or physiological stress	[148]
Textile thermoelectric sensor	Copper/liquid crystal polymer	Temperature	Accuracy of $\pm$ 0.5 °C for 63% of measurements	Monitors temperature fluctuations	[149]
Textile thermoelectric sensor	rGO/CNTs and PBT	Temperature	Sensitivity of -0.737% $°C^{-1}$ and resolution of 0.1 °C between 25 °C and 45 °C	Measures temperature variations	[126]
Textile thermoelectric sensor	Reduced graphene oxide/polyurethane	Temperature	Accuracy of $\pm$ 0.37 °C; resolution of 0.1 °C	Monitors temperature patterns associated with stress	[128]
Textile electrochemical sensor	Bromocresol green and methyl orange	Sweat pH and lactate	Able to estimate the sweat pH (1-14) and the lactate level (0-25 mM)	Tracks stress-induced changes in biochemical markers	[150]
Textile electrochemical sensor	Enzyme/graphite	Glucose, lactate, ascorbic acid, uric acid, Na^+, and K^+ in sweat	High sensitivity, good selectivity, and long-term stability	Measure stress-induced changes in biochemical markers	[136]
Textile electrochemical sensor	Glucose/silver	Glucose in sweat	High sensitivity (18.41 $\mu A\ mM^{-1}\ cm^{-2}$, R^2 = 0.996)	Monitors glucose fluctuations linked to stress and energy metabolism under loneliness	[137]
Textile electrochemical sensor	Iron oxide/carbon	Cortisol in sweat	Good linearity ($R^2 = 0.998$) under wide range (1 fg - 1 µg)	Measures cortisol levels to assess psychosocial stress and loneliness	[138]

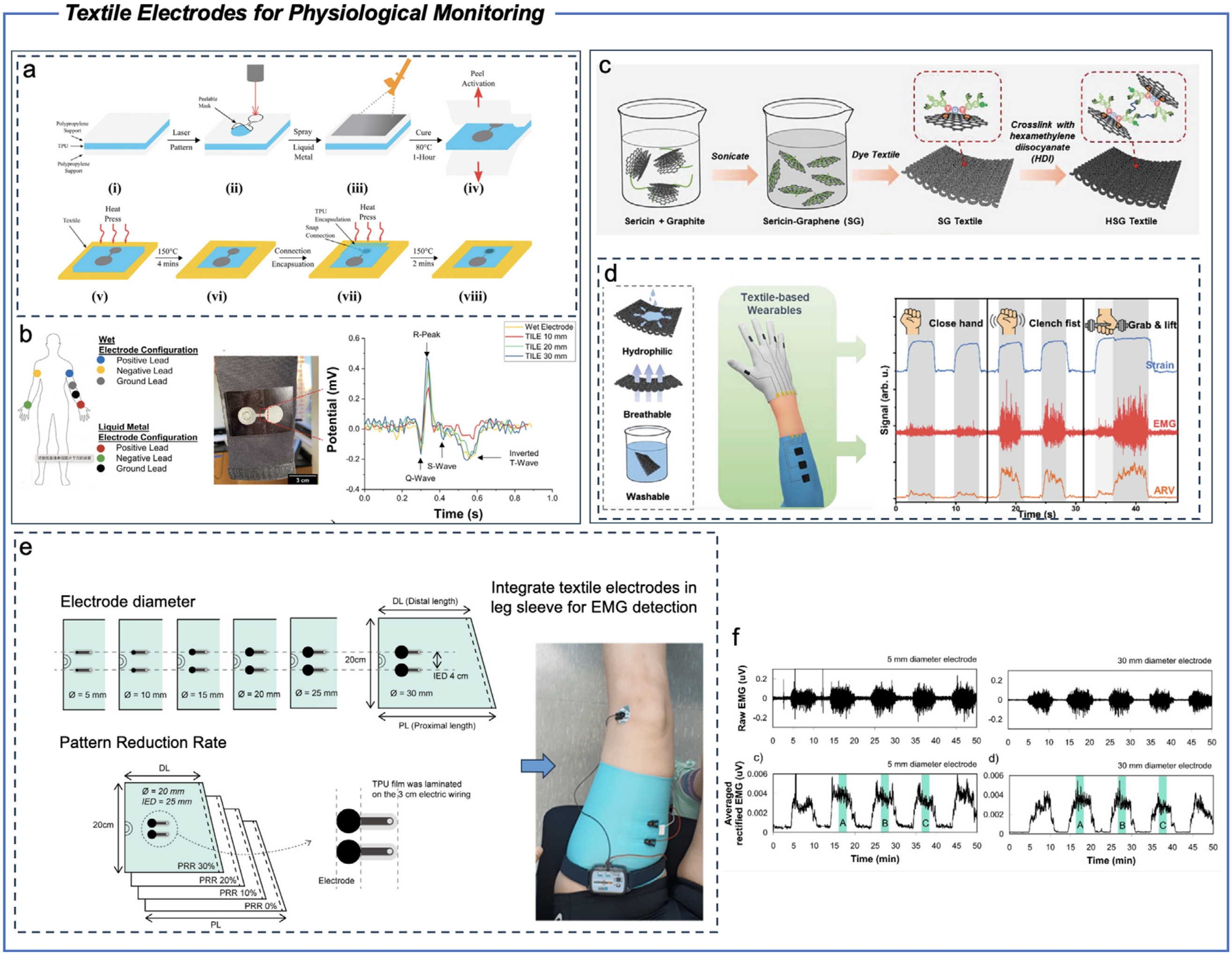


Figure 4. Textile electrodes for physiological monitoring. a) Spray-coating textile using liquid metal nanoparticles suspension to develop a multi-electrode system. b) Textile-integrated system for detecting various ECG features. Reproduced with permission.[99] Copyright 2022, John Wiley and Sons. c) Developing textile electrodes by dyeing commercial textiles with an aqueous graphene ink stabilized by silk sericin. d) Integrating sensor into wearables for hand gesture monitoring. Reproduced with permission.[106] Copyright 2022, John Wiley and Sons. e) Coating textiles with silver and carbon paste to produce EMG electrodes f) Textile electrodes system for analyzing muscle activation. Reproduced with permission.[107] Copyright 2020, MDPI.

into swimwear and successfully detected ECG signals underwater. In addition to metallic yarns, carbon-based materials such as CNTs, carbon nanofibers, and graphite coatings have also been employed in the development of textile electrodes. For instance, Lee et al.[101] fabricated textile electrodes using a single-walled carbon nanotube/silver nanowire-treated polyurethane nanoweb and validated their performance against conventional silver chloride electrodes. Their textile electrodes demonstrated comparable ECG monitoring capabilities during human testing. Furthermore, some studies have highlighted that the yarn materials and textile structures may affect the performance of textile electrodes. Beckmann et al.[102] evaluated eight different knitted and woven structures and found that woven structures can improve the contact impedance of textile electrodes. Despite these advancements, there are still significant challenges in translating textile electrodes into commercial ECG monitoring systems. Challenges such as poor electrical contact between electrodes and the skin and the degradation of electrodes' electrical properties during washing or prolonged wear remain largely unresolved.[96] Further efforts are required to improve textile structures and conductive coatings and advance the development of reliable textile-based ECG monitoring systems.

Textile electrodes have been extensively applied in EMG monitoring to record the electrical activity of muscles during contraction and relaxation cycles, facilitating the analysis of muscle fatigue or stress levels.[103,104] Similar to ECG textile electrodes, EMG textile electrodes often require multiple units to comprehensively monitor muscle activity. For instance, Taelman et al.[105] embroidered conductive yarn into a shirt to work as EMG electrodes for muscle stress analysis, providing users with insights into muscle activity and stress states. Additionally, EMG electrode can also be fabricated through conductive coating and screen-printings. Liang et al.[106] developed textile electrodes by dyeing commercial textiles with an aqueous graphene ink stabilized by silk sericin (Figure 4c). Their work demonstrated high conductivity and biocompatibility, enabling reliable collection of both mechanical and myoelectrical signals, which makes them suitable to be integrated into wearables for hand gesture monitoring (Figure 4d). Research has also indicated that the pressure exerted by garments integrated with textile electrodes significantly affects their performance. Kim et al.[107] fabricated circular bipolar EMG electrodes on leg sleeves using carbon and silver pastes and tested various garment pressures (Figure 4e,f). Their findings suggested that a minimum pressure of 10 mmHg is necessary for textile electrodes to achieve performance comparable to commercial electrodes.

In the context of loneliness monitoring, textile electrodes have shown significant potential in monitoring physiological parameters associated with emotional and psychological states, such as HRV and other ECG-derived measures. These metrics are key indicators of stress, emotional arousal, and mental health.[108] For example, irregular heart patterns or reduced HRV can indicate emotional distress or social withdrawal, enabling early detection of loneliness-related conditions. Recent clinical evidence further supports the relationship between HRV and loneliness. In a controlled study involving 316 healthy women aged 18–28, chronic loneliness was found to significantly predict lower resting heart rate variability (HRV), even after controlling for age, BMI, respiration, depression, anxiety, and perceived stress.[109] Specifically, higher levels of chronic loneliness were associated with significantly reduced parasympathetic activity, as indicated by lower high-frequency HRV ($\beta = -0.15$, $p = 0.006$). This blunted autonomic response is considered a risk factor for cardiovascular disease and emotional dysregulation. The study protocol was approved by the local ethics board, further highlighting the clinical validity and reliability of these findings.

3.2.2. Textile Optoelectronic Sensors

Optoelectronic sensors mainly rely on light-based mechanisms to detect physiological signals by analyzing changes in light absorption, reflection, or transmittance after being in contact with the human body. These changes are often caused by variations in blood flow, tissue properties, or mechanical deformation.[110] Typically, optoelectronic sensors consist of a light source, a photodetector, and an optical fiber. The light source emits a beam of light that interacts with the target area, while the photodetector captures the modulated light signals after they have passed through, reflected, or scattered from the tissue.[111] This setup allows precise detection of physiological parameters such as blood oxygen saturation, heart rate, and breathing rate, which are critical for assessing emotional states and stress levels.[110,112,113]

In wearable applications, optical fibers, such as Fiber Bragg Grating (FBG) filaments can be integrated into textiles using techniques such as weaving, stitching, and adhesive coatings to create sensors that maintain flexibility and comfort. For instance, Lo Presti et al.[114] developed an FBG sensor encapsulated in Dragon Skin silicone rubber, which was then stitched into an elastic chest band for simultaneously monitoring of respiration and heart rate. They also investigated the effects of environmental conditions (temperature, humidity, and washing) on the sensor, confirming its capability for physiological monitoring in real-world applications. Due to their immunity to electromagnetic interference, optoelectronic sensors have been explored for clinical medical monitoring. Filosa et al.[115] developed a respiration monitoring system using a wearable chest device embedded with FBG sensors and an inertial unit (**Figure 5**a). Applying long–short term memory based network, their proposed sensor system can accurately measure and predict respiratory flow, achieving a high correlation coefficient (r = 0.9) and low root mean square error even under dynamic conditions (Figure 5b). Similarly, Nedoma et al.[116] created an FBG textile sensor encapsulated in biocompatible polydimethylsiloxane (PDMS), which could be stitched onto elastic bands for monitoring ballistocardiography (BCG) signals, respiration, and heart rate under MRI (Figure 5c,d). Additionally, textile optoelectronic sensors based on thermoplastic silicon fibers have been reported. Due to their high flexibility and low stiffness, these sensors can be easily stitched into clothing for breathing monitoring under various application conditions (Figure 5e,f).[117] Beyond physiological monitoring, textile optoelectronic sensors are widely used for monitoring human joint flexion and posture. For example, Stupar et al.[118] integrated optical fiber sensors into knee sleeves to estimate knee flexion, and Li et al.[119] developed a smart elbow sleeve based on optical fiber sensors to assist physical therapists in assessing patients' performance by monitoring elbow and wrist joint angles.

The multifunctionality of textile optoelectronic sensors extends to their application in monitoring subtle physiological signals that are directly linked to loneliness and emotional distress. Signals such as HRV, oxygen saturation, and breathing provide valuable insights into an individual's emotional state and overall well-being.[120] These parameters are essential for detecting early signs of loneliness, which often manifest through elevated stress levels or changes in physiological patterns. For example, a comparative study on older participants demonstrated that improvements in oxygen saturation (from 96.4% $\pm$ 1.39 to 97.05% $\pm$ 1.19) and reduced breath rate (from ≈21 to ≈19 breaths per minute) were significantly associated with reductions in stress and depression levels after a three-month relaxation and breathing intervention.[50] These findings support the potential role of oxygen saturation and respiratory parameters as quantifiable markers for emotional state monitoring, particularly in older adults at risk of loneliness. However, the application of optoelectronic sensors in wearable systems faces several challenges. The brittleness and limited strain resistance of optical fibers are prone to durability issues, particularly under physical forces or repeated movements.[121] Furthermore, optoelectronic sensors face challenges in ensuring accurate signal capture under dynamic conditions, such as daylight interference when walking and other activities, and. Addressing these limitations through innovations in fiber materials and real-time noise reduction algorithms could enhance the feasibility of using optoelectronic sensors in long-term health monitoring applications for older people.

3.2.3. Textile Thermoelectric Sensors

Thermoelectric sensors are designed to monitor temperature variations. These sensors typically operate based on the principle of the Seebeck effect, where a temperature gradient across thermoelectric materials induces a voltage, enabling the

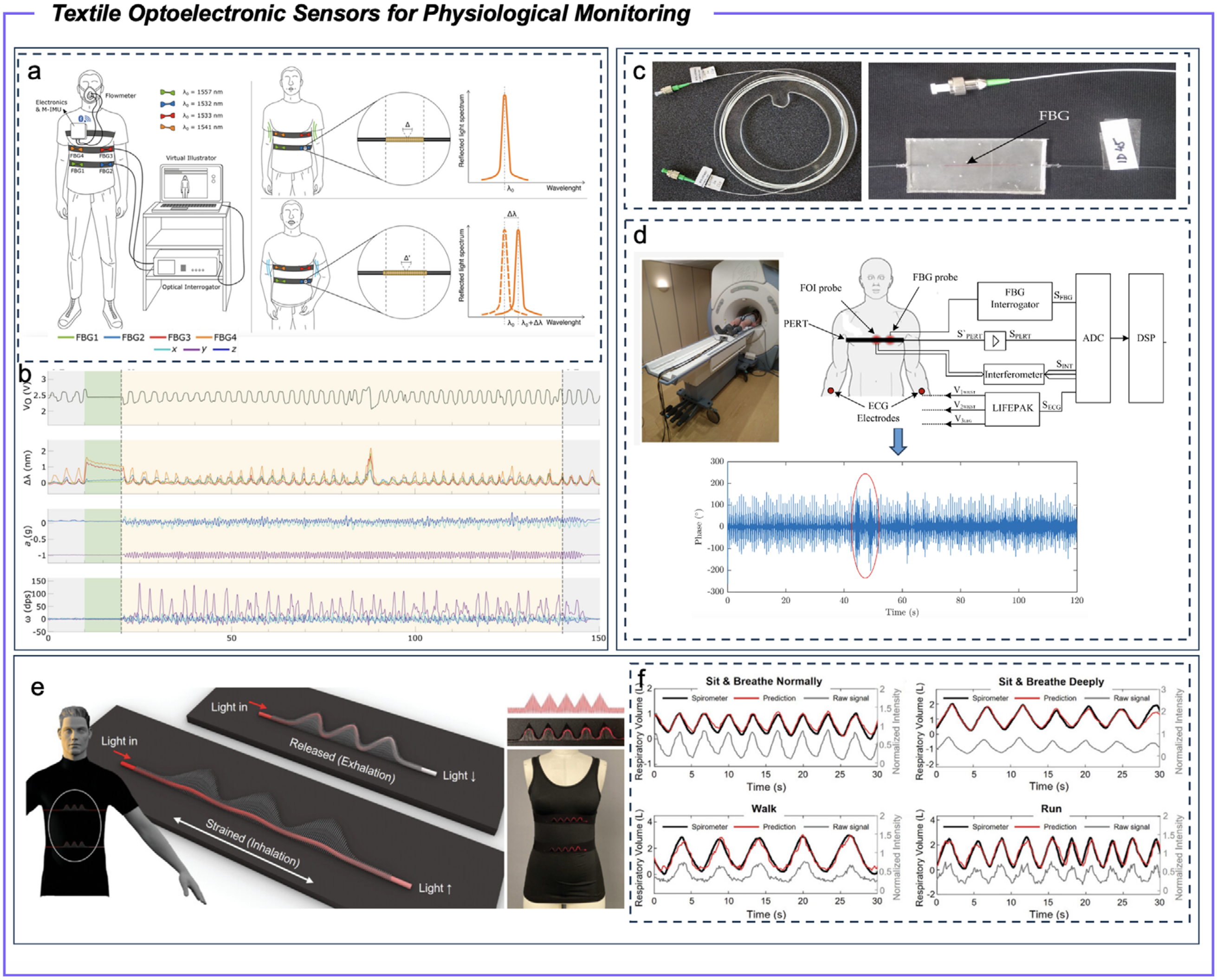


Figure 5. Textile optoelectronic sensors for physiological monitoring. a) Developing a respiration monitoring system using a wearable chest device embedded with FBG sensors and an inertial unit. b) Sensor system for monitoring respiratory flow. Reproduced with permission.[115] Copyright 2022, Elsevier. c) Stitching PDMS encapsulated FBG sensor on an elastic band for monitoring BCG signals, respiration and heart rate. d) The performance of FBG sensing system under MRI. Reproduced with permission.[116] Copyright 2018, MDPI. e) Stitching thermoplastic silicon fibers into clothing for breathing monitoring. f) Sensing clothing can detect breathing under various activities. Reproduced with permission.[117] Copyright 2023, John Wiley and Sons.

measurement of thermal changes.[122] This functionality makes them valuable for wearable applications where changes in skin temperature can provide insights in assessing stress and emotional arousal.

Textile-based thermoelectric sensors are commonly fabricated using flexible thermoelectric materials, allowing for seamless integration into fabrics. For instance, Lugoda et al.[123] developed a wearable temperature sensor by incorporating conductive polymer composite yarns. They integrated gold (Au) onto a 1 mm wide polyimide flexible substrate, which was then wrapped with polyester yarns to create a temperature sensing yarn. Their sensor can be seamlessly embedded into an armband and demonstrates high sensitivity to temperature variations, with a response time of less than 10 s, making it capable of long-term physiological monitoring applications. Additionally, Zhao et al.[124] introduced an all-textile temperature sensor using natural cotton fabric and temperature-sensitive polypyrrole in a sandwiched structure (**Figure 6a**). The sensor demonstrated excellent linearity and a sensitivity of 1.1% K^{-1} over a temperature range of 30–80 °C, with good stability and repeatability. Their sensor also exhibits multimodal sensing capabilities, including pressure and proximity detection, making it suitable for comprehensive health monitoring applications (Figure 6b). As wearable sensors need to cope with the challenges of daily care, such as exposure to washing, researchers have developed a wearable temperature sensing system with encapsulation using thermoplastic polyurethane and a washable encapsulant to protect sensor from mechanical and chemical stresses (Figure 6c).[125] Except for metallic materials, carbon-based materials like reduced graphene oxide (rGO), and CNTs have been applied to develop flexible textile

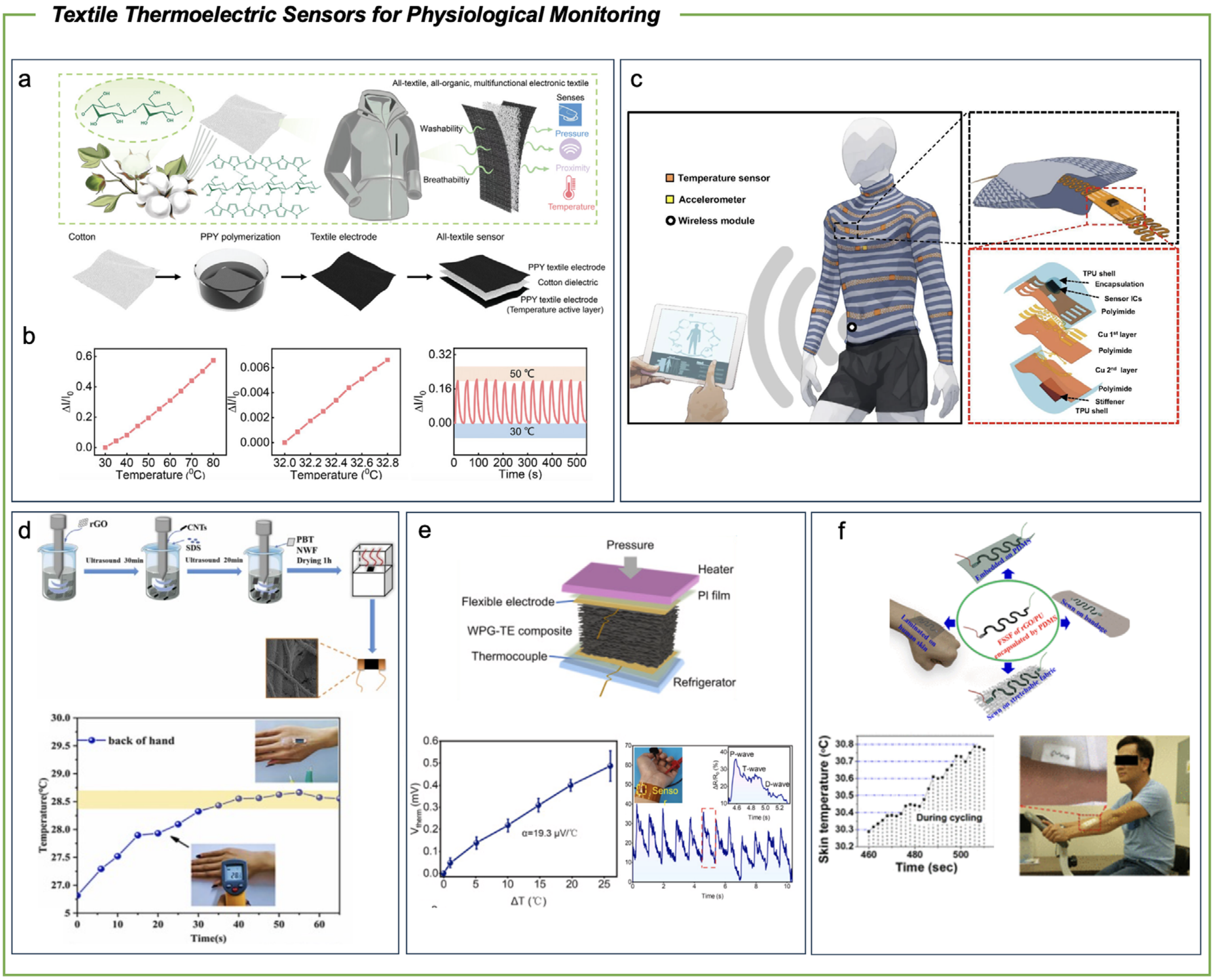


Figure 6. Textile thermoelectric sensors for physiological monitoring. a) Developing all-textile temperature sensor using natural cotton fabric and temperature-sensitive polypyrrole in a sandwiched structure. b) Sensing Performance of sensor over a temperature range of 30–80 °C. Reproduced with permission.[124] Copyright 2023, John Wiley and Sons. c) Integrating textile sensor with TPU encapsulation for real-time temperature monitoring. Reproduced with permission.[125] Copyright 2020, Springer Nature. d) Coating rGO and CNTs with nonwoven fabrics to develop wearable temperature sensor. Reproduced with permission.[126] Copyright 2022, Elsevier. e) Hybrid thermoelectric sensor for temperature and pulse rate detection. Reproduced with permission.[127] Copyright 2023, Elsevier. f) Printing rGO/polyurethane woven fabrics for skin temperature monitoring. Reproduced with permission.[128] Copyright 2019, American Chemistry Society.

temperature sensors. Wang et al.[126] utilized a mechanical ultrasonic method to integrate rGO and CNTs into melt-blown polybutylene terephthalate nonwoven fabrics to develop wearable temperature sensors (Figure 6d). The conductive rGO and CNTs can be adhered firmly to the nonwoven fabric surface, resulting in sensor with high sensitivity (–0.737% $°C^{-1}$) and linearity (R^2 = 0.98). Additionally, hybrid thermoelectric sensors have been proposed in recent studies, combining temperature sensing with other functions such as pressure or motion detection (Figure 6e). These multifunctional sensors enhance the effectiveness of wearable systems by enabling simultaneous monitoring of multiple physiological and behavior parameters.[127] However, textile-based thermoelectric sensors still face challenges in performance under dynamic conditions. For example, the electrical output of temperature sensors may be affected by strain induced by body movements. To address this, Trung et al.[128] developed a stretchable temperature sensor by geometrically engineering self-standing stretchable fibers composed of rGO/polyurethane composites, effectively decreasing strain-induced interference (Figure 6f). Moreover, heat transfer through textiles may not always align with rapid physiological changes, and environmental factors, such as environmental temperature and humidity, can also impact the accuracy and reliability of these sensors.[122] Therefore, more effort is needed to address the impact of fabric thermal conductivity and environmental challenges on the sensitivity and response time of the sensor.

Monitoring skin temperature is a valuable component in assessing loneliness, as variations in skin temperature can reflect changes in emotional and psychological states. Studies have shown that social exclusion or feelings of loneliness can lead to a decrease in skin temperature, which may be due to reduced blood flow resulting from autonomic nervous system responses.[129] In one experimental study using the Cyberball paradigm, participants who were socially excluded exhibited a drop in fingertip temperature up to 0.378 °C lower than their baseline. While socially included participants maintained or slightly increased their temperature.[130] This temperature decline became more pronounced over time, suggesting a physiological "cold response" to social disconnection. These findings provide evidence that skin temperature not only correlates with subjective emotional states but may serve as an early and quantifiable physiological marker of perceived social isolation. By integrating textile thermoelectric sensors into wearable systems, continuous monitoring of skin temperature becomes feasible, providing real-time data that can be analyzed to identify patterns indicative of loneliness.

3.2.4. Textile Electrochemical Sensors

Textile electrochemical sensors are designed to detect chemical or biological substances by combining conductive fibers or functionalized textile materials with electrochemical sensing elements.[131] Their sensing mechanism is mainly based on electrochemical reactions between target analytes and the sensor surface, resulting in changes of electrical signals such as current, voltage, or resistance.[132] Many textile electrochemical sensors have been reported to identify a range of chemical substances, from ions (e.g., Na^{+}, H^{+}, Ca^{2+}, NH_4^{+}) to hormones like cortisol and adrenaline, allowing for real-time and non-invasive monitoring.[15,133]

The development of textile electrochemical sensors focuses on incorporating conductive materials into fabrics to maintain flexibility and durability. Specific recognition elements, such as enzymes or antibodies, are often applied to the textile surface to achieve selective interaction with target analytes.[134] For example, For example, Zhou et al.[135] used a spin-coating method to coat cotton fabric with methyl orange and bromocresol green as pH indicators, along with glucose oxidase and horseradish peroxidase for glucose detection, developing a textile-based sweat sensor capable of simultaneously detecting pH and glucose (**Figure 7a**). The sensor demonstrated accurate and stable performance, offering a practical solution for non-invasive health monitoring through sweat analysis. Similarly, He et al.[136] applied digital laser writing to develop a flexible carbon-based sweat sensor using a silk fabric as the substrate, which can detect glucose, lactate, ascorbic acid, uric acid, Na^{+}, and K^{+}. Their proposed sensor exhibited high sensitivity, long-term stability, and excellent selectivity, highlighting potential for personalized healthcare applications (Figure 7b). In addition, many research works have been conducted to enhance the wearability of textile electrochemical sensors due to the characteristics of textiles being light, breathable and comfortable. For instance, Khosravi et al.[137] introduced a flexible enzymatic electrochemical glucose sensor using screen-printing technology on textile substrates. Their glucose biosensor showed a linear response within the 20–1000 µM range with high sensitivity (18.41 µA mM^{-1} cm^{-2}, $R^2 = 0.996$), making it ideal for diabetes management. The ability to integrate these sensors seamlessly into existing garments, such as socks, pants, and gloves, enhances their effectiveness for comprehensive sweat monitoring (Figure 7c). Similarly, Mugo et al.[134] developed a wearable textile-based electrochemical sensor to monitor cortisol levels in human sweat. The sensor was fabricated on a flexible cotton textile substrate coated with a conductive nanoporous carbon nanotube/cellulose nanocrystal composite, polyaniline, and a selective cortisol-imprinted poly(glycidylmethacrylate-co-ethylene glycol dimethacrylate) decorated with gold nanoparticles. This design offers a flexible, cost-effective, and scalable wearable monitoring solution. Sekar et al.[138] further demonstrated the potential of functionalized electrochemical fibers by incorporating Fe_2O_3 into conductive carbon yarn. The Fe_2O_3 modification facilitated the immobilization of cortisol-specific antibodies via 1-Ethyl-3-(3-dimethylaminopropyl) carbodiimide (EDC) and N-Hydroxysuccinimide (NHS) chemistry. The resulting yarn sensors exhibited excellent linearity ($R^2 = 0.998$) with a detection limit of 0.005 fg mL^{-1}, enabling highly sensitive detection of cortisol in sweat to analyze stress hormone levels (Figure 7d). Additionally, recent research has focused on chemical sensing mechanisms integrated into wearable systems for detecting environmental biomarkers. For instance, Zhang et al.[139] introduced a highly sensitive NO_2 gas sensor using a ternary hierarchical nanocomposite, which exhibited fast response and recovery at room temperature, along with high selectivity and long-term stability. Although primarily intended for gas detection, such nanocomposite strategies offer promising insights into enhancing sensor reliability and responsiveness in textile-based wearable applications.

In the context of loneliness monitoring, textile electrochemical sensors can be crucial in assessing physiological parameters linked to stress and emotional well-being.[134] For example, elevated cortisol levels in sweat are indicative of increased stress, which is closely associated with loneliness. Cortisol plays an important role in metabolic regulation, electrolyte balance, and blood pressure control, all of which influence cognitive processes such as memory, sleep patterns, and emotional stability.[140] A study in healthy older adults found that loneliness was significantly associated with higher bedtime cortisol levels ($\beta = 0.366$, $p = 0.001$), and that this elevated cortisol partially mediated the relationship between loneliness and poorer cognitive performance, particularly in attention, executive function and verbal memory.[141] Therefore, cortisol is considered a key biomarker for psychosocial stress, anxiety, depression, and mental health. Traditional methods for cortisol detection require invasive sampling of blood or urine, which are not suitable for real-time analysis.[142] Textile electrochemical sweat sensors offer a convenient, comfortable, and non-invasive solution for personalized health and physiological monitoring, providing timely insights into stress and emotional states that may be linked to loneliness. Despite these advancements, textile electrochemical sensors for sweat monitoring face challenges that limit their widespread application. A key limitation is that most sweat monitoring sensors are often disposable in design, and their detection capabilities saturate over time, leading to reduced lifespan and sensitivity and hindering long-term use.[143] Additionally, the stability of enzymes or antibodies used as recognition elements will degrade under prolonged exposure to environmental factors such as temperature,

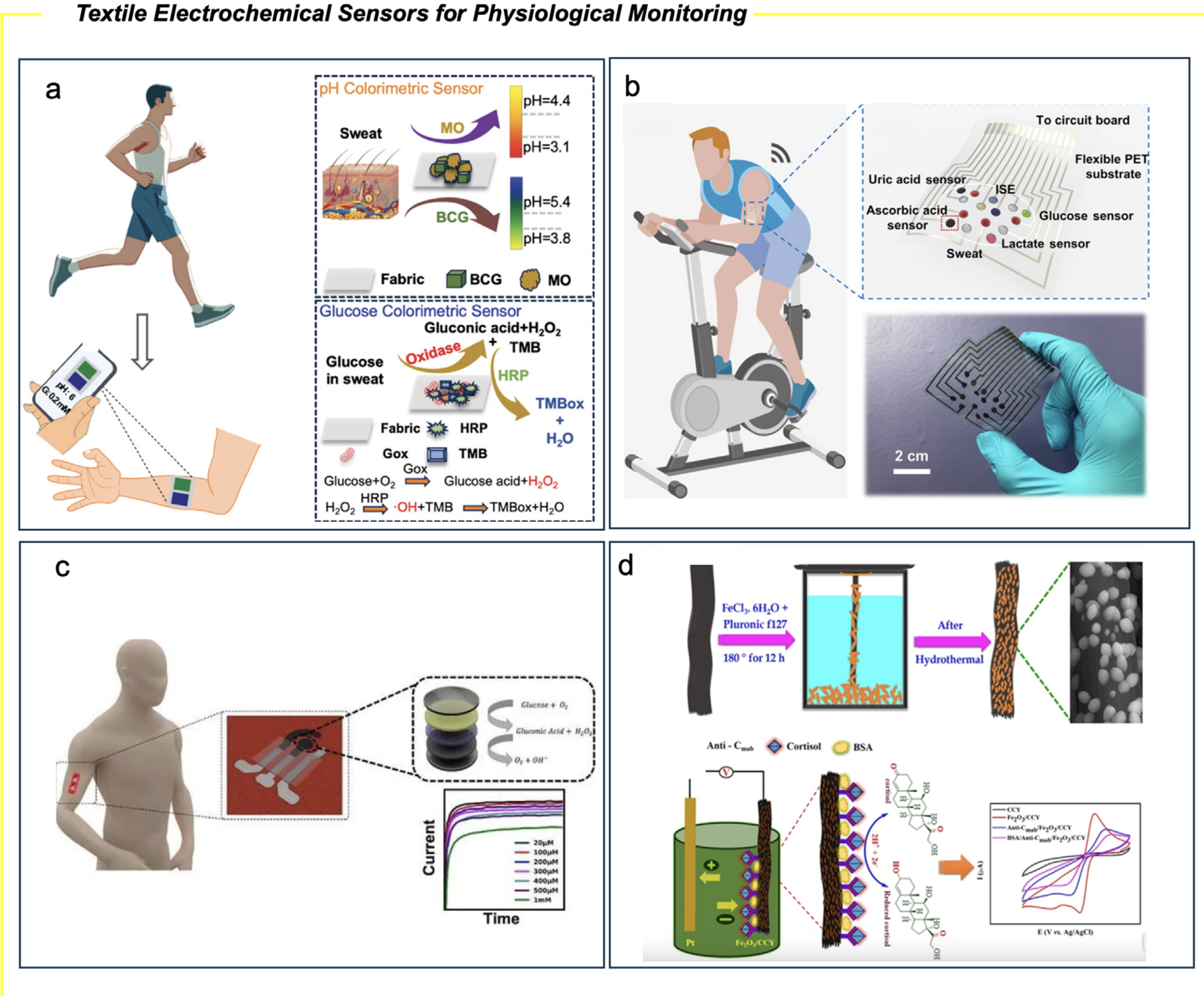


Figure 7. Textile electrochemical sensors for physiological monitoring. a) Spin-coating cotton fabrics with methyl orange, bromocresol green, glucose oxidase and horseradish peroxidase for pH and glucose detection. Reproduced with permission.[135] Copyright 2024, John Wiley and Sons. b) Using digital laser writing to produce sweat sensor for monitoring acid, uric acid, Na^+, and K^+. Reproduced with permission.[136] Copyright 2019, American Association for the Advancement of Science. c) Inkjet printing silver and graphene on polyimide substrate for cortisol detection. Reproduced with permission.[137] Copyright 2023, MDPI. d) Coating carbon-based yarn using Fe_2O_3 for monitoring cortisol in sweat. Reproduced with permission.[138] Copyright 2019, Springer Nature.

humidity, and pH fluctuations, affecting measurement accuracy and reproducibility.[144] Further research is needed to enhance sensor design, focusing on improving stability and reliability for real-world applications.

4. Integrated Wearable Monitoring System

4.1. Wearable Sensing Interface

The final component of a wearable monitoring system is the sensing wearable interface, which connects the data collected by the sensors to external systems for analysis and real-time monitoring. This interface typically includes circuit connection, microcontrollers and wireless communication modules that transmit data to cloud-based platforms or mobile devices for further processing.[151]

The design of wearable interfaces needs to consider user-friendliness and unobtrusiveness, allowing older users to interact with the system seamlessly. Recent advancements in circuit conductive technologies, such as conductive fibers, yarns, and fabrics, have made it possible to create more integrated and flexible interfaces.[152] Studies have reported on the development of scalable conductive yarns that combine fine steel with cotton fiber, which can be easily sewn or woven into garments for connecting textile sensors or micro-sensors.[153–155] Researchers at MIT have proposed a method using embroidery techniques to create circuit connections within smart sensing garments. Embroidery patterns can be designed via CAD software, enabling the development of flexible circuit connection and sensing surfaces.[156] Guo et al.[157] also introduced a novel encoded sewing methodology that allows programmable deformation and actuation in textile-based systems through seam constraint design. This approach enables the construction of highly integrated and mechanically adaptive wearable platforms, which could improve comfort and customization in smart clothing applications. Additionally, printing technologies such as screen printing or inkjet printing using conductive inks enable electronic components to be directly printed onto textiles, offering both flexibility and aesthetic appeal. For example, Guo et al.[158] applied a printing technique of liquid metal circuit onto thermal transfer paper, which can then be transferred onto textile substrates for sensor integration.

In terms of microcontrollers and wireless communication modules suitable for integration into smart wearable systems, many commercial technologies have been developed including ESP32 and Arduino Nano 33 BLE, which offer low-power operation and built-in wireless communication. These microcontrollers support Bluetooth Low Energy (BLE) and Wi-Fi, enabling efficient data transfer to mobile devices or cloud-based systems for real-time monitoring.[159] Additionally, Near Field Communication (NFC) technology can be used for short-range communication, allowing data to be quickly accessed by healthcare providers when they are in close distance. The compact size and low energy requirements of these modules make them ideal for unobtrusive integration into smart clothing, keeping the garment's comfort and wearability.[160]

Energy efficiency is a potential consideration for wearable sensing systems, as it reduces the need for frequent recharging, thereby enhancing usability for older people. For example, Yu et al.[161] have developed yarns that can generate power from body movements and knitted into everyday clothing like socks and shirts. Additionally, printing techniques can be applied to integrate active inks into garments, enabling the collection of kinetic energy as an alternative to traditional charging methods.[162] These technologies offer a flexible and convenient self-sustaining power source, allowing continuous data collection without the need for regular battery replacement.

4.2. Signal Processing and Analysis

The implementation of wearable systems requires not only a robust sensing interface to coordinate sensors, power supply, and data transmission but also effective data processing and analysis to translate complex sensor outputs into meaningful insights.

As previously discussed, wearable monitoring technology collects physiological signals and motion data from the human body through sensing systems. During the data collection process, the signals obtained may be affected by artifacts such as motion interference or environmental noise, therefore requiring initial noise reduction to remove extra signal disturbances.[25] Noise reduction algorithms have been widely applied to improve measurement accuracy. These algorithms often rely on filtering techniques or signal decomposition methods that confine the signal's frequency within a target bandwidth, thereby excluding unwanted frequencies.[163] For instance, since subtle physiological signals like PPG and ECG may easily be affected by motion interference, adaptive filters have been developed to enable accurate monitoring even during movement.[164] Zou et al.[165] developed an algorithm combining noise-assisted multivariate empirical mode decomposition (NAMEMD) and multiset canonical correlation analysis (MCCA) to improve the accuracy of heartbeat monitoring using textile-based sensors. Additionally, as some physiological signals may be quite weak, wearable monitoring systems can also employ integrated amplifiers to facilitate more effective analysis.[166]

With advancements in wearable technology, the integration of machine learning algorithms has offered transformative approaches to analyzing loneliness among older people (**Table 5**). One of the most widely used machine learning methods is supervised learning, which involves training models on labeled datasets to predict outcomes or classify data into categories.[167] Currently, much research has employed supervised learning to analyze and predict physiological parameters and activity patterns in the older people, thereby identifying loneliness or social isolation. For example, Dawadi et al.[168] used support vector regression (SVR), linear regression (LR), and random forest regression (RFR) models to analyze relationships between older people's daily activity data in the home and their actual physical health status, predicting health scores. This approach is particularly useful for identifying loneliness or social isolation in older people, as it enables automated health monitoring to provide real-time assessments for healthcare providers. Supervised learning is also commonly applied to classification tasks. Researchers have explored the efficacy of techniques such as Naïve Bayes (NB),[169] K-nearest neighbors (KNN),[170] and support vector machines (SVM)[36,63,171] for classifying biological signals and activities, making them applicable to loneliness monitoring in older people care. Among these models, SVM is widely used for posture and activity classification due to its ease of training and high accuracy in wearable sensor data analysis. Tsang et al.[63] applied an SVM model to classify accelerometer and gyroscope data collected from older people, achieving an impressive accuracy of up to 99.8% in indoor activity monitoring. This high level of accuracy can be attributed to the well-controlled experimental conditions applied in the study. As this study focuses on a limited indoor activity and excludes outdoor and unpredictable movements which can avoid reducing accuracy in real-world settings. Additionally, it is important to note that the training time of SVM models may significantly rise when the feature space and dataset size increase.[172]

Deep learning, a subset of machine learning, exhibits exceptional capabilities for processing and interpreting complex datasets compared to traditional machine learning methods. For example, Convolutional neural networks (CNNs) have been widely applied for activity and posture recognition due to their outstanding learning ability. Gochoo et al.[173] applied CNNs to classify activity data in older people, achieving an accuracy of 99.3% in daily activity classification. However, their study was only conducted on one older resident under home monitoring setting. This setup minimized variability caused by differing participant behaviors and living environments. Additionally, wearable sensors typically output time-series data, and CNNs are highly effective in capturing spatial features from these signals. However, due to their lack of memory capabilities, CNNs may struggle with accurately recognizing continuous dynamic

Table 5. Monitoring sensors with related machine learning algorithms for physiological and behavior monitoring.

Sensor	Algorithm	Output	Performance	Refs.
Textile strain sensor	NAMEMD+MCCA	Detection of heartbeat rate	Standard variation = 2.47	[165]
Motion sensors; light sensors	SVR; LR; RFR	Detection of daily activities in home	95% accuracy	[168]
Bioimpedance sensor	NB	Biometrics	98% accuracy	[169]
Accelerometer	KNN	Detection of human motion	90% accuracy in walking and falling; 80% accuracy in climbing up/down stairs	[170]
Accelerometer; gyroscope	SVM	Detection of indoor activities	99.8% accuracy	[63]
Ultrasonic sensor	SVM	Detection of human motion	81 - 90% accuracy	[171]
Passive infrared sensor	CNN	Detection of daily activities	99.36% accuracy	[173]
Motion sensor; temperature sensor; door sensor	RNN	Detection of daily activities	91.7% accuracy	[174]
Passive infrared sensor	LSTM/GRU	Detection of daily activities	NA	[175]
ECG sensor	CNN/LSTM	Detection of stress levels	98.99% accuracy	[176]

activity signals. To address this problem, many sequential models, such as recurrent neural networks (RNNs)[174] and long short-term memory (LSTM) networks[175] have been developed to incorporate temporal information without the need for manual feature extraction. Despite their effectiveness, training these models may require substantial data and time. To address these limitations, Bharathi Vidhya et al.[176] proposed a CNN+LSTM neural network, which combines the advantages of different recognition algorithms and achieved a classification accuracy of 98.3% for mental stress levels.

As previously discussed, while machine learning algorithms demonstrate great promise in the context of wearable sensing and loneliness monitoring, their performance remains highly dependent on experimental conditions. In real-world applications, it is important to recognize their limitations and potential sources of error. Many of the high-accuracy results reported in earlier studies were obtained under controlled conditions with small and homogeneous participant groups, which may limit their generalizability to diverse and practical settings. Factors such as user variability, inconsistent sensor placement and environmental noise can introduce significant errors during data collection, thereby reducing the reliability of model predictions.[177,178] Recent study has proposed probabilistic models to address motion artifacts caused by body movement in smart clothing.[179] Their findings show that sensors embedded in loose-fitting garments can achieve higher accuracy of motion recognition at 76.5% $\pm$ 0.9 than rigidly attached sensors at 73.8% $\pm$ 0.9. This suggests a promising solution for data collection in uncontrolled practical environments, where user variability and movement dynamics pose significant challenges to traditional wearable sensing configurations. In addition to algorithmic limitations, the reliability of certain sensing technologies such as electrochemical sweat sensors also poses challenges in real-world use, especially among low-activity older adults. These users may generate insufficient sweat volumes during daily activities, leading to signal dropout or reduced temporal resolution in physiological monitoring.[180] Moreover, variations in skin hydration, ambient temperature, and clothing pressure can affect sweat composition and sensor contact, further complicating consistent data acquisition. To address this challenge, Sowmyalakshmi et al.[181] developed a novel Class Imbalance Data Handling approach combined with an Optimal Deep Belief Network, which has demonstrated effectiveness in managing class imbalance in healthcare datasets. Furthermore, given that loneliness lacks a single measurable physiological marker, future systems can incorporate ground truth validation through psychosocial assessments such as the UCLA Loneliness Scale, enabling meaningful alignment between sensor outputs and users' emotional experiences.[17]

4.3. Design Considerations

The design of smart textile systems for loneliness monitoring in older people must address several critical factors to ensure the product is both effective and acceptable to users. These factors include comfort and wearability, aesthetics and emotional impact, as well as durability and maintenance. Each of these elements plays an important role in the overall success of the garment, as older users may be more sensitive to discomfort, have unique aesthetic preferences, and require solutions that are easy for aftercare.[14,182] The design requirements presented in **Figure 8** are grounded in findings from our previous qualitative co-design workshops with older people.[23,27] These workshops specifically explored user perspectives and requirements on smart textile systems for loneliness monitoring.

4.3.1. Comfort and Wearability

Comfort is one of the most essential considerations when designing smart wearables for older people. Previous studies have shown that smart textile systems are generally more accepted by users compared to traditional rigid wearable devices due to their outstanding comfort and unobtrusiveness. For example, Baskan et al.[183] found that users rated smart T-shirt significantly higher in comfort and willingness to wear in public compared to accessory-based chest band. Similarly, In our co-design sessions, older participants explicitly expressed a preference for smart textile systems over traditional wearables. They viewed garments as a natural extension of the body, as opposed to medical devices that draw attention to their health conditions.[23]

Insights from our previous focus group studies have highlighted the important role of comfort in ensuring long-term

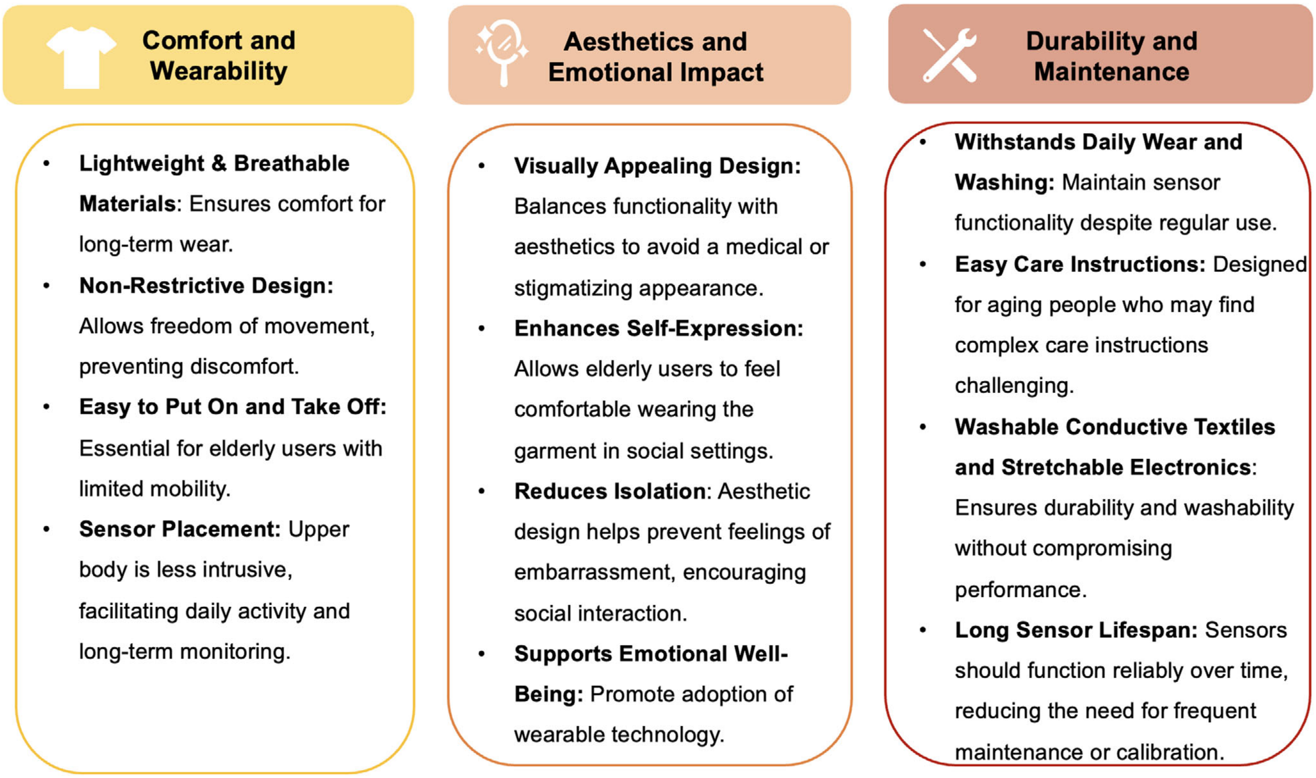


Figure 8. Design requirements of the smart textile wearables for loneliness monitoring in older people care.

wearing adoption, emphasizing the importance of selecting breathable, lightweight, and non-restrictive materials.[23] Garments with less design consideration may cause discomfort, which result in users being unwilling to wear the clothing consistently, thereby compromising the effectiveness of the loneliness monitoring system.[184] Additionally, wearability needs to be addressed during design process as it involves flexibility of putting on and taking off the clothing, particularly for individuals with limited mobility or dexterity. Older patients with limited dexterity might not be able to put on such clothing without external help.[185] Also, the placement of sensors is important to comfort. As previous studies have stated, the upper body (including the torso and arms) may be considered the most comfortable and least intrusive location for sensor placement.[23,160] This ensures that users can carry out daily activities without feeling restricted by the garment, making it suitable for continuous, long-term monitoring.

In smart clothing development, textiles design can play a vital role in achieving comfort and wearability. Textile used in wearable sensors and smart clothing typically require stretchability and recovery properties, making them suitable for close-fitting wear to enable accurate body signal collection.[26] For example, natural fibers such as silk, cotton and wool can offer breathability and softness. Synthetic fibers like polyester provide durability, stretchability and chemical stability.[186–189] Blended materials combining natural and synthetic fibers have shown great potential in achieving a balance between elasticity, flexibility, and sensor performance, making them ideal for smart clothing applications.[190] For example, Souri et al.[154] found that the use of blended yarns can enhance the performance of textile strain sensors, achieving a balance between sensor sensitivity and material elasticity, demonstrating the promise of blended yarns in developing textile sensors for smart clothing applications. Additionally, textile structures such as knitted fabrics are known for their outstanding elasticity and comfort, and they are particularly suitable for wearable applications requiring high resilience and adaptability.[191]

4.3.2. Aesthetics and Emotional Impact

Aesthetics play a significant role in the user acceptance of smart wearables. Clothing is tied to self-expression and identity.[190] If the design of the garment is perceived as medical or unattractive, users may feel stigmatized and negatively affect their emotional well-being.[192] Therefore, it is essential to create designs that are both functional and visually appealing, keeping a balance between fashion design and engineering. Our previous Co-design and focus group studies with older adults revealed a strong preference for non-medicalized, emotionally supportive design features. Participants explicitly rejected sterile aesthetics and harsh color cues, describing traditional monitoring wearables as “cold,” “surgical,” and “not pretty.” One participant compared the visual appearance to “everything was black, black, or black,” highlighting the emotional disengagement triggered by monochrome clinical design. Based on this feedback, participants recommended avoiding red or warning-like indicators and instead using soothing color fabrics to promote warmth, dignity and discretion in social contexts.[23,27] Designing aesthetically pleasing smart wearables can help older people feel more comfortable wearing the garments in social settings, reducing the likelihood of isolation caused by feelings of embarrassment or stigma. Research has shown that clothing designed with attention to aesthetic qualities can enhance the emotional engagement of older people, encouraging greater adoption of wearable technologies.[14,182] Research has also indicated that loneliness can be a maladaptive or negatively orientated emotional state in which the individual is unduly focused on their loneliness,[193,194] therefore it may be important to avoid reminding users of their loneliness through aesthetic design that cannot act as a negative prompt.

4.3.3. Durability and Maintenance

Durability and ease of maintenance need to be included for determining whether smart wearables is suitable for older users.[185] In our previous user study, participants have highlighted the importance of smart clothing that can withstand daily wear and tear, including frequent washing, while maintaining the functionality of the integrated sensors and electronics.[23] Many older people may find complex instructions challenging, so the wearables need to be designed for easy after-care and keep long-term reliability without requiring frequent maintenance.[27]

In terms of long-term usability, one of the key technical challenges for smart clothing is maintaining the sensing performance and reliability of integrated textile sensors after repeated washing and everyday mechanical stress. Traditional conductive materials and electronic components are often susceptible to degradation caused by washing detergents, moisture exposure and friction.[113] To address these issues, recent research has explored various strategies, including the use of waterproof or stretchable polymer encapsulation, as well as pre-treatment and post-treatment techniques to retain sensor's conductivity and mechanical properties after multiple washing cycles. For example, Sanchez-Botero et al.[78] developed a textile-based capacitive strain sensor that was integrated into garment for human motion detection. Their sensor was constructed from breathable fabric layers and encapsulated using a thermoplastic fabric adhesive, demonstrating up to 90% strain and high breathability, while maintaining consistent performance after three washing cycles. Kim et al.[195] proposed a washable polyester fibre coated with PEDOT:PSS, which exhibited outstanding electrical conductivity after four washing and dry cleaning cycles. Additionally, Zhang et al.[196] has focused on the development of self-protective and reproducible textile sensors. They applied a hierarchical construction technology integrating carbon nanotube networks, a combined polypyrrole-polydopamine-perfluorodecyltrlethoxysilane polymer layer and textile substrates. Their sensor can retain stable sensing performance under daily wear and tear, showing great potential in long-term monitoring of human behaviors under real-world settings.

Design of textiles can further enhance durability and wearability of smart clothing. For example, woven fabrics which are constructed through the interlacing of warp and weft yarns can provide structural stability and wash resistance when applied for everyday clothing. However, they typically lack stretchability leading to poor adaptability to the human body.[155] Knitted fabrics with their looped structures can offer superior elasticity and comfort, making them particularly suitable for the development of smart clothing. Moreover, many researchers have developed knitted textile sensors which can maintain functionality after repeated washing. This further demonstrate the potential of knitted fabrics for long-term use in wearable technologies.[54,197]

5. Challenges and Opportunities

While this review has explored the technological and design advancements in the development of smart textile wearables for older people care, several technical challenges and potential opportunities remain for seamlessly incorporating such wearables into the daily lives of older people.

5.1. Multimodal Wearable Sensing System

As discussed previously, combining clothing with sensing monitoring for older people requires the construction of an integrated wearable sensing system. Various sensors need to be incorporated into a single wearable system to capture different physiological and behavioral parameters, in order to accurately monitor loneliness in older users. One of the main challenges is reliably collecting data in real time from multiple sensors, particularly when dealing with different data streams from different types of sensors. Cross-sensor signal interference can significantly degrade data accuracy, especially when sensors operate at overlapping frequencies or when signal synchronization is not well managed.[198] Advanced sensor fusion algorithms and synchronized sampling strategies are needed to reduce redundancy and avoid conflict between signal sources. In addition, environmental noise such as motion artifacts, ambient temperature variation and fabric movement poses a challenge to reliable signal capture in daily-life settings.[177,178] Future systems must incorporate robust filtering techniques and adaptive denoising methods to suppress such noise, ensuring that physiological signals remain valid across different usage conditions. Furthermore, a critical technical bottleneck in multidimensional index integration lies in differentiating loneliness from other overlapping psychological states such as anxiety, stress or depression, which may manifest similar physiological patterns such as elevated heart rate or reduced heart rate variability.[199] Without appropriate data fusion strategies, it remains difficult to differentiate loneliness-specific physiological markers from general emotional arousal. Future research should investigate feature-level fusion approaches and context-aware machine learning models capable of learning subtle temporal and multimodal distinctions across emotional states. For example, integrating ECG, skin temperature and respiratory data with behavioral cues like reduced social interaction or sedentary patterns may enhance specificity in loneliness detection.

A complete wearable monitoring system requires a control unit to coordinate data collection, transmission, and storage. Wireless data transmission and connectivity are essential for wearable systems in older people care to minimize restrictions on users' movements and minimise the risk of falls. Currently, wireless communication technologies widely used in smart clothing, such as Bluetooth and WIFI, present several challenges, particularly regarding data quality, sampling rate, and transmission range. Data loss or delays can result in inaccurate or incomplete monitoring, potentially leading to misinterpretations of the user's health status. Furthermore, the limited transmission range of Bluetooth and WIFI could restrict mobility for older users, especially in larger living spaces or when the user is away from home.

Effective loneliness monitoring requires long-term data collection to observe behavioural and physiological trends over time. However, storing large amount of data on a wearable device is impractical due to storage capacity constraints. Offloading data to cloud storage or local servers is a potential solution, but it raises privacy and data security concerns, as well as challenges in ensuring stable connectivity for continuous data upload. More effort is needed in addressing the complexities of multimodal sensor integration, data transmission, and storage solutions in wearable monitoring systems.

5.2. Mobile Health Cloud System

To enable continuous and effective data management and analysis, future study can integrate mobile health cloud platforms into wearable sensing systems. By using smartphones and cloud-based systems, data collected by smart clothing can be transmitted, stored, and analyzed in real time. This enhances the accessibility and continuity of health monitoring systems, providing caregivers and healthcare providers with valuable insights into the mental health and well-being of older people.

Within the mobile health cloud system, data flows from smart wearables to mobile devices and then transmits to cloud storage for real-time analysis and long-term monitoring. The main components of this system include smart clothing software, mobile application, and health cloud software. The smart clothing software is responsible for data collection and initial processing, ensuring that raw data from different sensors is converted into a legible format before transmission. Basic filtering techniques can be implemented to reduce noise from environmental factors to optimize data accuracy for transmission. The mobile application acts as a bridge between smart clothing and the cloud system. It collects data from smart clothing via Bluetooth or Wi-Fi, allowing users and healthcare providers to view real-time health metrics and alerts. The app also can provide personalized service such as sending reminders for regular wear and maintenance of the smart clothing to ensure consistent monitoring. The health cloud software can detect and manage behavior patterns over time and identify signs of loneliness or social isolation. The cloud platform's ability to store large datasets enables long-term trend analysis and more accurate health predictions. This further provide healthcare workers with alerts to potential risks.

One of the main challenges for a reliable mobile health cloud system is maintaining a seamless data stream from the wearable device to the mobile app and subsequently to the cloud. This continuous flow of data may face connectivity issues and delays, particularly in areas with limited internet access. This may interrupt real-time monitoring and data transmission, delaying critical health alerts to caregivers. Furthermore, transmitting sensitive health data over the internet requires robust data protection and security strategies to ensure privacy and compliance with health information regulations.[200] Recent research has investigated encryption techniques, anonymization protocols and blockchain-based solutions to enhance the privacy and security of patient data.[201,202] For example, Das et al.[203] developed a secure cloud computing algorithm using multi-party computation and homomorphic encryption, enabling data processing without exposing raw data. Fareed et al.[204] also proposed a privacy-preserving E-healthcare system based on role-based access control (RBAC) and intelligent multi-factor authentication, ensuring that only authorized users can access patient data while improving risk tolerance, scalability and adaptability. In addition, privacy-preserving machine learning methods such as federated learning allow AI models to be trained directly on devices without transferring sensitive data to the servers.[177] Furthermore, smart healthcare systems increasingly align with global data protection standards such as the Health Insurance Portability and Accountability Act (HIPAA) and ISO/IEC 27001, which offer frameworks for managing data confidentiality, integrity and availability.[205] These strategies can be particularly important for older people, as they may be more vulnerable to data misuse and express concerns about surveillance and data tracking. Therefore, integrating secure data processing mechanisms and privacy-aware system architectures is essential for building trust and promoting the adoption of such technologies among older people.

6. Conclusion

This paper presents a comprehensive review of smart textile technologies for loneliness monitoring in older people, focusing sensing and design innovations to monitor and prevent further development of loneliness. The review highlights the critical research gap in the lack of textile-based sensing systems specifically designed for loneliness detection. While existing wearable technologies can monitor individual physiological parameters related to stress or activity, none have been designed to capture the complex, multidimensional nature of loneliness through a unified, multimodal sensing system.

By integrating advanced sensing technologies with user-centered design principles, smart textile systems present a promising solution for addressing the mental and emotional well-being of older people. Various types of sensors, sensing materials, and fabrication methods were examined to evaluate their effectiveness of accurate loneliness monitoring. Also, we explored the integration of these sensors into complete wearable systems, with a focus on circuit connection, data acquisition and analysis. Moreover, design considerations including comfort, aesthetics and durability were discussed to ensure user compliance and long-term wearability.

While current advancements demonstrate the potential of smart textile wearables to transform older people care, significant challenges still remain. These include the need for reliable multimodal sensor integration, which goes beyond hardware embedding to include synchronized data acquisition, signal-level fusion and context-aware analysis algorithms that can distinguish loneliness-specific biosignals from other psychological states such as stress or depression. Achieving this integration will require interdisciplinary collaboration between materials scientists, wearable electronics engineers, clinical psychologists and data scientists. Additionally, future research should establish standardized physiological markers for loneliness, develop robust sensor fusion frameworks, and validate system performance in real-life long-term use scenarios. Integrating these technical and user-centered pathways into a comprehensive framework can enable smart textile system to become a valuable tool for improving the quality of life and emotional well-being of older people.

Acknowledgements

This work was supported by the UK Engineering and Physical Sciences Research Council (EPSRC) and the National Institute of Health and Care Research (NIHR) (grant number EP/W031434/1).

Conflict of Interest

The authors declare no conflict of interest.

Keywords

biomedical monitoring, electronic textiles, flexible electronics, textile sensors, wearable technology

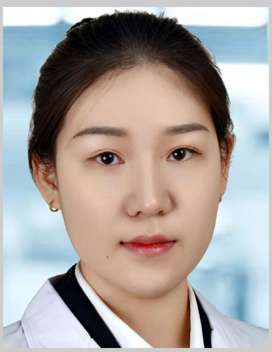
Received: May 2, 2025
Revised: July 10, 2025
Published online:

[1] N. J. Donovan, D. Blazer, *Am. J. Geriatr. Psychiatry* **2020**, *28*, 1233.
[2] E. National Academies of Sciences, D. o. B. a. S. S. Education, H. a. M. Division, C. Board on Behavioral, B. o. H. S. Policy, C. o. t. H. a. M. D. o. S. I. a. L. i. O. Adults, in *Social Isolation and Loneliness in Older Adults: Opportunities for the Health Care System*, National Academies Press (US), Washington, DC **2020**.
[3] O. A. Fakoya, N. K. McCorry, M. Donnelly, *BMC Public Health* **2020**, *20*, 129.
[4] L. C. Hawkley, J. T. Cacioppo, *Aging Health* **2010**, *6*, 415.
[5] S. Schrempft, M. Jackowska, M. Hamer, A. Steptoe, *BMC Public Health* **2019**, *19*, 74.
[6] K. Hanna, J. Cross, A. Nicholls, D. Gallegos, *Appetite* **2023**, *191*, 107051.
[7] L. C. Hawkley, J. T. Cacioppo, *Ann. Behav. Med.* **2010**, *40*, s12160.
[8] R. Mushtaq, S. Shoib, T. Shah, S. Mushtaq, *J Clin Diagn Res* **2014**, *8*, WE01.
[9] N. Xia, H. Li, *Antioxid. Redox Signaling* **2018**, *28*, 837.
[10] J. Rees, W. Liu, J. Canson, L. Crosby, A. Tinker, F. Probst, S. Ourselin, M. Antonelli, E. Molteni, N. Mexia, Y. Shi, F. Matcham, *Int J Qual Stud Health Well-being* **2024**, *19*, 2398259.
[11] M. Lette, A. Stoop, L. C. Lemmens, Y. Buist, C. A. Baan, S. R. d. Bruin, *BMC Geriatrics* **2017**, *17*, 132.
[12] S. Gedam, S. Paul, *IEEE Access* **2021**, *9*, 84045.
[13] D. Prabhu, M. Kholghi, M. Sandhu, W. Lu, K. Packer, L. Higgins, D. Silvera-Tawil, *SENSORS* **2022**, *22*, 24.
[14] K. Moore, E. O'Shea, L. Kenny, J. Barton, S. Tedesco, M. Sica, C. Crowe, A. Alamäki, J. Condell, A. Nordström, S. Timmons, *JMIR mHealth and uHealth* **2021**, *9*, e23832.
[15] F. Gao, C. Liu, L. Zhang, T. Liu, Z. Wang, Z. Song, H. Cai, Z. Fang, J. Chen, J. Wang, M. Han, J. Wang, K. Lin, R. Wang, M. Li, Q. Mei, X. Ma, S. Liang, G. Gou, N. Xue, *Microsyst. Nanoeng.* **2023**, *9*, 1.
[16] A. Ejupi, C. Menon, *Sensors* **2018**, *18*, 2474.
[17] M. M. Qirtas, E. Zafeiridi, D. Pesch, E. B. White, *JMIR mHealth and uHealth* **2022**, *10*, e34638.
[18] M. Kim, S.-i. Hong, S. Youm, *Sci. Rep.* **2022**, *12*, 18855.
[19] T. Kalisch, C. Theil, G. Gosheger, T. Ackmann, I. Schoenhals, B. Moellenbeck, *Ther Adv Musculoskelet Dis* **2022**, *14*, 1759720X221079256.
[20] V. Natale, M. Drejak, A. Erbacci, L. Tonetti, M. Fabbri, M. Martoni, *Sleep Biol Rhythms* **2012**, *10*, 287.
[21] C. Auepanwiriyakul, S. Waibel, J. Songa, P. Bentley, A. A. Faisal, *Sensors* **2020**, *20*, 7313.
[22] M. Ahsan, S. H. Teay, A. S. M. Sayem, A. Albarbar, *Signals* **2022**, *3*, 113.
[23] F. Probst, J. Rees, Z. Aslam, N. Mexia, E. Molteni, F. Matcham, M. Antonelli, A. Tinker, Y. Shi, S. Ourselin, W. Liu, *JMIR Aging* **2024**, *7*, e57622.
[24] D. Jiang, M. Xu, Q. Wang, *Conf Proc IEEE Eng Med Biol Soc* **2023**, *2023*, 1.
[25] M. Azeem, M. Shahid, I. Masin, M. Petru, *J. Text. Inst.* **2025**, *116*, 80.
[26] Y. Zhou, Y. Sun, Y. Li, C. Shen, Z. Lou, X. Min, R. Stewart, *Advanced Intelligent Systems* **2024**, *6*, 2400124.
[27] F. Probst, W. Liu, *DRS Biennial Conference Series*, DRS, Boston, USA **2024**.
[28] J. A. Benson, V. E. McSorley, L. C. Hawkley, D. S. Lauderdale, *Sleep* **2021**, *44*, zsaa140.
[29] J. Wang, F. Mann, B. Lloyd-Evans, R. Ma, S. Johnson, *BMC Psychiatry* **2018**, *18*, 156.
[30] S. J. Meredith, N. J. Cox, K. Ibrahim, J. Higson, J. McNiff, S. Mitchell, M. Rutherford, A. Wijayendran, S. D. Shenkin, A. H. M. Kilgour, S. E. R. Lim, *Age and Ageing* **2023**, *52*, afad145.
[31] G. Bouaziz, D. Brulin, E. Campo, *Sensors* **2022**, *22*, 8802.
[32] N. Schutter, T. J. Holwerda, M. L. Stek, J. J. M. Dekker, D. Rhebergen, H. C. Comijs, *J. Psychosom. Res.* **2017**, *95*, 19.
[33] J. Rees, F. Matcham, F. Probst, S. Ourselin, Y. Shi, M. Antonelli, A. Tinker, W. Liu, *Gerontechnology* **2023**, *22*, 1.
[34] E. Emerson, N. Fortune, G. Llewellyn, R. Stancliffe, *Disabil Health J* **2020**, *14*, 100965.
[35] R. Latikka, R. Rubio-Hernández, E. S. Lohan, J. Rantala, F. N. Fernández, A. Laitinen, A. Oksanen, *J. Med. Internet Res.* **2021**, *23*, e28022.
[36] L. Vuegen, B. Van Den Broeck, P. Karsmakers, H. Van Hamme, B. Vanrumste, in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, IEEE, New York **2015**, pp. 4966–4969.
[37] J. Petersen, S. Thielke, D. Austin, J. Kaye, *Aging Ment. Health* **2016**, *20*, 1084.
[38] C. McCrory, C. Finucane, C. O'Hare, J. Frewen, H. Nolan, R. Layte, P. M. Kearney, R. A. Kenny, *J. Gerontol. B* **2016**, *71*, 463.
[39] P. Eggenberger, M. Bürgisser, R. M. Rossi, S. Annaheim, *Front. Aging Neurosci.* **2021**, *13*.
[40] R. K. Nath, H. Thapliyal, *SN Computer Science* **2021**, *2*, 359.
[41] M. Frayn, S. Livshits, B. Knäuper, *Int. J. Eat. Disord.* **2018**, *6*, 23.
[42] A. Bedri, R. Li, M. Haynes, R. P. Kosaraju, I. Grover, T. Prioleau, M. Y. Beh, M. Goel, T. Starner, G. Abowd, *Proc. of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, ACM, New York **2017**, *1*, 37.
[43] J. v. d. Boer, A. v. d. Lee, L. Zhou, V. Papapanagiotou, C. Diou, A. Delopoulos, M. Mars, *JMIR mHealth and uHealth* **2018**, *6*, e9781.
[44] K. S. Chun, S. Bhattacharya, E. Thomaz, *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* **2018**, *2*, 4:1.
[45] R. Chong, A. Willis, S. Kakaiya, C. Schambach, C. Todd, A. Young, *Asian Journal of Physical Therapy* **2024**, *1*, 2023.
[46] Y.-H. Lin, B.-Y. Wong, S.-H. Lin, Y.-C. Chiu, Y.-C. Pan, Y.-H. Lee, *J. Psychiatr. Res.* **2019**, *110*, 9.

[47] Z. Chen, M. Lin, F. Chen, N. Lane, G. Cardone, R. Wang, T. Li, Y. Chen, T. Choudhury, A. Cambell, in *2013 7th Int. Conf. on Pervasive Computing Technologies for Healthcare and Workshops*, IEEE, New York **2013**, pp. 145-152.
[48] X. Sun, L. Qiu, Y. Wu, Y. Tang, G. Cao, *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* **2017**, *1*, 104:1.
[49] X. Ji, X. Li, A. Yuh, C. Kendell, A. Watson, J. Weimer, H. Nagahara, T. Higashino, T. Mizumoto, V. Erdelyi, G. Demiris, O. Sokolsky, I. Lee, in *Proceedings of the 8th ACM/IEEE International Conference on Connected Health: Applications, Systems and Engineering Technologies*, CHASE '23. Association for Computing Machinery, New York, NY, USA **2024**, pp. 148–152.
[50] P. C. Bhat, K. U. D. Kumar, S. Rai, K. B. R. Basheer, *Asian J. Med. Health* **2021**, *19*, 107.
[51] J. Austin, H. H. Dodge, T. Riley, P. G. Jacobs, S. Thielke, J. Kaye, *IEEE Journal of Translational Engineering in Health and Medicine*, IEEE, New York **2016**, *4*, 1.
[52] Z. He, G. Zhou, Y. Oh, B. M. Jung, M. K. Um, S. K. Lee, J. I. Song, J. H. Byun, T. W. Chou, *Materials Today Nano* **2022**, *18*, 100214.
[53] C. Linti, H. Horter, P. Osterreicher, H. Planck, in *International Workshop on Wearable and Implantable Body Sensor Networks (BSN'06)*, Vol. *3*, **2006**, pp.–137.
[54] Y. Zhou, R. Stewart, *Polym. Adv. Technol.* **2022**, *33*, 4250.
[55] S. Afroj, N. Karim, Z. Wang, S. Tan, P. He, M. Holwill, D. Ghazaryan, A. Fernando, K. S. Novoselov, *ACS Nano* **2019**, *13*, 3847.
[56] C. Gonçalves, A. Ferreira da Silva, J. Gomes, R. Simoes, *Inventions* **2018**, *3*, 14.
[57] C.-Y. Huang, C.-W. Chiu, *ACS Appl. Electron. Mater.* **2021**, *3*, 676.
[58] L. Mo, X. Ma, L. Fan, J. H. Xin, H. Yu, *Chem. Eng. J.* **2023**, *454*, 140473.
[59] Hexoskin, Hexoskin Smart Shirts - Cardiac, Respiratory, Sleep & Activity Metrics, https://hexoskin.com/ (online).
[60] M. Zwilling, A. Romano, H. Hoffman, M. Lotan, R. Tesler, *Front. Behav. Neurosci.* **2022**, *16*.
[61] N. Halín, M. Junnila, P. Loula, P. Aarnio, *J. Telemed. Telecare* **2005**, *11*, 41.
[62] Advancing Smart Clothing Technology with Haptic Feedback, https://www.2mel.nl/projects/smart-clothing-sensor-haptic-feedback/ (accessed: December 2024).
[63] N. W.-H. Tsang, U. M. Qureshi, K.-Y. Lam, J. K.-Y. Ng, S. Han, I. Papavasileiou, in *2017 IEEE 31st Int. Conf. on Advanced Information Networking and Applications (AINA)*, IEEE, New York **2017**, 431.
[64] Y. Li, Y. Zhou, C. Shen, R. Stewart, in *Proceedings of the Eighteenth International Conference on Tangible, Embedded, and Embodied Interaction*, ACM, Cork Ireland **2024**, 1.
[65] M. Wagih, O. Malik, A. S. Weddell, S. Beeby, *Eng. Proc.* **2022**, *15*, 9.
[66] O. Atalay, *Materials* **2018**, *11*, 768.
[67] D. Geißler, B. Zhou, H. Bello, J. Sorysz, L. Ray, H. Javaheri, M. Rüb, J. Herbst, E. Zahn, E. Woop, S. Bian, H. D. Schotten, G. Joost, P. Lukowicz, *Sci. Rep.* **2024**, *14*, 15797.
[68] A. Atalay, V. Sanchez, O. Atalay, D. M. Vogt, F. Haufe, R. J. Wood, C. J. Walsh, *Adv. Mater. Technol.* **2017**, *2*, 1700136.
[69] S. D. Min, Y. Yun, H. Shin, *IEEE Sens. J.* **2014**, *14*, 3245.
[70] A. Hatamie, S. Angizi, S. Kumar, C. M. Pandey, A. Simchi, M. Willander, B. D. Malhotra, *J. Electrochem. Soc.* **2020**, *167*, 037546.
[71] B. Zhao, Z. Dong, H. Cong, *Sensors Actuators A: Phys.* **2022**, *340*, 113558.
[72] D. Sengupta, L. Lu, Y. Pei, A. G. P. Kottapalli, in *2022 IEEE 35th International Conference on Micro Electro Mechanical Systems Conference (MEMS)*, IEEE, New York **2022**, 341.
[73] J. S. Meena, S. B. Choi, T. D. Khanh, H. S. Shin, J. S. Choi, J. Joo, J.-W. Kim, *Appl. Surf. Sci.* **2023**, *613*, 155961.
[74] R. Tchantchane, H. Zhou, S. Zhang, A. Dunn, E. Sariyildiz, G. Alici, *Adv. Mater. Technol.* **2025**, *10*, 2401458.
[75] C.-M. Yang, T. Kao, N. N. Y. Chu, C.-C. Wu, T.-L. Yang, in *Proceedings of 2012 IEEE-EMBS Int. Conf. on Biomedical and Health Informatics*, IEEE, New York **2012**, 875.
[76] S. Takamatsu, T. Yamashita, T. Itoh, *Microsystem Technologies* **2016**, *22*, 451.
[77] T. Dong, Y. Gu, T. Liu, M. Pecht, *Sensors and Actuators A: Physical* **2021**, *326*, 112720.
[78] L. Sanchez-Botero, A. Agrawala, R. Kramer-Bottiglio, *Adv. Mater. Technol.* **2023**, *8*, 2300378.
[79] A. Sinha, A. K. Stavrakis, M. Simić, G. M. Stojanović, *ACS Omega* **2022**, *7*, 44928.
[80] M. Martinez-Estrada, B. Moradi, R. Fernández-Garcia, I. Gil, *Sensors* **2018**, *18*, 3824.
[81] L. Chen, M. Lu, H. Yang, J. R. Salas Avila, B. Shi, L. Ren, G. Wei, X. Liu, W. Yin, *ACS Nano* **2020**, *14*, 8191.
[82] S. Raman, R. S. A, *J. Micromech. Microeng.* **2024**, *34*, 083001.
[83] M. Tian, R. Zhao, L. Qu, Z. Chen, S. Chen, S. Zhu, W. Song, X. Zhang, Y. Sun, R. Fu, *Macromol. Mater. Eng.* **2019**, *304*, 1900244.
[84] M. Stoppa, A. Chiolerio, *Sensors* **2014**, *14*, 11957.
[85] R. Aigner, F. Hepper, *IEEE Sens. J.* **2024**, *24*, 6293.
[86] J. Chai, G. Wang, G. Wang, R. Shao, J. Zhao, G. Zhao, C. B. Park, *Adv. Funct. Mater.* **2025**, *35*, 2416428.
[87] Y. Zhou, C. Myant, R. Stewart, *J. Appl. Polym. Sci.* **2022**, *139*, e52755.
[88] C. Sevoz-Couche, S. Laborde, *Neurosci. Biobehavioral Rev.* **2022**, *135*, 104576.
[89] F. Shaffer, J. P. Ginsberg, *Frontiers in Public Health* **2017**, *5*, 258.
[90] A. Voss, R. Schroeder, A. Heitmann, A. Peters, S. Perz, *PLOS ONE* **2015**, *10*, 0118308.
[91] A. Liang, R. Stewart, N. Bryan-Kinns, *Sensors* **2019**, *19*, 3618.
[92] M. Yang, J. Pan, A. Xu, L. Luo, D. Cheng, G. Cai, J. Wang, B. Tang, X. Wang, *Polymers* **2018**, *10*, 568.
[93] C. Mattmann, F. Clemens, G. Tröster, *Sensors* **2008**, *8*, 3719.
[94] K. Arquilla, A. K. Webb, A. P. Anderson, *Sensors* **2020**, *20*, 1013.
[95] S. F. Kamarudin, M. Mustapha, J.-K. Kim, *Polymer Reviews* **2021**, *61*, 116.
[96] T. Blachowicz, G. Ehrmann, A. Ehrmann, *Sensors* **2021**, *21*, 6042.
[97] C. Cochrane, C. Hertleer, A. Schwarz-Pfeiffer, *Smart Textiles and their Applications*, (ed: V. Koncar) Woodhead Publishing Series in Textiles, Vol. *9–32*, Woodhead Publishing, Oxford **2016**.
[98] M. R. Miah, M. Yang, M. M. Hossain, S. Khandaker, M. R. Awual, *Sensors and Actuators A: Physical* **2022**, *344*, 113696.
[99] B. M. Li, B. L. Reese, K. Ingram, M. E. Huddleston, M. Jenkins, A. Zaets, M. Reuter, M. W. Grogg, M. T. Nelson, Y. Zhou, B. Ju, B. Sennik, Z. J. Farrell, J. S. Jur, C. E. Tabor, *Advanced Healthcare Materials* **2022**, *11*, 2200745.
[100] M. Silva, A. P. Catarino, H. Carvalho, A. Rocha, J. L. Monteiro, G. Montagna, Intelligent Textiles and Mass Customisation Int. Conf., Casablanca, Morocco **2009**.
[101] E. Lee, G. Cho, *Smart Materials and Structures* **2019**, *28*, 045004.
[102] L. Beckmann, C. Neuhaus, G. Medrano, N. Jungbecker, M. Walter, T. Gries, S. Leonhardt, *Physiological Measurement* **2010**, *31*, 233.
[103] R. Di Giminiani, S. Lancia, M. Ferrari, V. Quaresima, H. Tilma Vistisen, A. Kliltgaard, R. Arbjerg Heick, K. Oestergard, K. Yndgaard Soerensen, M. Cardinale, in *2018 IEEE Int. Symp. on Medical Measurements and Applications (MeMeA)*, IEEE, New York **2018**, pp. 1–5.
[104] H. Zhang, L. Tian, L. Zhang, G. Li, in *2013 IEEE International Conference on Body Sensor Networks*, IEEE, New York **2013**, pp. 1–5.
[105] J. Taelman, T. Adriaensen, C. van der Horst, T. Linz, A. Spaepen, in *2007 29th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society*, IEEE, New York **2007**, pp. 3966–3969.
[106] X. Liang, M. Zhu, H. Li, J. Dou, M. Jian, K. Xia, S. Li, Y. Zhang, *Adv. Funct. Mater.* **2022**, *32*, 2200162.
[107] S. Kim, S. Lee, W. Jeong, *Polymers* **2020**, *12*, 2406.

[108] H.-G. Kim, E.-J. Cheon, D.-S. Bai, Y. H. Lee, B.-H. Koo, *Psychiatry Investigation* **2018**, *15*, 235.
[109] C. M. Roddick, F. S. Chen, *Annals of Behavioral Medicine* **2021**, *55*, 460.
[110] T. Hussain, S. Ullah, R. Fernández-García, I. Gil, *Sensors* **2023**, *23*, 7518.
[111] S. N. Khonina, N. L. Kazanskiy, M. A. Butt, *Biosensors* **2023**, *13*, 835.
[112] R. He, L. Shen, Z. Wang, G. Wang, H. Qu, X. Hu, R. Min, *Results in Optics* **2023**, *11*, 100386.
[113] I. I. Shuvo, A. Shah, C. Dagdeviren, *Adv. Intell. Syst.* **2022**, *4*, 2100223.
[114] D. Lo Presti, C. Massaroni, J. D'Abbraccio, L. Massari, M. Caponero, U. G. Longo, D. Formica, C. Oddo, E. Schena, *IEEE Sens. J.* **2019**, *19*, 7391.
[115] M. Filosa, L. Massari, D. Ferraro, G. D'Alesio, J. D'Abbraccio, A. Aliperta, D. L. Presti, J. Di Tocco, M. Zaltieri, C. Massaroni, M. C. Carrozza, M. Ferrarin, M. Di Rienzo, E. Schena, C. M. Oddo, *Artificial Intelligence in Medicine* **2022**, *130*, 102328.
[116] J. Nedoma, S. Kepak, M. Fajkus, J. Cubik, P. Siska, R. Martinek, P. Krupa, *Sensors* **2018**, *18*, 3713.
[117] J. Jo, H. T. Park, *Adv. Sensor Res.* **2024**, *3*, 2300017.
[118] D. Z. Stupar, J. S. Bajic, L. M. Manojlovic, M. P. Slankamenac, A. V. Joza, M. B. Zivanov, *IEEE Sens. J.* **2012**, *12*, 3424.
[119] M. Li, B. He, X. Zhao, J. Xie, W. Yao, G. Xu, *Advanced Robotics* **2021**, *35*, 400.
[120] N. Gomes, M. Pato, A. R. Lourenço, N. Datia, *Sensors* **2023**, *23*, 1330.
[121] C. Broadway, R. Min, A. G. Leal-Junior, C. Marques, C. Caucheteur, *J. Lightwave Technol.* **2019**, *37*, 2605.
[122] T. Dinh, T. Nguyen, H.-P. Phan, V. Dau, D. Dao, N.-T. Nguyen, in *Encyclopedia of Sensors and Biosensors (First Edition)*, (ed: R. Narayan), Vol. *20–33*, Elsevier, Oxford **2023**.
[123] P. Lugoda, J. C. Costa, C. Oliveira, L. A. Garcia-Garcia, S. D. Wickramasinghe, A. Pouryazdan, D. Roggen, T. Dias, N. Münzenrieder, *Sensors* **2020**, *20*, 73.
[124] P. Zhao, Y. Song, P. Xie, F. Zhang, T. Xie, G. Liu, J. Zhao, S.-T. Han, Y. Zhou, *Adv. Funct. Mater.* **2023**, *33*, 2301816.
[125] I. Wicaksono, C. I. Tucker, T. Sun, C. A. Guerrero, C. Liu, W. M. Woo, E. J. Pence, C. Dagdeviren, *npj Flexible Electronics* **2020**, *4*, 1.
[126] N. Wang, H. Sun, X. Yang, W. Lin, W. He, H. Liu, G. Bhat, B. Yu, *Sensors and Actuators A: Physical* **2022**, *339*, 113519.
[127] N. Wang, Z. Xia, S. Yang, J. Pan, T. Lei, W. Qiao, L. Wu, *Composites Part B: Engineering* **2023**, *264*, 110928.
[128] T. Q. Trung, T. M. L. Dang, S. Ramasundaram, P. T. Toi, S. Y. Park, N.-E. Lee, *ACS Appl. Mater. Interfaces* **2019**, *11*, 2317.
[129] J. A. Bargh, I. Shalev, *Emotion (Washington, D.C.)* **2012**, *12*, 154.
[130] H. IJzerman, M. Gallucci, W. T. J. L. Pouw, S. C. Weigerber, N. J. Van Doesum, K. D. Williams, *Acta Psychologica* **2012**, *140*, 283.
[131] A. Sinha, Dhanjai, A. K. Stavrakis, G. M. Stojanović, *Talanta* **2022**, *244*, 123425.
[132] C. Li, K. Jia, Q. Liang, Y. Li, S. He, *Interdisciplinary Materials* **2024**, *3*, 270.
[133] M. Kang, K. Chai, *Sensors (Basel, Switzerland)* **2022**, *22*, 3.
[134] S. M. Mugo, W. Lu, S. Robertson, *Biosensors* **2022**, *12*, 854.
[135] L. Zhou, S. S. Menon, X. Li, M. Zhang, M. H. Malakooti, *Adv. Mater. Technol.* **2025**, *10*, 2401121.
[136] W. He, C. Wang, H. Wang, M. Jian, W. Lu, X. Liang, X. Zhang, F. Yang, Y. Zhang, *Sci. Adv.* **2019**, *5*, eaax0649.
[137] S. Khosravi, S. Soltanian, A. Servati, A. Khademhosseini, Y. Zhu, P. Servati, *Biosensors* **2023**, *13*, 684.
[138] M. Sekar, M. Pandiaraj, S. Bhansali, N. Ponpandian, C. Viswanathan, *Sci. Rep.* **2019**, *9*, 403.
[139] J. Zhang, J. Zhou, H. Chen, Y. Liu, D. Liang, Y. Guo, Y. Zhao, Y. Fu, H. Duan, *Chem. Eng. J.* **2024**, *482*, 149067.
[140] N. A. S. Mohd Azmi, N. Juliana, S. Azmani, N. Mohd Effendy, I. F. Abu, N. I. Mohd Fahmi Teng, S. Das, *Int. J. Environmental Res. Public Health* **2021**, *18*, 676.
[141] T. Montoliu, V. Hidalgo, A. Salvador, *Psychoneuroendocrinology* **2019**, *107*, 270.
[142] V. Vignesh, B. Castro-Dominguez, T. D. James, J. M. Gamble-Turner, S. Lightman, N. M. Reis, *ACS Sensors* **2024**, *9*, 1666.
[143] N. F. A. Ibrahim, N. Sabani, S. Johari, A. A. Manaf, A. A. Wahab, Z. Zakaria, A. M. Noor, *Sensors* **2022**, *22*, 7670.
[144] H. Duan, S. Peng, S. He, S.-Y. Tang, K. Goda, C. H. Wang, M. Li, *Adv. Sci.* **2025**, *12*, 2411433.
[145] M. Alizadeh Meghrazi, Y. Tian, A. Mahnam, P. Bhattachan, L. Eskandarian, S. Taghizadeh Kakhki, M. R. Popovic, M. Lankarany, *BioMed. Eng. OnLine* **2020**, *19*, 48.
[146] D. Pani, A. Achilli, A. Spanu, A. Bonfiglio, M. Gazzoni, A. Botter, *IEEE Trans. Neural Syst. Rehabilitation Eng.* **2019**, *27*, 1370.
[147] M. Ciocchetti, C. Massaroni, P. Saccomandi, M. A. Caponero, A. Polimadei, D. Formica, E. Schena, *Biosensors* **2015**, *5*, 602.
[148] M. D. Dankoco, G. Y. Tesfay, E. Benevent, M. Bendahan, *Mater. Sci. Eng.: B* **2016**, *205*, 1.
[149] T. Hughes-Riley, P. Lugoda, T. Dias, C. L. Trabi, R. H. Morris, *Sensors* **2017**, *17*, 1804.
[150] N. Promphet, P. Rattanawaleedirojn, K. Siralertmukul, N. Soatthiyanon, P. Potiyaraj, C. Thanawattano, J. P. Hinestroza, N. Rodthongkum, *Talanta* **2019**, *192*, 424.
[151] M. Chen, Y. Ma, J. Song, C.-F. Lai, B. Hu, *Mobile Networks Appl.* **2016**, *21*, 825.
[152] B. Moradi, R. Fernández-García, I. Gil, *Materials* **2018**, *11*, 955.
[153] J. Pu, K. Ma, Y. Luo, S. Tang, T. Liu, J. Liu, M. Leung, J. Yang, R. Hui, Y. Xiong, X. Tao, *Int. J. Extreme Manufacturing* **2023**, *5*, 042007.
[154] H. Souri, D. Bhattacharyya, *Sens. Actuators A: Phys.* **2019**, *285*, 142.
[155] X. Li, H. Hu, T. Hua, B. Xu, S. Jiang, *Nano Research* **2018**, *11*, 5799.
[156] R. K. Y. Tong, *Wearable Technology in Medicine and Health Care*, Academic Press, Cambridge, MA **2018**.
[157] X. Guo, W. Li, F. Fang, H. Chen, L. Zhao, X. Fang, Z. Yi, L. Shao, G. Meng, W. Zhang, *Sci. Adv.* **2024**, *10*, eadk3855.
[158] R. Guo, T. Li, Z. Wu, C. Wan, J. Niu, W. Huo, H. Yu, X. Huang, *ACS Appl. Mater. Interfaces* **2022**, *14*, 37028.
[159] A. Pantelopoulos, N. G. Bourbakis, *IEEE Trans. Syst. Man Cybernetics, Part C (Appl. Rev.)* **2010**, *40*, 1.
[160] D. Dias, J. Paulo Silva Cunha, *Sensors* **2018**, *18*, 2414.
[161] A. Yu, X. Pu, R. Wen, M. Liu, T. Zhou, K. Zhang, Y. Zhang, J. Zhai, W. Hu, Z. L. Wang, *ACS Nano* **2017**, *11*, 12764.
[162] Y. Zou, L. Bo, Z. Li, *Fundamental Res.* **2021**, *1*, 364.
[163] K. T. Sweeney, T. E. Ward, S. F. McLoone, *IEEE Trans. Inform. Technol. Biomed.* **2012**, *16*, 488.
[164] S. H. Kim, D. W. Ryoo, C. Bae, in *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, New York **2007**, pp. 2564–2567.
[165] L. Zou, X. Chen, A. Servati, S. Soltanian, P. Servati, Z. J. Wang, *IEEE Sens. J.* **2016**, *16*, 762.
[166] A. Servati, L. Zou, Z. J. Wang, F. Ko, P. Servati, *Sensors* **2017**, *17*, 1622.
[167] S. Wei, Z. Wu, *Sensors* **2023**, *23*, 7667.
[168] P. N. Dawadi, D. J. Cook, M. Schmitter-Edgecombe, *IEEE J. Biomed. Health. Inf.* **2016**, *20*, 1188.
[169] C. Cornelius, R. Peterson, J. Skinner, R. Halter, D. Kotz, in *Proceedings of the 12th annual international conference on Mobile systems, applications, and services*, MobiSys '14. Association for Computing Machinery, New York, NY, USA **2014**, pp. 55–67.
[170] T. Brezmes, J.-L. Gorricho, J. Cotrina, in *Distributed Computing, Artificial Intelligence, Bioinformatics, Soft Computing, and Ambient Assisted Living*, (Eds.: S. Omatu, M. P. Rocha, J. Bravo, F. Fernández, E.

Corchado, A. Bustillo, J. M. Corchado), Springer, Berlin, Heidelberg **2009**, 796.
[171] A. Ghosh, A. Sanyal, A. Chakraborty, P. K. Sharma, M. Saha, S. Nandi, S. Saha, in *2017 9th Int. Conf. on Communication Systems and Networks (COMSNETS)*, IEEE, New York **2017**, pp. 488–491.
[172] S. B. Kotsiantis, I. D. Zaharakis, P. E. Pintelas, *Artif. Intell. Rev.* **2006**, *26*, 159.
[173] M. Gochoo, T.-H. Tan, S.-C. Huang, S.-H. Liu, F. S. Alnajjar, in *2017 International Conference on Electrical and Computing Technologies and Applications (ICECTA)*, IEEE, New York **2017**, pp. 1–5.
[174] T.-H. Tan, L. Badarch, W.-X. Zeng, M. Gochoo, F. S. Alnajjar, J.-W. Hsieh, *Sensors* **2021**, *21*, 5371.
[175] S. H. Oh, J. G. Kim, in *2024 Fifteenth International Conference on Ubiquitous and Future Networks (ICUFN)*, IEEE, New York **2024**, pp. 505–509.
[176] R. Bharathi Vidhya, S. Jerritta, *Soft Computing* **2023**, 1.
[177] S. Singh, S. Rathore, O. Alfarraj, A. Tolba, B. Yoon, *Future Gener. Comput. Syst.* **2022**, *129*, 380.
[178] D. Neupane, M. R. Bouadjenek, R. Dazeley, S. Aryal, *Neurocomputing* **2025**, *627*, 129588.
[179] T. Shen, I. Di Giulio, M. Howard, in *2023 IEEE International Conference on Robotics and Automation (ICRA)*, IEEE, New York **2023**, pp. 12659–12664.
[180] N. Gao, G. Xu, G. Chang, Y. Wu, *Adv. Sci.* **2025**, *12*, 2409178.
[181] R. Sowmyalakshmi, P. M. Venkatesh, T. Jayasankar, K. Shankar, in *Wearable Telemedicine Technology for the Healthcare Industry* (Eds.: H. D. Jude, D. Gupta, A. Khanna, A. Khamparia), Academic Press, Cambridge, MA **2022**, 123.
[182] L. A. Bove, *J Nurse Pract* **2019**, *15*, 535.
[183] A. Baskan, G. Goncu-Berk, *Appl. Sci.* **2022**, *12*, 11154.
[184] A. K. Roy Choudhury, P. K. Majumdar, C. Datta, in *Improving Comfort in Clothing*, (Eds.: G. Song), Woodhead Publishing Series in Textiles, Cambridge, UK **2011**, 3.
[185] J. Chung, W. Tang, J. E. Yoon, S. Ha, J. Y. Kang, S. H. Koo, *PloS one* **2024**, *19*, 0299434.
[186] S. O. Han, H. J. Ahn, D. Cho, *Composites Part B: Eng.* **2010**, *41*, 491.
[187] B. Li, Y. Dong, L. Li, *Cellulose* **2015**, *22*, 1295.
[188] L. Ammayappan, G. K. Prasad, T. Senthilkumar, G. T. V. Prabhu, S. Basak, N. K. Jha, in *The Wool Handbook*, The Textile Institute Book Series, (Eds.: S. Jose, S. Thomas, G. Basu), Woodhead Publishing, Cambridge, UK **2024**, pp. 1–23.
[189] Z. Liu, *J. Mater. Civ. Eng.* **2015**, *27*, 04015004.
[190] S. Tiwari, P. Shah, V. Nainani, *Int. J. Sci. Res.* **2024**, *13*, 69.
[191] S. Dinparast Tohidi, A. Zille, A. P. Catarino, A. M. Rocha, *IEEE Sens. J.* **2018**, *18*, 4529.
[192] N. Hester, E. Hehman, *Pers. Soc. Psychol. Rev.* **2023**, *27*, 414.
[193] J. Ratcliffe, M. Kanaan, P. Galdas, *Social Sci. Med.* **2023**, *332*, 116129.
[194] L. C. Hawkley, M. Kocherginsky, *Res. on Aging* **2018**, *40*, 365.
[195] M. L. Kim, E. H. Otal, N. R. Sinatra, K. Dobson, M. Kimura, *ACS Omega* **2023**, *8*, 3971.
[196] L. Zhang, J. He, Y. Liao, X. Zeng, N. Qiu, Y. Liang, P. Xiao, T. Chen, *J. Mater. Chem. A* **2019**, *7*, 26631.
[197] Z. Zhou, S. Padgett, Z. Cai, G. Conta, Y. Wu, Q. He, S. Zhang, C. Sun, J. Liu, E. Fan, K. Meng, Z. Lin, C. Uy, J. Yang, J. Chen, *Biosens. Bioelectron.* **2020**, *155*, 112064.
[198] H. Banaee, M. U. Ahmed, A. Loutfi, *Sensors* **2013**, *13*, 17472.
[199] K. A. James, J. I. Stromin, N. Steenkamp, M. I. Combrinck, *Front. Endocrinol.* **2023**, *14*.
[200] O. Aouedi, A. Sacco, K. Piamrat, G. Marchetto, *IEEE J. Biomed. Health Inform.* **2023**, *27*, 790.
[201] A. J, D. P. Isravel, K. M. Sagayam, B. Bhushan, Y. Sei, J. Eunice, *J. Netw. Comput. Appl.* **2023**, *215*, 103633.
[202] T. Alam, R. Gupta, *Future Internet* **2022**, *14*, 246.
[203] D. Das, in *2018 International Conference on Information Networking (ICOIN)*, IEEE, New York **2018**, pp. 391–396.
[204] M. Fareed, A. A. Yassin, *Bulletin of Electrical Eng. Inform.* **2022**, *11*, 2131.
[205] A. Ahmed, A. Shahzad, A. Naseem, S. Ali, I. Ahmad, *PLOS ONE* **2025**, *20*, 0324285.



Yi Zhou is a Postdoctoral Research Associate funded by the Engineering and Physical Sciences Research Council (EPSRC) at King';s College London (UK), working on the design and development of smart monitoring systems to assess and address loneliness in older adults. She completed her PhD in Design Engineering at Imperial College London, where her research focused on smart wearable electronic textiles, particularly wearable technology for human motion monitoring.

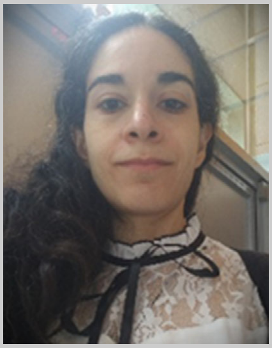
ADVANCED ELECTRONIC MATERIALS Open Access
www.advelectronicmat.de

John Ratcliffe is a Research Fellow in the School of Healthcare at the University of Leeds (UK), working with Nurturing Innovation in Care Home Excellence (NICHE) to raise standards of living for residents, staff, and people living and interacting in care environments. His work has primarily focused on loneliness, particularly in relation to men, older adults, technology, and the conceptualization of loneliness.

Erika Molteni received her PhD in Biomedical Engineering from Politecnico di Milano (Italy), with a thesis on biomedical signal processing and photonics. Since then, she has developed signal processing methods for pediatric intensive care and neurorehabilitation. Erika's work focuses on techniques for monitoring the restructuring of consciousness, sleep and circadian rhythms through polysomnography and neuroimaging, and for the prediction of outcome after a paediatric coma. She is Lecturer in Health Data Science at University College London (UK).

Ashay Patel is a Research Assistant at the school of Biomedical Engineering and Imaging Sciences at King's College London (UK). He specialises in the use of deep learning techniques utilising multimodal data for medical applications.

Jingqi Liu is Research Fellow at University of Leeds, working on electronic and smart textile in Litac Leeds. She finished her PhD in electronic at University of Southampton, where her research expertise is on printed electronics, thin film devices, embedded system and circuit design on wearable electronics textile, healthcare sensor development.



Nikitia Mexia is a Research Fellow in Bioprocessing for Healthcare and Functional Materials in the School of Design of the University of Leeds. A pharmacist by education, her fields of expertise comprise natural products chemistry, organic synthesis and sensor development.

Jessica Rees is a post-doctoral research associate at King's College London (UK), and Chartered Psychologist. Her research interests focus on psychological aspects of health and ageing and her expertise is in qualitative methodologies.

Faith Matcham is a Health Psychologist and Associate Professor of Clinical Psychology at the University of Sussex (UK). She specializes in the interface between mental and physical health, and the use of digital technologies to improve how we measure and manage long term conditions.

Michela Antonelli researches in the area of AI applied to healthcare, with particular focus on cancer imaging and epidemiology. With foundations in computer engineering and AI, her work has led to AI applications in prostate cancer diagnosis and insights during the COVID-19 pandemic. Her research extends to national and international healthcare policies in epidemiology and public health. She lectures at King's College London (UK).

ADVANCED ELECTRONIC MATERIALS Open Access
www.advelectronicmat.de

Anthea Tinker is Professor of Social Gerontology at King's College London (UK). Her research interests are Social Policy and Research Ethics. Recent research includes projects on community care, housing for older people, elder abuse, health trends, carers, falls and accidents, information needs, older workers and technology/communication systems (including navigation aids, mobility of older people, introducing assistive technology into older people's homes and remodelling sheltered housing and residential care homes).

Yu Shi researches on smart composite materials and smart textiles with embedded electronics (printed and weaved/embroidered) for engineering applications (e.g. Aerospace, Space, Automotive, Wind and Hydrogen energy) and wearables (textile, E-Skin) for healthcare and ecology (e.g. wildlife, farming). He is Chair of Textile Innovation and Smart Composite Materials at the Leeds Institute of Textiles and Colouring (LITAC), School of Design, University of Leeds (UK).

Sebastien Ourselin's research vision is to create a unique ecosystem, enabling academia, industry and the national healthcare systems to work in synergy and develop health technologies (including medical devices), workforce and operational improvements that will be of global significance. For 20 years he has fostered translation and commercialisation of healthcare technology, as Professor and Head of School at King's College London (UK). He is a co-founding member of two academic spin#x02010;out companies.

Wei Liu is a Professor of Design Engineering and Innovation at King's College London. She earned her PhD from the University of Cambridge and was a Visiting Fellow at Harvard University. With extensive experience in interdisciplinary research, she brings a wealth of professional design expertise gained from leading businesses and design consultancies. Her contributions to the field have been recognised with a Fellowship from the Royal Society for the Encouragement of Arts, Manufactures and Commerce (FRSA).

