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REVIEW ARTICLE

Review of applications and user perceptions of smart home technology for health and environmental monitoring

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Abstract

In recent decades, smart home technology has advanced, improving the well-being and quality of life of its users. Thus, its applications have expanded, particularly in health and environmental monitoring. Numerous devices have been developed to accommodate user requirements of monitoring; however, the adoption of monitoring devices is closely related to user perception. User perception can be considered from different perspectives. One method of understanding different user perceptions is comparing wearable and nonwearable devices, owing to the differences in their obtrusiveness. The aim of this study was to systematically review the applications and user perceptions of health and environmental monitoring devices, emphasizing on the wearable and nonwearable distinction. We conducted a focused search of articles related to smart home technology and its user perceptions based on its applications. The inclusion criteria were original and peer-reviewed articles centered on health and environmental monitoring devices. We identified and analysed 159 of the 4476 relevant articles and divided the articles into two categories. The first category comprised health and environmental monitoring and their applications by the type of device. The second category comprised user perceptions of monitoring devices. The devices were grouped into wearable and nonwearable devices for our analysis. We identified user perceptions based on usefulness, ease of use, and privacy. Because wearable and nonwearable devices complement their limitations, we recommend their integration for improving user perception.

Keywords: smart home technology; user perception; health monitoring; environmental monitoring; wearable device; nonwearable device

1. Introduction

Over the last decade, information and communication technology, the Internet of Things, and sensing technologies have been utilized to enhance smart home technology (Risteska Stojkoska & Trivodaliev, 2017; Yang *et al.*, 2018). Smart home technology refers to a sensor network that links domestic devices and appliances in a residence and provides services tailored to respond to user demands (Chan *et al.*, 2008; Reeder *et al.*, 2016; Marikyan *et al.*, 2019). Smart home technology collects information from its users and the surrounding environment and accordingly

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Table 1: Keywords used to search databases.

Keywords 1	Keywords 2	Keywords 3	Keywords 4
"Smart home" AND	"Device" AND OR "Sensor" AND	"Application" AND OR "Perception" AND	"Health" OR "Environment"

responds to provide tailored support for individual requirements, consequently improving their well-being and quality of life (QoL; Robles & Kim, 2010; Balta-Ozkan *et al.*, 2014). The versatility and efficiency of smart home technology enable various applications, including remote services, home automation, security systems, health monitoring, energy management, and indoor air quality (iAQ) monitoring (Liu *et al.*, 2016; Majumder *et al.*, 2017; Ghazali & Zakaria, 2018; Pal *et al.*, 2018a; Marikyan *et al.*, 2019).

Previous research efforts have identified that smart home technology has significant potential for in-home health care and well-being (Demiris *et al.*, 2008; Liu *et al.*, 2016; Marikyan *et al.*, 2019). For example, health monitoring devices, such as wearables and mobile monitoring systems, capture and analyse the health status and mobility of users in real time to identify any potential health-related risks and take appropriate actions if necessary for users. In addition, various environmental monitoring systems collect data related to environmental conditions and alert users in a timely manner when various environmental issues occur, such as excessive heat, fire and smoke, and property damage (Saeed *et al.*, 2018; Teslyuk *et al.*, 2018). Moreover, they can support a sustainable home by its monitoring energy efficiency (Balta-Ozkan *et al.*, 2013; Alaa *et al.*, 2017; Hosseini *et al.*, 2017). Particularly, these technologies have been regarded as an effective solution for successful aging of its users (Demiris *et al.*, 2017). The lengthened life expectancy in the society has increased the aging population, which has become more vulnerable to health and safety issues in daily life. The older adults, who suffer from reduced vision and decreased mobility, are exposed to high health-related risks at their homes, which could lower the levels of well-being and increase the demand for care (Carnemolla, 2018). The use of smart home technology designed to maximize the well-being of residents and minimize the negative impact from the environment allows older adults to maintain independence and autonomy and live safely and well at home (Liu *et al.*, 2016; Majumder *et al.*, 2017; Siegel & Dorner, 2017).

Despite the technological advancements in health and environmental monitoring devices, their adoption at the consumer level is still lagging owing to the complexity of the systems and various existing barriers from a user perspective (Sanguinetti *et al.*, 2018; Hubert *et al.*, 2019; Nikou, 2019). Therefore, according to previous research, it is important to understand user perception of monitoring devices to lower the complexity and barriers to users and increase their acceptance and adoption (Paetz *et al.*, 2012; Yang *et al.*, 2017; Hubert *et al.*, 2019; Marikyan *et al.*, 2019; Nikou, 2019). Regarding user perception of such devices, one of the critical factors is whether they are wearable or nonwearable devices (Chan *et al.*, 2008; Marikyan *et al.*, 2019). In general, wearable devices are portable and cost-effective; however, they are highly obtrusive, whereas nonwearable devices are nonportable and relatively expensive; however, they are less obtrusive (Lara & Labrador, 2013; Lo *et al.*, 2017; Schneider & Banerjee, 2018; Sadek *et al.*, 2020; Lumetzberger *et al.*, 2021; Ometov *et al.*, 2021). Because smart home systems must incorporate multisensor approaches by data fusion technologies, understanding the impact of wearableness on the perception of smart home users provides a comprehensive solution to better design an overall smart home system. This involves considering not only system performance but also user acceptance. Owing to the increasing need for understanding user perception of smart home technology, Marikyan *et al.* (2019) and Li *et al.* (2021) have reviewed the current state of the literature. They focused on user perception of both standalone devices and integrated systems for smart homes. However, the wearableness of devices and systems and the corresponding impact on user perception have not been fully investigated thus far.

Therefore, this article aims to provide a comprehensive review of the applications and user perceptions of health and environmental monitoring devices, considering their wearableness. This article contributes to the research on health and environmental monitoring devices by presenting a literature review of articles from 2010 to 2021 and contributes to a better understanding of smart home technology.

2. Study Selection

2.1 Search strategy

We conducted a literature review of articles on smart home technology related to the applications and user perceptions of health and environmental monitoring devices. We limited our search to the period between January 2010 and January 2021 owing to the significant development of monitoring devices in smart home technology during that period (Morris *et al.*, 2014; Liu *et al.*, 2016). A comprehensive review, with a focus on health and environmental monitoring of smart homes, was conducted in the field of applied and social sciences. Thus, we selected two interdisciplinary databases and one technology-focused database for our review, in which we found most of the cited articles in previous studies in the relevant fields. The databases we used are as follows: Science Direct, Web of Science, and IEEE Xplore. (1) ScienceDirect offers access to a large database of publications in physical sciences and engineering, life sciences, health sciences, and social sciences and humanities (Elsevier, 2022). (2) Web of Science offers indexing of multidisciplinary research in sciences, social sciences, arts, and humanities (Clarivate, 2022). (3) IEEE Xplore delivers a wide range of articles in the fields of computer science, electrical engineering, and electronics (IEEE, 2022). A combination of these three databases would provide an overview of existing research on the applications and user perceptions of smart home technology. We extracted articles using the following search terms in different combinations using the logical operators of "AND" and "OR": "smart home," "device," "sensor," "application," "perception," "health," and "environment." The keyword combinations are listed in Table 1.

2.2 Article selection

Using the keywords listed in Table 1, we extracted a total of 4476 articles. Figure 1 shows the selection flow of the articles used in our study. After the initial database search and extraction, we removed duplicate articles, retaining the remainder 3509

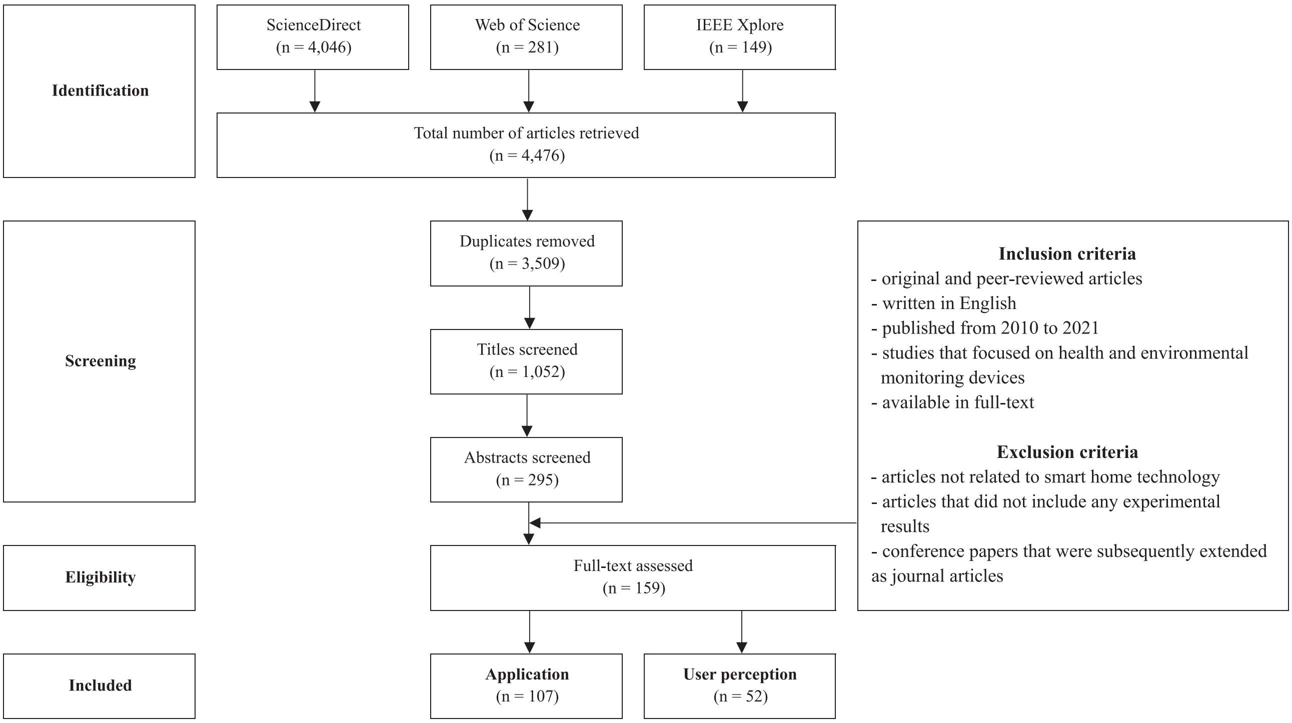

Figure 1: Study selection procedure.

articles. We evaluated the titles, abstracts, and full contents of the remainder articles and compared them with the inclusion criteria. The title and abstract screening yielded 295 articles; after the eligibility assessment of the inclusion and exclusion criteria, 159 articles remained. The inclusion criteria were original and peer-reviewed articles written in English between 2010 and 2021, articles that focused on health and environmental monitoring devices, and articles that were available in full text. The exclusion criteria were articles that were not related to smart home technology, articles that did not include any experimental results, and conference papers that were subsequently extended as journal articles. For doubtable articles, the inclusion and exclusion criteria were discussed and determined. Consequently, we divided the 159 articles into two categories: 107 and 52 articles on applications and user perceptions of smart home technology, respectively.

3. Applications of Smart Home Technology

In this section, we address the applications of smart home technology, emphasizing on the types of devices used in health and environmental monitoring. When discussing these devices, we focus on fall detection, activity of daily living (ADL) monitoring, and healthcare monitoring devices for health monitoring and on energy consumption monitoring and iAQ monitoring devices for environmental monitoring. A total of 107 articles are reviewed in this section, including 81 articles on health monitoring and 26 articles on environmental monitoring. We divided the health monitoring section into six subsections: (i) fall detection monitoring using wearable devices (15 articles), (ii) ADL monitoring using wearable devices (13 articles), (iii) healthcare monitoring using wearable devices (9 articles), (iv) fall detection monitoring using nonwearable devices (17 articles), (v) ADL monitoring using nonwearable devices (13 articles), and (vi) healthcare monitoring using nonwearable devices (15 articles). One article (Jiménez & Seco, 2018) was counted twice as it included both wearable and nonwearable devices for the ADL monitoring. Similarly, environmental monitoring was divided into two subsections: (i) energy consumption monitoring using nonwearable devices (16 articles) and (ii) iAQ monitoring using nonwearable devices (10 articles). The taxonomy of reviewed articles on the applications of smart home technology is presented in Fig. 2 and further described in detail in Table 2.

3.1 Health monitoring devices

3.1.1 *Fall detection devices*

Residential environments are some of the most common locations where falls occur, particularly in older adults (Wild *et al.*, 1981). Various devices have been employed for fall detection to reduce the probability of such falls and the severity of the associated injuries (Lim *et al.*, 2014). Wearable radio-frequency identification (RFID) sensors attached to various parts of the human body have been used to detect falls (Toda & Shinomiya, 2018). For example, Chen and Lin (2010) developed a fall detection method using RFID sensors consisting of wearable RFID readers attached to room shoes and RFID tags mounted on the floor. They detected falls in terms of the variation in the RFID data based on the gait pattern of a user. In some studies (Shinmoto Torres *et al.*, 2013; Wickramasinghe *et al.*, 2017), RFID sensors were attached to the chest of a user for fall detection. These methods detected falls near beds by analysing the received signal strength indicator (RSSI) using machine-learning-based classification.

Wearable accelerometers are also frequently used to detect falls (Sucerquia *et al.*, 2018; Santos *et al.*, 2019). They are commonly attached to the wrists and waists of users to measure acceleration data, whose changes based on the actions of the users are analysed to detect falls (Pierleoni *et al.*, 2015). For instance, Yacchirema *et al.* (2019) developed a fall detection device that detects the falls of a user in real time

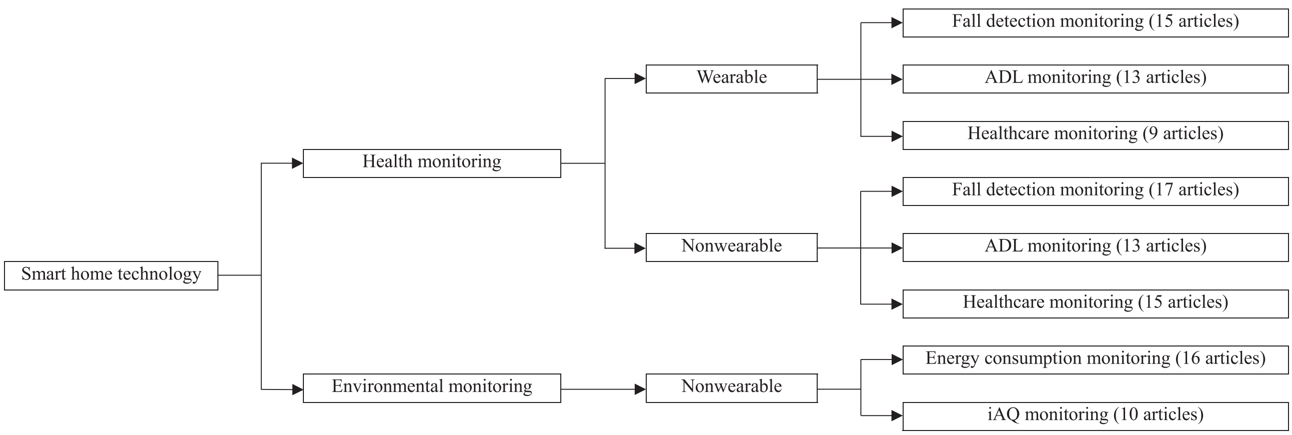

Figure 2: Taxonomy of studies on applications of smart home technology.

using a waist-worn accelerometer and by machine-learning-based classification. Some studies (Mauldin *et al.*, 2018; Yoo & Oh, 2018) used wrist-worn accelerometers and analysed their data by deep-learning-based classification and achieved higher fall detection accuracy than traditional machine-learning-based classification (Santos *et al.*, 2019). However, wearable accelerometers can cause discomfort to users because they must be worn during their daily lives. Several studies have developed fall detection methods using accelerometers embedded in the smartphones of users (Koshmak *et al.*, 2013; Lee *et al.*, 2018; Sucerquia *et al.*, 2018; Mrozek *et al.*, 2020). For example, Shahzad & Kim (2019) used a smartphone-embedded accelerometer to detect falls and provide alert notifications in real time based on machine-learning-based classification. However, these methods can detect falls only when users are carrying smartphones, and their detection accuracies depend on the positions of the smartphones (Dai *et al.*, 2010).

Owing to the abovementioned limitations, fall detection is also monitored using nonwearable devices. Cameras are frequently used as nonwearable devices and considered a more appropriate method when used with computer vision techniques than when employed alone (Alhimale *et al.*, 2014; Núñez-Marcos *et al.*, 2017). Such methods subtract the shape of a user from the camera-captured images using computer vision techniques, such as median filtering and the Gaussian mixture model (GMM), and subsequently detect falls based on the features of the shape of the falling user (Chua *et al.*, 2015). To develop these methods, several studies have used red–green–blue (RGB) cameras. For example, Rougier *et al.* (2011) developed a fall detection method using multiple RGB cameras installed on a ceiling. This method detects falls by classifying the shapes of users by GMM analysis. Albawendi *et al.* (2016) used motion history images captured using an RGB camera to detect falls by user shape analysis. However, RGB cameras raise severe privacy concerns and require appropriate lighting conditions to capture images.

Because of the limitations of RGB cameras, depth cameras are frequently employed for fall detection (Bian *et al.*, 2015; Kong *et al.*, 2018; Zhao *et al.*, 2019). They can capture three-dimensional depth images of users, which contain discerning information to be used in fall detection, thereby enabling the detection of falls more accurately than RGB cameras (Yang *et al.*, 2016). Moreover, depth cameras have the advantage of reducing privacy concerns because they detect falls using the depth images of users and operate even in a dark room; thus, they can be used to detect falls occurring near a bed while someone sleeps (Zhao *et al.*, 2019). For example, Kong *et al.* (2018) developed a fall detection method using depth cameras, involving analysis of the skeleton shapes of a user extracted from the captured depth images by machine-learning-based classification. Nevertheless, installing depth cameras in residential environments still raises privacy concerns and causes user discomfort (Williams *et al.*, 2007).

Because of the privacy concerns of users, various nonwearable devices, which are less invasive than cameras, such as Wi-Fi sensors (Wang *et al.*, 2017), floor sensors (Minvielle *et al.*, 2017), and passive infrared (PIR) sensors (Popescu *et al.*, 2012), have been employed for fall detection. For example, in several studies (Luo *et al.*, 2012; Popescu *et al.*, 2012; Guan *et al.*, 2017), PIR sensors, which measure the infrared radiation that occurs when objects move, were used to detect falls. Here, the fall detection principle is the variation in the measurements of PIR sensors with the speed and orientation of objects (Fan *et al.*, 2017). Nonwearable RFID sensors have also been employed for fall detection. Ruan *et al.* (2015) developed a fall detection method that classified user behaviors into fall and normal behavior by analysing the variation in the RSSI patterns measured using RFID tags and antennas deployed in a room.

3.1.2 Activity of daily living monitoring devices

The ADLs of a subject are closely related to human health (De *et al.*, 2015; Meng *et al.*, 2017). Thus, in many studies, methods for monitoring ADL have been developed using various devices. In several studies (Gao *et al.*, 2014; Moncada-Torres *et al.*, 2014; Bhargava *et al.*, 2018), wearable accelerometers, which can recognize activities and estimate the indoor location of users, were used for ADL monitoring. For example, Awais *et al.* (2019) attached wearable accelerometers at various positions of the human body, such as the thigh, chest, and wrist, and analysed acceleration data by machine-learning-based classification to recognize activities. Bhargava *et al.* (2018) used wearable accelerometers to monitor the ADLs of users with mental disorders in residential environments. They employed pedestrian dead reckoning to estimate the user location based on the body orientation and the limb behavior by analysing the acceleration data.

Other types of wearable devices, such as wearable RFID, Wi-Fi, and Bluetooth low-energy (BLE) beacons, have also been used to monitor ADLs. Belmonte-Fernández *et al.* (2017) used wearable Wi-Fi sensors to monitor ADLs based on the indoor

Table 2: Studies on applications of smart home technology.

Device types		References	Aim	Application description
Radio-frequency identification (RFID) sensors	Wearable (room shoes, chest-worn band)	(Chen & Lin, 2010; Torres *et al.*, 2013; Wickramasinghe *et al.*, 2017; Toda & Shinomiya, 2018)	Fall detection monitoring	RFID tags were attached to body of user using room shoes or chest-worn bands. Falls were detected based on variations in received signal strength indicator (RSSI) measured by RFID readers deployed in space.
	Nonwearable	(Ruan *et al.*, 2015)		
Accelerometers	Wearable (wrist-worn band, waist-worn band, smartphone)	(Dai *et al.*, 2010; Koshmak *et al.*, 2013; Lim *et al.*, 2014; Pierleoni *et al.*, 2015; Lee *et al.*, 2018; Mauldin *et al.*, 2018; Sucerquia *et al.*, 2018; Yoo & Oh, 2018; Shahzad & Kim, 2019; Yacchirema *et al.*, 2019; Mrozek *et al.*, 2020)	Fall detection monitoring	Accelerometers embedded in wrist-worn bands or smartphones were used to detect falls or recognize ADLs by analysing acceleration data varied according to movements of users.
		(Alvarez-Alvarez *et al.*, 2013; Gao *et al.*, 2014; Moncada-Torres *et al.*, 2014; De *et al.*, 2015; Meng *et al.*, 2017; Bhargava *et al.*, 2018; Jiménez & Seco, 2018; Awais *et al.*, 2019; Sridharan *et al.*, 2020)	ADL monitoring	
	Wearable (chest patch)	(Chan *et al.*, 2013)	Healthcare monitoring	Patches embedding accelerometers were attached to the chest of user to estimate respiration rate based on variations in acceleration data.
Red–green–blue (RGB) cameras	Nonwearable	(Rougier *et al.*, 2011; Alhimale *et al.*, 2014; Chua *et al.*, 2015; Albawendi *et al.*, 2016; Núñez-Marcos *et al.*, 2017)	Fall detection monitoring	RGB cameras were installed to detect falls or recognize daily activities by analysing RGB images of users using computer vision techniques.
		(Ni *et al.*, 2011)	ADL monitoring	
		(Poh *et al.*, 2011; Zhao *et al.*, 2013; Tarassenko *et al.*, 2014; Al-Naji *et al.*, 2017; Casalino *et al.*, 2019)	Healthcare monitoring	RGB cameras were used to estimate vital signals of users, such as respiration and heart rate, by analysing variations in their skin color using computer vision techniques.
Depth cameras	Nonwearable	(Bian *et al.*, 2015; Yang *et al.*, 2016; Kong *et al.*, 2018; Zhao *et al.*, 2019)	Fall detection monitoring	Depth cameras were used to recognize daily activities or detect falls by analysing depth images of shapes of users by computer vision techniques.
		(Ni *et al.*, 2011; Giakoumis *et al.*, 2015)	ADL monitoring	
		(Bernacchia *et al.*, 2014)	Healthcare monitoring	Heart and respiration rates of users were estimated by analysing depth images of chests and throats of users captured by depth cameras.
Wi-Fi sensors	Nonwearable	(Wang *et al.*, 2017)	Fall detection monitoring	Wi-Fi sensor was employed to detect falls by analysing variations in channel state information of Wi-Fi signals occurred by movements of users in indoor spaces.
	Wearable (wrist-worn band, smartphone)	(Alvarez-Alvarez *et al.*, 2013; Belmonte-Fernández *et al.*, 2017)	ADL monitoring	Localization technique using Wi-Fi sensors and fingerprinting algorithm were used to monitor ADLs based on indoor locations of users.
Acoustic sensors	Nonwearable	(Vacher *et al.*, 2011; Guyot *et al.*, 2013; Alsina-Pagès *et al.*, 2017; Vafeiadis *et al.*, 2020)	ADL monitoring	Acoustic sensors were employed to detect falls, recognize ADLs, and identify operation of home appliances by analysing sound features of acoustic events by machine-learning-based classification.

Table 2: Continued

Device types		References	Aim	Application description
		(Taysi *et al.*, 2010; Englert *et al.*, 2013; Pathak *et al.*, 2015; Pandya & Ghayvat, 2021)	Energy consumption monitoring	
Passive infrared sensor (PIR) sensors	Nonwearable	(Luo *et al.*, 2012; Popescu *et al.*, 2012; Fan *et al.*, 2017; Guan *et al.*, 2017)	Fall detection monitoring	PIR sensors, which can estimate presence and movements of users, were used to detect falls, monitor ADLs based on indoor locations of users, and analyse occupancy patterns to understand energy demands of users.
		(Crandall & Cook, 2013; Fanti *et al.*, 2016; Kim *et al.*, 2017; Luo *et al.*, 2017; Jiménez & Seco, 2018)	ADL monitoring	
		(Byun *et al.*, 2012; Machorro-Cano *et al.*, 2020; Paredes-Valverde *et al.*, 2020)	Energy consumption monitoring	
Floor sensors	Nonwearable	(Minvielle *et al.*, 2017)	Fall detection monitoring	Floor sensors, which measure pressure on floor, were used to detect falls and track indoor locations of users to monitor ADLs.
		(Braun *et al.*, 2012; Contigiani *et al.*, 2014; Jiménez & Seco, 2018)	ADL monitoring	
Bluetooth low-energy (BLE) beacons	Wearable (wrist-worn band, smartphone, chest-worn band)	(De *et al.*, 2015; Jiménez & Seco, 2018; Morita *et al.*, 2018; Tegou *et al.*, 2018; Zambrano-Montenegro *et al.*, 2018; Sridharan *et al.*, 2020)	ADL monitoring	BLE beacons, which track indoor locations of users based on RSSI of Bluetooth signals, were employed to monitor ADLs.
Electrocardiogram (ECG)	Wearable (chest-worn band, chest-worn patch)	(Lee *et al.*, 2010, 2014; Chan *et al.*, 2013; Crifaci *et al.*, 2013)	Healthcare monitoring	ECG sensors were used as various types of wearable and nonwearable sensors to measure electrical activity of hearts in real time.
	Nonwearable (sensorized furniture)	(Lim *et al.*, 2011; Baek *et al.*, 2012)		
Galvanic skin response (GSR) sensors	Wearable (chest-worn patch, sensorized garment)	(Crifaci *et al.*, 2013; Sugathan *et al.*, 2013)	Healthcare monitoring	GSR sensors, which measure emotional arousal of users, were embedded into patches, garments, and furniture for remote healthcare monitoring.
	Nonwearable (sensorized furniture)	(Hesse *et al.*, 2017)		
Photoplethysmogram (PPG) sensors	Wearable (finger patch, ring)	(Duun *et al.*, 2010; Haahr *et al.*, 2012)	Healthcare monitoring	PPG containing information of blood volume change was measured using PPG sensors developed as finger patch, ring, and sensorized chair.
	Nonwearable (sensorized furniture)	(Lim *et al.*, 2011; Baek *et al.*, 2012)		
Body temperature sensors	Wearable (wrist-worn band, sensorized garment)	(Boano *et al.*, 2011; Sugathan *et al.*, 2013)	Healthcare monitoring	Sensorized shirt and wrist band equipped with body temperature sensors were developed to continuously monitor body temperature to detect illness and analyse circadian rhythm of users.
Heart rate sensors	Wearable (sensorized garment, wrist-worn band)	(Shu *et al.*, 2015)	Healthcare monitoring	Sensorized chair, shirt, and glove swaddle embedding heart rate sensors were developed to monitor heart rate continuously in residential environments.
	Nonwearable (sensorized furniture)	(Hesse *et al.*, 2017)		
Ballistocardiograph (BCG) sensors	Nonwearable (sensorized furniture)	(Kortelainen *et al.*, 2010; Lim *et al.*, 2011; Baek *et al.*, 2012; Su *et al.*, 2019)	Healthcare monitoring	Sensorized chair and beds equipped with BCG sensors that measure BCG signals containing information on activity of heart were developed.

Table 2: Continued

Device types		References	Aim	Application description
Doppler radar sensors	Nonwearable	(Zakrzewski *et al.*, 2012; Yang *et al.*, 2017; Nosrati & Tavassolian, 2018; Petrovic *et al.*, 2019)	Healthcare monitoring	Doppler radar sensors, which can estimate movements of chests of users by transmitting signals, were used to monitor respiration and heart rate unobtrusively.
Power meters	Nonwearable	(Golzar & Tajozzakerin, 2010; Byun *et al.*, 2012; Chen *et al.*, 2014; Filho *et al.*, 2014; Liu *et al.*, 2014; Fletcher & Malalasekera, 2016; Gajowniczek & Zabkowski, 2017; Ullah & Kim, 2017; Matsui *et al.*, 2019; Khan *et al.*, 2020; Machorro-Cano *et al.*, 2020; Paredes-Valverde *et al.*, 2020)	Energy consumption monitoring	Power consumption of entire household or individual appliances was monitored using power meters for efficient energy management considering energy consumption patterns of users.
Indoor temperature sensors	Nonwearable	(Byun *et al.*, 2012; Matsui *et al.*, 2019; Machorro-Cano *et al.*, 2020; Paredes-Valverde *et al.*, 2020)	Energy consumption monitoring	Indoor air temperature was monitored by power consumption in residential environments to manage energy consumption efficiently while considering comfort of users.
		(Saad *et al.*, 2015; Fang *et al.*, 2016; Marques & Pitarma, 2016; Tiele *et al.*, 2018; Zhou *et al.*, 2020)	iAQ monitoring	Environmental parameters (indoor temperature, humidity, and CO_2) that are closely associated with thermal comfort and health of users were monitored using sensors.
Humidity sensors	Nonwearable	(Saad *et al.*, 2015; Fang *et al.*, 2016; Marques & Pitarma, 2016; Zhou *et al.*, 2020)		
CO_2 sensors	Nonwearable	(Jiang *et al.*, 2013; Saad *et al.*, 2015; Marques & Pitarma, 2016; Tiele *et al.*, 2018)		
Particulate matter (PM) sensors	Nonwearable	(Kim & Paulos, 2010; Jiang *et al.*, 2013; Saad *et al.*, 2015; Fang *et al.*, 2016; Moore *et al.*, 2018; Tiele *et al.*, 2018; Gillooly *et al.*, 2019; Zhou *et al.*, 2020)	iAQ monitoring	PM and VOC sensors were used to monitor air pollutants that are difficult to detect by human eyes while significantly affecting the health of users.
Volatile organic compounds (VOCs)	Nonwearable	(Kim *et al.*, 2014; Saad *et al.*, 2015; Fang *et al.*, 2016; Tiele *et al.*, 2018)		

locations of users. Wi-Fi sensors estimate the indoor locations of users based on Wi-Fi signals with different RSSI values. BLE beacons have also been employed to monitor ADLs based on the indoor locations of users (Zambrano-Montenegro *et al.*, 2018). BLE beacons continuously transmit signals, which decrease with distance, and BLE receivers carried by users or deployed in spaces are employed to receive these signals (Baek & Cha, 2019). Based on the RSSI measured by BLE receivers, an indoor location can be estimated using localization techniques, such as trilateration, proximity, and fingerprinting (Qureshi *et al.*, 2018). Morita *et al.* (2018) used BLE beacons to estimate the indoor locations of individual users for the automation of ADL monitoring. Tegou *et al.* (2018) also developed an ADL monitoring method based on the indoor locations of users using BLE beacons and smartphones as BLE receivers.

However, the use of wearable devices to monitor ADLs is inconvenient because users must wear them during daily activities. Thus, several studies have explored ADL monitoring using nonwearable devices. Cameras are frequently employed to monitor ADLs by recognizing user activities (Ni *et al.*, 2011). Giakoumis *et al.* (2015) used depth cameras to estimate indoor locations and recognize daily activities, such as cooking, watching TV, and eating, by analysing silhouette images of a user using computer vision techniques.

Nonwearable acoustic sensors have also been employed to monitor ADLs based on the recognition of user activity (Vacher *et al.*, 2011; Guyot *et al.*, 2013; Alsina-Pagès *et al.*, 2017; Vafeiadis *et al.*, 2020). For example, Alsina-Pagès *et al.* (2017) used acoustic sensors and recognized activities, such as talking, water boiling, and knocking on a door, in residential environments by analysing audio data using machine-learning-based classification. Vafeiadis *et al.* (2020) used acoustic sensors and analysed audio data using convolutional neural network-based classification, automatically extracting features from audio data to increase activity-recognition accuracy in residential environments. However, using cameras and acoustic sensors raises severe privacy concerns for users in residential environments (Crandall & Cook, 2013). In addition, these methods require complex data processing and analysis for feature extraction and classification of the streams of video or audio data (Arning & Ziefle, 2015; Luo *et al.*, 2017).

Other types of nonwearable devices, such as PIR and floor sensors, do not highly intrude privacy. Several studies (Crandall & Cook, 2013; Fanti *et al.*, 2016; Kim *et al.*, 2017; Luo *et al.*, 2017) used PIR sensors, which can detect the presence of users for ADL monitoring, because they are inexpensive and not highly privacy invasive. Kim *et al.* (2017) used PIR sensors with door-switch sensors to estimate the indoor locations of users in a residential environment for the detection of mental disorders based on the changes in ADLs. Crandall and Cook (2013) deployed multiple PIR sensors on a ceiling to track the indoor locations of users based on the sequence detected by each PIR sensor. In some studies (Braun *et al.*, 2012; Contigiani *et al.*, 2014), floors equipped with capacitive and piezoelectric sensors (hereafter, floor sensors) were used to monitor the ADLs of users unobtrusively. Floor sensors can determine the indoor locations of users by analysing the changes in the pressure on the floor.

To achieve highly accurate and detailed ADL monitoring, several studies have used multiple sensors and even combined wearable and nonwearable devices (Alvarez-Alvarez *et al.*, 2013; De *et al.*, 2015; Meng *et al.*, 2017; Jiménez & Seco, 2018; Sridharan *et al.*, 2020). De *et al.* (2015) used diverse sensors, such as BLE beacons, environmental sensors, and accelerometers, and analysed their combined data to accurately recognize various user activities to monitor ADLs. Jiménez and Seco (2018) also used integrated multiple sensors—BLE beacons, wrist-worn accelerometers, floor sensors, PIR sensors, and door-switch sensors—for highly accurate ADL monitoring. They found that the activity recognition accuracy was increased when multiple sensor data were reflected in the analysis. Finally, Sridharan *et al.* (2020) used multifunctional wearable sensors equipped with BLE beacons, magnetometers, and accelerometers to monitor ADLs in significant detail based on accurate location tracking.

3.1.3 *Healthcare monitoring devices*

Currently, the development of biomedical sensors has enabled users to measure vital signals, such as an electrocardiogram (ECG), galvanic skin response (GSR), and body temperature, for diagnosing diseases (Crifaci *et al.*, 2013; Tu & Lin, 2016). These biomedical sensors allow users to receive medical services without visiting healthcare institutions, thereby reducing healthcare costs (Pantelopoulos & Bourbakis, 2010; Majumder *et al.*, 2017). Moreover, critical accidents, such as heart attacks, acute respiratory distress, and chronic diseases, can be effectively diagnosed by long-term and real-time healthcare monitoring (Chan *et al.*, 2013). Therefore, various biomedical sensors have been used in healthcare monitoring, particularly for patients and older adults living alone in residential environments.

Biomedical sensors have been used in various ways as wearable sensors, attached to the body of a user to measure vital signals (Aliverti, 2017). Some studies developed wearable patches using biomedical sensors for healthcare monitoring in residential environments (Duun *et al.*, 2010; Haahr *et al.*, 2012; Chan *et al.*, 2013). Chan *et al.* (2013) developed wireless BLE patches equipped with two ECG sensors and an accelerometer to measure vital signals, such as heart rate (HR) and respiratory rate. Considering the comfort of users, several studies developed clothes equipped with biomedical sensors (hereafter, sensorized garments) (Sugathan *et al.*, 2013; Perego *et al.*, 2015). Sugathan *et al.* (2013) developed a shirt equipped with a GSR sensor and body temperature sensors. However, these methods have limitations for practical applications because users must wear sensorized garments daily for healthcare monitoring and their accuracy for measuring vital signals has not yet been proven.

Several studies have developed bands equipped with biomedical sensors in a more practical manner than sensorized clothes. Lee *et al.* (2010) developed a chest-worn band equipped with ECG sensors; however, the band presented a limitation in stably measuring ECG signals owing to its unstable contact with the human body. To overcome this limitation, Lee *et al.* (2014) supplemented a chest belt equipped with ECG sensors with interspatial materials to ensure stable contact. A wrist-worn band was also used to embed biomedical sensors (Boano *et al.*, 2011; Shu *et al.*, 2015). Shu *et al.* (2015) developed an elastic band embedded with an HR sensor. Although many studies have explored reducing discomfort by developing various types of wearable biomedical sensors, wearing sensors in residential environments can cause physical and psychological discomfort, as well as pose the risk of injury and interference with daily activities (Petrovic *et al.*, 2019).

Owing to the abovementioned limitations, several studies (Lim *et al.*, 2011; Baek *et al.*, 2012; Su *et al.*, 2019) developed sensorized furniture by embedding biomedical sensors into furniture, such as chairs and beds. Hesse *et al.* (2017) developed a sensorized chair equipped with multiple sensors, such as GSR and HR sensors. For healthcare monitoring of sleeping users in residential environments, Kortelainen *et al.* (2010) integrated ballistocardiograph (BCG) sensors into a bed mattress to measure heartbeat intervals. Although sensorized furniture can measure vital signals with lower discomfort than using wearable sensors, they have limitations in accurate data measurements because of the impedance of clothes between sensors and the body of a user (Lim *et al.*, 2011). In addition, these methods only enable healthcare monitoring using sensorized furniture.

Thus, several studies used other types of nonwearable devices such as cameras (Bernacchia *et al.*, 2014; Kranjec *et al.*, 2014; Tarassenko *et al.*, 2014) and Doppler radars (Nosrati & Tavassolian, 2018; Petrovic *et al.*, 2019) to develop healthcare monitoring methods. Healthcare monitoring using cameras indirectly measures vital signals, such as HR, RR, and SpO_2, based on variations in skin RGB color (Poh *et al.*, 2011; Casalino *et al.*, 2019) and brightness (Zhao *et al.*, 2013; Al-Naji *et al.*, 2017). Although a camera can measure user vital signals without discomfort, it has a critical limitation in that it raises user privacy concerns. To address this limitation, some studies used Doppler radar sensors to measure the vital signals of users (Zakrzewski *et al.*, 2012; Yang *et al.*, 2017; Nosrati & Tavassolian, 2018; Petrovic *et al.*, 2019). A Doppler radar sensor continuously transmits signals to moving objects and receives reflected signals to estimate their displacements; thus, by targeting the chest of a user, the HR can be estimated (Zakrzewski *et al.*, 2012). However, a Doppler radar sensor requires a clear line-of-sight condition because any obstacles prevent continuous healthcare monitoring.

3.2 Environmental monitoring devices

3.2.1 *Energy consumption monitoring devices*

With the increase in population and technology development, the energy consumption of overall residential environments has significantly increased, resulting in a rise in environmental and economic costs (Mineno *et al.*, 2010; Kim & Cho, 2019). Monitoring energy consumption enables the detection of wasted energy and understanding of the energy demands of users in residential environments to establish optimal energy management strategies, thus aiding households in reducing energy consumption (Fletcher & Malalasekera, 2016; Khan *et al.*, 2020). Therefore, in previous studies, various energy consumption monitoring methods have been developed using sensorized devices. Power meters, which can measure the energy consumption of an appliance or an entire household, are frequently employed to monitor energy consumption (Golzar & Tajozzakerin, 2010; Liu *et al.*, 2014; Fletcher & Malalasekera, 2016; Gajowniczek & Zabkowski, 2017;

Khan *et al.*, 2020). Filho *et al.* (2014) monitored the energy consumption of home appliances using power meters and detected wasted energy using a Markov chain model and by machine-learning-based classification. Liu *et al.* (2014) used power meters to monitor the use of each appliance to devise optimal energy management strategies customized for individual households. Chen *et al.* (2014) analysed historical power meter data to establish an energy management strategy that minimizes the energy cost of a household.

To establish demand-driven energy management strategies that consider the comfort and behavior of users in residential environments, some studies developed energy monitoring methods by integrating power meters with sensors to measure related parameters (Byun *et al.*, 2012; Ullah & Kim, 2017; Matsui *et al.*, 2019; Machorro-Cano *et al.*, 2020). For example, Paredes-Valverde *et al.* (2020) developed an energy consumption monitoring method by integrating multiple sensors: power meters, PIR sensors, and indoor temperature sensors. They provided recommendations for energy saving based on the energy consumption patterns of a household by analysing data of the sensors. Matsui *et al.* (2019) used power meters and indoor temperature sensors to analyse the correlation between energy consumption and indoor temperature according to the type of household to understand energy demand.

Although power meters are commonly used in the direct monitoring of the energy consumption of appliances, using multiple power meters is expensive. Therefore, in some studies (Englert *et al.*, 2013; Pathak *et al.*, 2015), acoustic sensors were employed to monitor energy consumption in a residential environment. These methods are based on acoustic event detection using machine-learning-based classification, which classifies acoustic events based on their unique sound features, such as mel-frequency cepstral coefficients (Pandya & Ghayvat, 2021). Taysi *et al.* (2010) developed a method to monitor the power consumption of each appliance using acoustic sensors with a single power meter to measure the overall energy consumption of a household. Pandya and Ghayvat (2021) monitored the wasted energy consumption in a residential environment by detecting acoustic events, such as appliance operation, water usage, and door opening, using acoustic sensors and deep-learning-based classification.

3.2.2 Indoor air quality monitoring devices

Because humans spend a majority of their time in residential environments, iAQ significantly affects the QoL (Alexandrova & Ahmadinia, 2018). Despite the significance of iAQ, it is frequently neglected in residential environments because most air pollutants and environmental parameters are difficult to identify with the human eye and many negative symptoms appear only after prolonged exposure (Fang *et al.*, 2016). Therefore, in many studies, iAQ monitoring methods have been developed using sensors that measure air pollutants and environmental parameters (Marques & Pitarma, 2016; Moore *et al.*, 2018; Morawska *et al.*, 2018). For example, Zhou *et al.* (2020) integrated particulate matter (PM), humidity, and indoor temperature sensors to develop a real-time iAQ monitoring method for residential environments. Kim and Paulos (2010) developed the inAir tool using a PM sensor that enables users to monitor air pollutants in residential environments by employing mobile devices. However, with these methods, users cannot identify the source of air pollutants and the severity of the circumstances; therefore, they cannot implement appropriate and immediate actions to improve the iAQ.

To overcome this limitation, Saad *et al.* (2015) developed an iAQ monitoring method that can identify sources of air pollutants by analysing data from multiple sensors—CO_2, volatile organic compound (VOC), PM, indoor temperature, and humidity sensors—using deep-learning-based classification. Fang *et al.* (2016) developed AirSense, which monitors air pollutants and estimates their source and severity by incorporating temperature, humidity, PM, and VOC sensors. Some studies (Jiang *et al.*, 2013; Kim *et al.*, 2014; Gillooly *et al.*, 2019) developed low-cost and portable iAQ monitoring methods to overcome the high cost of installing multiple sensors for iAQ monitoring of an entire house. For example, Jiang *et al.* (2013) developed MAQS, a personalized portable device that monitors the iAQ of the location of a user using a CO_2 sensor and a Bluetooth module. Tiele *et al.* (2018) developed a portable iAQ monitoring device incorporating multiple sensors—CO_2, indoor temperature, VOC, and PM sensors—to comprehensively monitor various air pollutants and environmental parameters.

4. User Perception of Smart Home Technology

Considering the potential capabilities of smart home technology addressed in the previous section, it is important to understand its user perceptions to contribute to providing a more effective user-friendly smart home and an overall improved QoL (Marikyan *et al.*, 2019; Lee & Kim, 2020). Studies have demonstrated the influence of user perception on the acceptance and intention of people to use new technologies (Pal *et al.*, 2018b; Li *et al.*, 2021). For example, Coughlin *et al.* (2007), Yang *et al.* (2017), and Hubert *et al.* (2019) identified usefulness, ease of use, and privacy as significant factors that influence the perceptions of users of smart home technology. Moreover, Coughlin *et al.* (2007) demonstrated that ease of use, reliability, trust, privacy, stigma, accessibility, and affordability are attributes that influence the perceptions of older adults of smart home technology. Yang *et al.* (2017) focused on user behavioral intentions to adopt and use smart home services based on the theory of planned behavior, and observed that mobility, privacy, and trust in the service provider are significant attributes. Hubert *et al.* (2019) and Nikou (2019) focused on the adaptation of smart home technology, and found that compatibility, usefulness, perceived usefulness, and ease of use are the crucial attributes. Finally, Pal *et al.* (2019) used a resistive approach and explored the negative perceptions of users of smart home technology, particularly targeting Asian older adults. They determined that innovativeness, reliability, interoperability, cost, privacy, psychological barriers, and policies are important attributes in adopting smart home technology. We reviewed and classified the perceptions of users of smart home technology into three different categories: perceived usefulness, perceived ease of use, and perceived privacy (Table 3).

In further detail, perceived usefulness refers to the perception of a user of the expected outcomes of the applications of smart home technology, specifically in our review on the benefit of devices for health and environment monitoring. Perceived usefulness is considered the most notable and powerful predictor of the intention of an individual to use smart home technology (Gao & Bai, 2014; de Boer *et al.*, 2019). Perceived ease of use refers to the perceived experience and difficulty of a user in interacting with, controlling, and maintaining smart home technology. It is also an assessment of the effort of an individual associated with the usability and learning of a technology, which not only influences the intention both directly and

Table 3: Evaluation factors of user perception of smart home technology.

Category	Definition
Perceived usefulness	- User perception of expected outcome of applications of smart home technology.
Perceived ease of use	- Perceived experience and difficulty of user in interacting, controlling, and maintaining smart home technology.
Perceived privacy	- User perception of privacy invasion of methods of smart home technology for collecting data and sharing collected data.

indirectly but also the perception of the usefulness and acceptance of the technology (Chen *et al.*, 2009; Lee, 2009; Puri *et al.*, 2017). Perceived ease of use is defined as the effectiveness, efficiency, and satisfaction of using smart home technology (Dimitrokali *et al.*, 2015). In addition, perceived cost and maintenance have been reported to affect the perceived ease of use of smart home technology (Kim & Shin, 2015; Nikou, 2019). Perceived privacy refers to the perception of a user regarding the privacy invasion of smart home technology in relation to collecting data and sharing the collected data. Smart home technology collects data on residents, such as indoor positioning, health conditions, and energy use, which leads to concerns regarding the security of personal information (Balta-Ozkan *et al.*, 2014). Thus, privacy concerns are emergent because of the storing and sharing of personal information to third parties and Internet cloud servers (Puri *et al.*, 2017).

In Table 4, we summarize user perceptions of smart home technology based on health and environmental monitoring factors in three main categories: (i) perceived usefulness, (ii) perceived ease of use, and (iii) perceived privacy. The rightmost column in Table 4 summarizes user perceptions in prior studies based on the aforementioned evaluation factors related to the use of smart home technology. Based on the findings from the considered studies, the general consensus is that the potential benefits of smart home technology applications are significant and necessary features of implementation for effective health monitoring (Pol *et al.*, 2016; Zhou *et al.*, 2018; Matt *et al.*, 2019; Ghorayeb *et al.*, 2021), environmental monitoring via energy consumption (Hargreaves *et al.*, 2010; Paetz *et al.*, 2012; Singh *et al.*, 2018), and managing iAQ (Parag & Butbul, 2018; Wong-Parodi *et al.*, 2018). As seen in Table 4, the participants in the studies had positive perceptions regarding usefulness, regardless of device type (wearable or nonwearable), age, gender, and nationality.

Of the 52 selected studies, 32 focused on human health monitoring devices, 14 on environmental monitoring devices, and 6 on both human health and environmental monitoring devices. Among the 32 human health monitoring studies, 20 used wearable human health monitoring devices, 7 used nonwearable human health monitoring devices, and 5 used both wearable and nonwearable human health monitoring devices. Among the 52 studies, most (44) mentioned perceived usefulness, 6% (32) mentioned perceived ease of use, and approximately half (25) mentioned perceived privacy. Moreover, many studies specifically focused on older adults; approximately half of the studies (27) selected older adults as participants, whereas only three studies focused on children.

4.1 Health monitoring devices

4.1.1 Perceived usefulness

In the analysed studies, the participants perceived human health monitoring devices as useful (Pol *et al.*, 2016; Zhou *et al.*, 2018; Matt *et al.*, 2019). The applications of health monitoring devices included effective emergency assistance (Govercin *et al.*, 2010; Willius *et al.*, 2019), remote real-time monitoring and sharing of their collected data to potentially useful entities (Casalino *et al.*, 2020; Reeder *et al.*, 2020), and improving the overall QoL of the users (Demiris *et al.*, 2004; Singh *et al.*, 2018; Mackintosh *et al.*, 2019).

Health monitoring wearable devices were also used to monitor ADLs, decline in mental health and cognition, and heart conditions (Liu *et al.*, 2016). In the analysed studies (Visutsak & Daoudi, 2017; Matt *et al.*, 2019; Jo *et al.*, 2021), it was found that the participants perceived the application of wearable devices as necessary owing to their potential benefits. Dhukaram *et al.* (2011) identified that wearable health monitoring devices enable medical professionals and patients to save time and improve their well-being. Holzinger *et al.* (2010) claimed that an alarm system operated through a wearable health monitoring device would be useful for patients with heart conditions. In a web-based large sample survey ($n = 2080$) of Chinese young adults, the respondents ranked health-related functions, such as HR monitoring, daily activity monitoring, and sleep monitoring, as the most useful functions of wearable health monitoring devices (Wen *et al.*, 2017; Jia *et al.*, 2018). The quality and accuracy of wearable devices are significantly related to their perceived usefulness (Li *et al.*, 2019). In addition, people with poor health conditions perceive wearable devices as highly useful (Li *et al.*, 2019). Wearable activity trackers are also considered beneficial. Some studies (Gualtieri *et al.*, 2016; Maher *et al.*, 2017) claim that an activity tracker increases the activity levels of participants by acting as a visible reminder and thus improves health and fitness. Wearable activity trackers are also advantageous for setting up objectives and function as motivators (Mercer *et al.*, 2016). Although they adequately reflect the activity level of children, they do not make children more active (Mackintosh *et al.*, 2019).

Nonwearable health monitoring devices are also considered useful; however, this is not as evident as for wearable devices. According to one study, although approximately three-quarters of college students considered nonwearable health monitoring devices as convenient, only approximately half of them responded that they would be useful (Wania, 2019). Pol *et al.* (2016) observed that the participants in their study felt safe and remained active at home because of a health monitoring device. In other studies, the participants rated the usefulness of nonwearable health monitoring devices highly, particularly when the devices were used for monitoring the health of family members (Choe *et al.*, 2012; Singh *et al.*, 2018). Interestingly, people in different countries perceive nonwearable health monitoring devices differently. In an investigation, German participants did not consider such devices to be useful for old adults, whereas British and Italian participants considered these devices to be beneficial for the older adults (Balta-Ozkan *et al.*, 2014).

Notably, positive perceptions of the necessity of health monitoring devices were occasionally mentioned after participants were provided with sufficient knowledge and increased awareness regarding the potential benefits of the studied devices (Chung *et al.*, 2017). For instance, participants initially raised

Table 4: Studies on user perceptions of smart home technology applications.

Device type		Authors	Participant (N) Age (A) Gender (M/F) Region (R)	Summary of key findings based on evaluation factors
Health monitoring devices				
Wearable devices	Smart band	(Holzinger *et al.*, 2010)	Nonspecific R = Switzerland	Usefulness/ease of use. Older adults/smart band to monitor vital signs and detect falls and unconsciousness. Most participants perceived usefulness of applications of devices negatively because they considered them as unnecessary. Additionally, participants considered devices difficult to use.
	ECG sensor	(Dhukaram *et al.*, 2011)	N = 34 A = 50–89 M = 65% F = 35% R = UK	Usefulness/ease of use/privacy. Older adults/focused on ECG sensor. Positive perceptions of usefulness of device for improving well-being, effective medical assistance, and ease of use were observed. However, discordant perceptions of perceived privacy were reported.
	Accelerometer (neck-worn sensor)	(Geraedts *et al.*, 2015)	N = 20 A = 70+ M = 20% F = 80% R = Netherlands	Usefulness. Older adults/accelerometer and barometric pressure sensor. Participants positively perceived usefulness of devices in detecting daily physical activities.
	Wearable devices (wrist-, arm-, and neck-worn sensors)	(Fang & Chang, 2016)	N = 24 A = 50+ M = 29% F = 71% R = Taiwan	Usefulness/ease of use. Older adults/compare different wearing locations of wearable devices. Attitudes of older adults to wearable devices were significantly different. Psychological comfort was related to wearing location and device size.
	Wearable activity trackers	(Mercer *et al.*, 2016)	N = 32 A = 50+ M = 28% F = 72% R = Canada	Usefulness/ease of use. Older adults/compared acceptance of five different wearable activity trackers. Overall, activity trackers were rated easy to use and comfortable. Activity trackers were useful in setting up objectives and functioned as motivators.
	Smart band (wearable activity trackers)	(Gualtieri *et al.*, 2016)	N = 10 A = 39–77 M = 20% F = 80% R = USA	Usefulness/ease of use. Mostly older adults/wearable activity trackers to measure physical activity. Despite positive perceptions of usefulness, implications of negative perceptions of cost factor of devices, discomfort in wearing device, and difficulty in accessing their information were indicated.
	Smart band (wearable activity trackers)	(Maher *et al.*, 2017)	N = 237 A = 18–70 M = 29.1% F = 70.9% R = Australia	Usefulness/ease of use. Adults/no specific smart band. Participants positively perceived usefulness of devices. Participants had positive overall ease-of-use experience with activity trackers; however, they addressed complexity in management of devices and experiencing technical difficulties.
	Smart band (wearable activity trackers)	(Puri *et al.*, 2017)	N = 20 A = 55–84 M = 40% F = 60% R = Canada	Usefulness/ease of use/privacy. Older adults/wearable activity trackers. Findings indicate positive perceptions of privacy of device application in terms of data collection and sharing. Implications on cost, comfort, and ease of use as critical factors for age-friendly devices were indicated.
	Accelerometer (wrist- and hip-worn sensors)	(Scott *et al.*, 2017)	N = 24 A = 14–15 M/F = Nonspecific R = Australia	Ease of use/comfort. Adolescents/comparing wrist- and hip-worn accelerometer. Findings on negative perceptions of ease of use owing to inconvenience of interruption to daily activities and negative psychological effects, such as embarrassment from wearing devices, were indicated.

Table 4: Continued

Device type		Authors	Participant (N) Age (A) Gender (M/F) Region (R)	Summary of key findings based on evaluation factors
	Wearable device (nonspecific)	(Wen *et al.*, 2017)	N = 2058 A = Nonspecific M = 48.3% F = 51.7% R = China	Usefulness/privacy. Mostly young adults/online survey of wearable devices. Findings demonstrate expectations for potential benefits of devices were positively perceived. However, negative perceptions of using wearable devices, concerns on privacy, and data security were also indicated.
	Smart band (wearable activity trackers)	(Ehn *et al.*, 2018)	N = 8 A = 75+ M = 25% F = 75% S = Sweden	Usefulness/ease of use. Older adults/activity monitors and tablet-based apps. Despite positive perception of usefulness, negative perceptions of difficulty in accessing information, discomfort from interruptions, wearing location, and concerns on device management were indicated.
	Smart band	(Jia *et al.*, 2018)	N = 388 A = Nonspecific M = 66.2% F = 33.8% R = Nonspecific	Usefulness/ease of use. Young adults/comparing seven different smart bands. Participants positively perceived usefulness of wearable devices for daily activity tracking, health monitoring, and fitness tracking. However, generally negative perceptions of financial cost of devices were indicated.
	Wearable device (nonspecific)	(Kekade *et al.*, 2018)	N = 233 A = Nonspecific M = 35.6% F = 64.4% R = Nonspecific	Usefulness/ease of use/privacy. Older adults/online survey of wearable devices. Minority of older generation population currently use wearable devices owing to insufficient awareness of smart home technology. Additionally, despite limitations on physical comfort, positive perceptions of usefulness were indicated.
	Smart band	(Zhou *et al.*, 2018)	N = 20 A = 58–68 M = 45% F = 55% R = China	Usefulness. Older adults/focus on effects on social capital. Potential to improve and manage health by monitoring using wearable devices was positively perceived. Moreover, sharing sensor-collected personal health information with family and friends increases social capital.
	Smart band (wearable activity trackers)	(Farina *et al.*, 2019)	N = 26 A = Average 79.8 M = 92.3% F = 7.7% R = UK	Usefulness/ease of use. Older adults/feasibility of activity monitors in older adults with dementia. Comfort of wrist-worn wearable devices for prolonged periods was perceived positively. Additional implications of implementation of necessary features for users to improve potential benefits were addressed.
	Smart band	(Kim & Choi, 2019)	N = 147 A = 61–96 M = 54.1% F = 45.9% R = Korea	Privacy. Older adults/focused on perceptions of older adults of privacy. Study findings indicate that older people are more selective about sharing private data than younger people are, in South Korea.
	Smart band, accelerometer, and ECG sensor	(Li *et al.*, 2019)	N = 146 A = 60+ M = 56.2% F = 43.8% R = China	Usefulness/ease of use. Older adults/explain smart wearable acceptance model. Negative implications of unfelt demand and reliability of potential benefits were observed. Additionally, emphasis on age-friendly ease of use, including instructions or technical support, and financial aid were indicated.
	Smart band (wearable activity trackers)	(Mackintosh *et al.*, 2019)	N = 36 A = 7–12 M = 50% F = 50% R = Australia	Usefulness/ease of use. Children/parental perspectives of wearable activity tracker for children. Perceived acceptability and ease of use of wearable activity trackers for children were explored. Parents reported that children found wearable activity trackers easy to use. Wearable activity trackers adequately reflect activity level of children; however, they did not make children more active.

Table 4: Continued

Device type		Authors	Participant (N) Age (A) Gender (M/F) Region (R)	Summary of key findings based on evaluation factors
	Fitness trackers (Nonspecific)	(Matt *et al.*, 2019)	N = 16 A = 22–62 M = 50% F = 50% R = Spain	Usefulness/ease of use/privacy. Adults/potential benefits and deficiencies of consumer health wearables. In addition to positive perceptions of benefits of physical activity monitoring and encouragement to improving health, overall perception on ease of use was positive. For ease of use, complexity of devices was indicated, and perceived privacy was related to continuous use of fitness trackers.
	Smart band	(Willius *et al.*, 2019)	N = 20 A = 65+ M/F = Nonspecific R = Chile	Usefulness/ease of use/privacy. Older adults/personal, portable electronic health device (DEPPAS) in disaster scenarios. Negative perceptions of concerns on device maintenance, cost, and design aesthetics were indicated. Additionally, although privacy was negatively perceived, findings indicate potential benefits outweighed perceived risks.
Nonwearable devices	In-home monitoring (IHM), motion, and contact sensors	(Boise *et al.*, 2013)	N = 119 A = 78–88 M = 22% F = 78% R = USA	Privacy. Older adults/focused on privacy concerns. Findings showed discordant perceptions of perceived privacy of devices; although participants did not negatively perceive collection of data, concerns of data security were indicated.
	IHM and motion sensors	(Reeder *et al.*, 2013)	N = 8 A = 79–86 M/F = Nonspecific R = USA	Usefulness/privacy. Older adults/acceptability of in-home devices. Participants positively perceived usefulness of devices. They also positively perceived privacy in terms of data sharing; however, there were indications of concerns of data security.
	IHM sensor	(Claes *et al.*, 2015)	N = 245 A = 60+ M = 32% F = 68% R = Belgium	Usefulness/privacy. Older adults/perceptions of monitoring ADLs. Findings identified significant concerns of financial burden of device acquisition and maintenance. Conversely, participants positively perceived privacy in terms of information sharing for effective assistance.
	IHM, motion, and contact sensors	(Pol *et al.*, 2016)	N = 11 A = 68–93 M = 38% F = 62% R = Netherlands	Usefulness/privacy. Older adults/analysed perceptions by interpretative phenomenological analysis. Findings indicate that participants did not negatively perceive privacy factor; they indicated that it was important that their collected information was continuously accessed by helpful entities for better assistance.
	IHM sensor (PIR motion sensors)	(Reeder *et al.*, 2016)	N = 8 A = 79–86 M/F = Nonspecific R = USA	Usefulness/privacy. Older adults/focused on obtrusiveness framework. Participants questioned necessity of devices because they believed they were healthy. Several participants indicated negative responses on privacy invasion of data collection and data security.
	IHM and motion sensors	(Chung *et al.*, 2017)	N = 21 A = 65+ M/F = Nonspecific R = USA, Korea	Usefulness/privacy. Older adults/emphasized in cultural context. Participants negatively perceived privacy invasion in terms of data collection owing to concerns of being video monitored (despite being informed of no-video recording features integrated into devices).
	IHM and video sensors	(Casalino *et al.*, 2020)	N = 30 A = 21–81 M = 70% F = 30% R = Italy	Usefulness/privacy. Adults/evaluating user perceptions of self-care cardiac monitoring devices. Positive perceptions of financial benefits (reduction in healthcare cost) were addressed. Although data collection and information sharing were generally positively perceived, uncertainties on ensuring privacy were mentioned.

Table 4: Continued

Device type		Authors	Participant (N) Age (A) Gender (M/F) Region (R)	Summary of key findings based on evaluation factors
Wearable and nonwearable devices	IHM, video, and motion sensors	(Gövercin *et al.*, 2010)	N = 22 A = 50–75 M = 37% F = 63% R = Germany	Ease of use/privacy. Older adults/user acceptance of fall detection and fall prevention. Perceived ease of use of IHM sensor negatively owing to its complex installation requirement. Additionally, negative implications of privacy invasion from application of video sensors were observed.
	IHM sensor	(Birchley *et al.*, 2017)	N = 20 A = Nonspecific M = 75% F = 25% R = Nonspecific	Privacy. Adults/focused on ethical perspectives. Participants had discordant perceptions of privacy invasion of data collection and management of devices.
	Nonspecific	(Visutsak & Daoudi, 2017)	N = 40 A = Nonspecific M/F = Nonspecific R = Thailand	Usefulness. Older adults/comparing preference of various device types. Necessity of smart home technology for older generation population was highly positively perceived. Additionally, preference of wearable devices over IHM video sensors was indicated.
	IHM sensor (visual and ambient sensors) and skin sensor	(Jaschinski & Ben Allouch, 2019)	N = 18 A = 45–65 M/F = Nonspecific R = Netherlands	Usefulness/ease of use/privacy. Adults/focused on perspectives of caregivers. Despite positive perceptions of usefulness of providing safety and peace of mind to users, privacy and ease-of-use factors of devices were generally perceived negatively.
	IHM sensor and accelerometer	(Reeder *et al.*, 2020)	N = 10 A = 60+ M = 0% F = 100% R = USA	Usefulness/ease of use/privacy. Older adults/focused on perceptions of older women. There were discordant perceptions of perceived ease of use; many participants perceived difficulty in ease of use and discomfort from interference to daily activities.
Environmental monitoring devices				
Nonwearable devices	Smart meter	(Hargreaves *et al.*, 2010)	N = 15 Households A = Nonspecific M/F = Nonspecific R = UK	Ease of use. Households/focused on feedback of households after using smart energy monitors. Participants perceived difficulty in ease of use and device management. In addition, mentions of requiring significant effort in changing their lifestyle were addressed as negative perceptions.
	Smart meter	(Patel *et al.*, 2010)	N = 73 A = 18+ M = 43% F = 57% R = USA	Ease of use/comfort. Adults/evaluation of power consumption sensor. Findings indicate positive perception of ease of use of contactless devices for their ease in installation compared with transformer-based devices.
	Smart meter	(Paetz *et al.*, 2012)	N = 29 A = 21–61 M = 62% F = 38% R = Germany	Usefulness/ease of use. Adults/focused on consumer perspective. Findings indicate positive perceptions of energy consumption monitoring. However, negative perceptions were observed for ease of use from having to sacrifice personal comfort for insignificant energy saving.
	Smart meter	(Balta-Ozkan *et al.*, 2013)	N = 60 A = Nonspecific M/F = Nonspecific R = UK	Usefulness/ease of use. N/A/focused on social barriers. Findings indicate significant negative perceptions of ease of use in terms of discomfort from having to significantly adapt to new daily routines to save energy costs; perceived potential benefit as insufficient.
	Smart meter	(Hargreaves *et al.*, 2013)	N = 11 Households A = Nonspecific M/F = Nonspecific R = UK	Usefulness. Households/focused on feedback of households after year of using smart energy monitors. Participants perceived smart meter as useful; it increased their knowledge and confidence on energy consumption. However, beyond certain level, energy consumption level of participants was not significantly changed.

Table 4: Continued

Device type		Authors	Participant (N) Age (A) Gender (M/F) Region (R)	Summary of key findings based on evaluation factors
	Smart meter	(Barnicoat & Danson, 2015)	N = 24 A = 50–92 M = 12.5% F = 87.5% R = Scotland	Usefulness/ease of use. Older adults/attitudes of older adults toward energy use. Although positive perceptions of provision on real-time information on energy consumption were indicated, negative perceptions of comfort owing to high consumption levels and sacrificing comfort to save energy costs were observed.
	Smart thermostat and smart meter	(Dimitrokali *et al.*, 2015)	N = 71 A = 25+ M = 84.5% F = 15.5% R = UK	Usefulness/ease of use. Adults/focused on smart home heating controller. Participants positively perceived convenience of remote controlling devices and their benefit in successfully changing their heating habits. Additionally, participants positively perceived ease of use of devices.
	IHM sensor (motion, temperature, and door sensors)	(Hu *et al.*, 2016)	N = 13 A = 54–85 M = 5 F = 8 R = USA	Ease of use. Older adults/focused on self-installed smart home technology. Findings indicate positively perceived ease of use owing to easy-to-understand instructions for installations and comfort.
	Smart meter	(Hargreaves *et al.*, 2018)	N = 10 Households A = Nonspecific M/F = Nonspecific R = UK	Usefulness. Households/nine-month field trial. Although learning about personal energy consumption habits and ability to optimize them for effective use were perceived positively, significant inconveniences were mentioned from limitations on changing behavior patterns.
	Smart thermostat	(Parag & Butbul, 2018)	N = 554 A = 21+ M = 54% F = 46% R = Israel	Usefulness/ease of use/privacy. Adults/focused on perceptions of Flexiwatts. Participants positively perceived usefulness of device in their homes owing to its potential benefits. Despite potential privacy invasion in data collection, participants were not deterred to negatively perceive it.
	iAQ sensor	(Wong-Parodi *et al.*, 2018)	N = 276/26 A = 18+ M/F = Nonspecific R = USA	Usefulness. Adults/focused on perceptions of iAQ sensors. Participants positively perceived usefulness of device to monitor and improve their iAQ. Despite this, they negatively perceived cost for device application to be significantly expensive.
	Smart meter	(Brown & Markusson, 2019)	N = 26 A = 25+ M = 57.7% F = 42.3% R = UK	Usefulness. Adults/compared responses of older adults to smart energy monitors with young adults. Positive perceptions of devices as adequate learning tools for effective management of energy consumption were observed. However, negative perceptions owing to sacrifice of comfort to save insignificant energy costs were also indicated.
	iAQ sensor	(Kim *et al.*, 2019)	N = 35 A = 7–12 (and caregivers) M = 31.5% F = 68.5% R = USA	Usefulness/ease of use. Children and their caregivers/focused on children in low-income families. Despite positive perceptions of usefulness of iAQ management, participants negatively perceived ease of use owing to difficulties in using and understanding displayed iAQ information.
	Smart meter	(Shirani *et al.*, 2020)	N = 24 A = 20–80 M/F = Nonspecific R = Wales	Usefulness. Adults/focused on perspectives of consumers. Participants positively perceived usefulness for monitoring their energy consumption and detecting which appliances consume most amount.

Table 4: Continued

Device type		Authors	Participant (N) Age (A) Gender (M/F) Region (R)	Summary of key findings based on evaluation factors
Health and environmental monitoring devices				
Nonwearable devices	IHM sensor (video camera, accelerometer, and smart meter)	(Choe *et al.*, 2012)	N = 22 A = 28–54 M = 54.5% F = 45.5% R = USA	Usefulness/privacy. Adults/perception and acceptance of IHM sensors. Participants perceived potential benefits to outweigh invasive privacy. However, they addressed negative perception toward using devices integrated with recording features.
Nonspecific	Nonspecific	(Balta-Ozkan *et al.*, 2014)	N = 144–180 A = Nonspecific M/F = Nonspecific R = UK, Germany, and Italy	Usefulness/privacy. N/A/comparing three countries on consumer perceptions. Participants of all three countries addressed negative perceptions on privacy; concerns of collection of their energy consumption data and security to maintain accumulated data were observed.
Nonspecific	Nonspecific	(Singh *et al.*, 2018)	N = 234 A = 50+ M = 58.1% F = 41.9% R = Nonspecific	Usefulness/ease of use/privacy. Adults/surveyed perception of smart home technology to participants in different continents. Generally, positive perceptions of application of devices to improve QoL and comfort in living were observed. However, negative implications of technology dependence and privacy invasion were indicated.
Nonwearable devices	IHM sensor (security monitor and smart thermostat)	(Wania, 2019)	N = 68 A = 18–21 M = 64.7% F = 35.3% R = Nonspecific	Usefulness/ease of use/privacy. Young adults/focused on perception of college students of smart homes. Although discordant perceptions on the usefulness and privacy of device application were observed, positive perceptions on the overall device application for its benefit in comfort, time saving, and financial savings were indicated.
Wearable and nonwearable devices	IHM sensor (accelerometer, smart meter, and iAQ sensor)	(Ghorayeb *et al.*, 2021)	N = 13 A = 65–89 M = 38% F = 62% R = UK	Usefulness/ease of use/privacy. Older adults/focused on perceptions of older adults of smart homes. Concerns on financial burden and necessity for device applications were commonly mentioned. Additionally, discordant perceptions of perceived privacy invasion were indicated.
Wearable and nonwearable devices	Smart band, smart meter, and iAQ sensor	(Jo *et al.*, 2021)	N = 9 A = 68–87 M = 0% F = 100% R = Korea	Usefulness/ease of use/privacy. Older adults/focused on perceptions of older adults of integrated smart home technology. Participants perceived ease of use negatively. In contrast, participants positively perceived privacy of device application in terms of both data collection and data security.

concerns regarding privacy invasion in relation to data collection (Reeder *et al.*, 2020; Jo *et al.*, 2021), as well as maintenance costs (Gualtieri *et al.*, 2016); thus, these factors limit the acceptance of monitoring devices. However, after acquiring sufficient knowledge on the potential benefits of such devices based on experience, participants showed greater interest in health monitoring devices (Chung *et al.*, 2017). Furthermore, participants found the usefulness of the health monitoring device to outweigh negatively perceived attributes, such as ease of use and privacy (Pol *et al.*, 2016; Willius *et al.*, 2019).

In the analysed studies, most older adults highlighted the potential usefulness of health monitoring systems based on the assistance that these devices provide in living longer at home safely and independently (Claes *et al.*, 2015). Older adults responded that wearable devices are more useful than nonwearable ones in fall detection because the former provide security and mobility (Gövercin *et al.*, 2010). Thus, older adults perceive health monitoring devices as necessary owing to their individual requirements (Holzinger *et al.*, 2010; Ghorayeb *et al.*, 2021). However, in several studies specific to older adults (Courtney *et al.*, 2008; Londei *et al.*, 2009; Chung *et al.*, 2017; Jaschinski & Ben Allouch, 2019; Ghorayeb *et al.*, 2021), the participants questioned the actual necessity of health monitoring devices and mentioned that they did not require their assistance. Specifically, although the participants agreed about the usefulness of health monitoring devices, they did not consider these devices to be necessary (Reeder *et al.*, 2013). In some studies (Londei *et al.*, 2009; Reeder *et al.*, 2016; Jaschinski & Ben Allouch, 2019), the older adult participants were sufficiently healthy to not require health monitoring devices and were unwilling to acknowledge their frailty in old age (Courtney *et al.*, 2008). Nevertheless, Li *et al.* (2019) determined that among older adults, perceived usefulness is influenced by the usage or opinions of others, emphasizing the influence of social factors on perceived usefulness. Similarly, in another study, 75% of the children who had participated agreed to wear the devices if their peers wore them, which highlights the effect of peer pressure (Mackintosh *et al.*, 2019).

4.1.2 *Perceived ease of use*

Findings from many studies indicate that participants perceive the ease of use of health monitoring devices negatively owing to maintenance concerns (Govercin *et al.*, 2010; Ehn *et al.*, 2018), discomfort (Farina *et al.*, 2019; Mackintosh *et al.*, 2019), and complexity (Holzinger *et al.*, 2010; Maher *et al.*, 2017). The maintenance of a health monitoring device is a common factor affecting its ease of use (Govercin *et al.*, 2010; Chung *et al.*, 2017; Ehn *et al.*, 2018). For instance, there are inconveniences and difficulties in controlling the battery supply of devices (Jo *et al.*, 2021), as well as concerns regarding damaging these devices during daily activities (Reeder *et al.*, 2020) and subsequent issues associated with repair and maintenance (Willius *et al.*, 2019). The use of a battery is particularly significant for older adults with dementia because they might forget to charge the device or switch it on again after charging (Farina *et al.*, 2019). Similarly, charging a wearable device and syncing it to an app for child users are inconvenient to the parents; thus, reducing the ease of use for children (Mackintosh *et al.*, 2019). In addition, the cost of installing devices limits the acceptance of health-monitoring devices (Gualtieri *et al.*, 2016; Puri *et al.*, 2017). Furthermore, maintenance support—including insurance and repairing through follow-up services in case of damage—is an important criterion for consideration with regard to health monitoring devices (Claes *et al.*, 2015; Willius *et al.*, 2019; Jo *et al.*, 2021). Nevertheless, in some studies (Casalino *et al.*, 2020), the participants believed that the cost of the health monitoring device considered would eventually be offset by reduced medical expenses. Moreover, activity trackers are rated as easy to use and comfortable (Mercer *et al.*, 2016; Mackintosh *et al.*, 2019).

Comfort is an attribute that significantly influences the ease of use of wearable devices. Farina *et al.* (2019) identified comfort as the most important attribute for older adults with dementia with regard to the use of wearable devices. However, most of the studies in Table 4 indicated negative perceptions regarding the comfort of devices, mostly for wearable health monitoring devices. This is due to the discomfort from wearing, inconvenient installation points (Ehn *et al.*, 2018; Mackintosh *et al.*, 2019), and the inconvenience in daily activities (Gövercin *et al.*, 2010; Reeder *et al.*, 2020; Jo *et al.*, 2021). The indicated discomfort was predominantly due to physical factors, such as itching and irritation (Kekade *et al.*, 2018). The inconvenience faced in daily activities was from regularly requiring the devices to be removed for recharging (Maher *et al.*, 2017; Puri *et al.*, 2017), activities that involve physical contact with water (Ehn *et al.*, 2018; Mackintosh *et al.*, 2019; Reeder *et al.*, 2020; Jo *et al.*, 2021), and other basic activities such as sleeping (Farina *et al.*, 2019).

Regarding the preference for wearable device applications based on comfort, wrist-worn wearable devices are perceived more positively than other types of wearable devices (Holzinger *et al.*, 2010; Fang & Chang, 2016; Visutsak & Daoudi, 2017; Jia *et al.*, 2018; Jo *et al.*, 2021), such as cloth-worn (Reeder *et al.*, 2020), neck-worn (Geraedts *et al.*, 2015; Maher *et al.*, 2017), and hip-worn sensors (Scott *et al.*, 2017). Participants generally preferred the wrist as a location because of the less effort required to read the information displayed on the device (Fang & Chang, 2016; Visutsak & Daoudi, 2017; Jia *et al.*, 2018). However, wrist-worn wearable devices have been reported to cause discomfort in many studies (Maher *et al.*, 2017; Ehn *et al.*, 2018; Mackintosh *et al.*, 2019).

The aesthetics of a device is one of the major factors affecting the desirability and psychological comfort of wearable devices (Mercer *et al.*, 2016). Psychological discomfort related to poor design has been reported (Maher *et al.*, 2017; Puri *et al.*, 2017; Reeder *et al.*, 2020), specifically in terms of the aesthetic features (color, size, and shape) being unappealing or unsuitable or a feeling of embarrassment from wearing the devices (Scott *et al.*, 2017). Female participants consider wearable devices to be less intrusive or odd when wearing them than male participants did; however, female participants did not seek to wear the devices in public (Fang & Chang, 2016). Moreover, they felt uncomfortable wearing a smart band for aesthetic reasons (Puri *et al.*, 2017). Wrist-worn wearable devices can be bulky for children; thus, children have reported discomfort when wearing such devices (Mackintosh *et al.*, 2019).

Nonwearable devices, such as PIR and pressure sensors, are generally perceived positively in terms of comfort (Demiris *et al.*, 2006, 2008; Casalino *et al.*, 2020). Most participants barely noticed in-home mobility monitoring sensors in everyday living and found them to be unobtrusive (Reeder *et al.*, 2013). In one study, approximately 60% of college students reported that smart security monitoring devices provide comfort (Wania, 2019). However, considering a limited budget, wearable devices are the preferred option for smart home technology over nonwearable devices (Visutsak & Daoudi, 2017). Applications of wearable and nonwearable devices are perceived differently; i.e. each device type has been observed to be suitable for participants with specific lifestyles. For instance, younger participants with active lifestyles, who spend more time outside than indoors, prefer wearable devices (Scott *et al.*, 2017; Reeder *et al.*, 2020) to track their healthcare constantly. This is different from older participants who spend more time indoors and prefer nonwearable devices (Reeder *et al.*, 2020).

As indicated by Pal *et al.* (2018b), the older generation perceives an increasing complexity of the ease of use of health monitoring devices, resulting in the refusal of acceptance. This claim is supported by further studies, which suggest that because older adults are more prone to suffer from cognitive decline, sensory capabilities, and chronic physical health conditions (Lee & Kim, 2020) and have decreased prospect and poor literacy (Ashraf *et al.*, 2020), they are more likely to experience difficulty in the ease of use of the recent advances in smart health monitoring devices. Furthermore, several studies (Kekade *et al.*, 2018) have addressed the general consensus that the awareness of existing health monitoring devices is inadequate among older adults. This awareness is directly associated with the challenges of experiencing difficulties in ease of use (Demiris *et al.*, 2008), and thus, tends to generate negative emotional responses from their frustration and difficulty in understanding devices (Lee & Kim, 2020). Therefore, many participants from further studies emphasized the relevance of requiring a significantly simple user interaction that is age friendly (Li *et al.*, 2019; Matt *et al.*, 2019) because of their difficulties in interacting and controlling health monitoring devices. It is also important to note that these findings were mostly concerning older adults. This is different for younger generation participants who experience fewer difficulties in use owing to the knowledge of accessing collected information, controlling devices, and managing device applications (Gualtieri *et al.*, 2016; Wen *et al.*, 2017; Ehn *et al.*, 2018; Jia *et al.*, 2018; Jo *et al.*, 2021). However, the perceived ease of use among older adults is related to the compatibility of their current smart devices, such as smartphones (Li *et al.*, 2019). For instance, older adults prefer a wearable activity tracker with a display panel, instead of a smartphone app, if they are unfamiliar with the smartphone (Mercer *et al.*, 2016; Puri *et al.*, 2017).

Additionally, further studies (Ehrenhard *et al.*, 2014; Tsuchiya *et al.*, 2021) suggested that the availability of health monitoring device operation instructions or training provided during sensor acquisition is another significant factor that influences the perception on ease of use among older participants. For instance, with insufficient knowledge of health monitoring devices, participants negatively perceived the high complexity of device installation within their residential homes (Gövercin *et al.*, 2010), experienced difficulty in accessing the collected information of the devices (Demiris *et al.*, 2006; Gualtieri *et al.*, 2016; Ehn *et al.*, 2018), and experienced difficulty in understanding the information provided by these (Claes *et al.*, 2015; Mackintosh *et al.*, 2019; Jo *et al.*, 2021). Therefore, with reference to this factor of influence, studies (Tsuchiya *et al.*, 2021) stated that the older participants perceived the ease of use for health monitoring devices when they were provided with easy-to-understand instructions and specific guidelines directed toward their age group population. Overall, based on the findings from previous studies, it is important to understand that devices must be designed for ease of use and sufficient information for operating them should be provided to their end users. Reeder *et al.* (2016) claimed that older adults use technologies; thus, their perceived difficulties in use decrease with time, and this result is consistent with a prior study (Demiris *et al.*, 2001).

4.1.3. Perceived privacy

Generally, the participants of the identified studies (Table 4) had conflicting perceptions of the perceived privacy of health monitoring device applications. Among the positive perceptions of privacy in terms of data collection, the participants of several studies (Boise *et al.*, 2013; Pol *et al.*, 2016; Singh *et al.*, 2018; Kim & Choi, 2019; Matt *et al.*, 2019; Reeder *et al.*, 2020; Jo *et al.*, 2021) firmly considered that there was a necessity to share their personal information with other entities, such as medical professionals, caregivers, and family members. This information sharing can help in receiving improved effective health management, emergency assistance, and overall QoL increase. The study by Puri et al. (2017) on wearable activity trackers demonstrated that the participants did not perceive the wearable activity tracker data (i.e. step counts, sleep time, and heart rate) private, and thus, were willing to share them. The benefits of wearable activity trackers may have exceeded the privacy concerns of the participants (Puri *et al.*, 2017).

Some studies (Reeder *et al.*, 2013; Kim & Choi, 2019) found that although the participants were willing to provide their health-related information to families and hospitals, they were not keen to share the same with researchers, government agencies, and private corporations, such as insurance companies. This preference for sharing health-related information is because of the concerns of older adults about the leakage of their information to people who do not have the right to access it (Boise *et al.*, 2013). The negative perceptions of privacy factors were more commonly addressed in association with management of data security. For instance, studies identified that their participants were uncomfortable sharing their health-related information on the internet because of the concerns about unwanted access to their information to unauthorized personnel (Dhukaram *et al.*, 2011). Owing to these privacy concerns, Kim and Choi (2019) observed that in their study, the participants with higher education levels, who have more knowledge of the intrusion of privacy, did not want to share their health information. Several studies (Boise *et al.*, 2013; Reeder *et al.*, 2013, 2020; Jaschinski & Ben Allouch, 2019) addressed the fact that the negative perceptions of participants were owing to their concerns of other entities misusing their data by accessing their analysed daily activity patterns to potentially break into homes. They also indicated that intrusion into their personal life violates their independence by the accumulation of continuous real-time monitoring data (Demiris *et al.*, 2006; Reeder *et al.*, 2020). Additionally, when there was a caregiver, the caregiver was uncomfortable monitoring the care receiver to avoid intrusion of their privacy (Jaschinski & Ben Allouch, 2019).

Residents did not prefer visual sensors in their living rooms for home security systems, even if they already had the same visual sensor for video games (Choe *et al.*, 2012). Based on these findings, there were also negative implications of the applications of other nonwearable in-home monitoring (IHM) sensors, specifically sensors integrated with video monitoring (Demiris *et al.*, 2004; Londei *et al.*, 2009; Govercin *et al.*, 2010; Casalino *et al.*, 2020) owing to their privacy-invasive nature. Claes *et al.* (2015) observed that most older adults (82.3%) perceived video sensors as useful. However, because of privacy concerns, they desired either acquisition of permission to view or only use them in emergency scenarios and participate in the installation process to decide the locations of the video sensors. People in different continents perceive visual sensors differently. Europeans and Australians had the highest standards for visual privacy; they did not even want video monitoring outside their houses. In contrast, Asians and Americans were comfortable with video monitoring outside their houses, whereas only mostly Americans agreed for video monitoring inside their houses (Singh *et al.*, 2018).

Pol *et al.* (2016) claimed that older adults considered the sense of safety as more significant than privacy; thus, there were fewer concerns about privacy with IHM sensors without video or audio recording. Singh *et al.* (2018) observed that older adults (aged 36–70 years) were more inclined to health monitoring and willing to share data with their doctors and caregivers than young adults (aged up to 35 years). Gövercin *et al.* (2010) observed that the importance of privacy is relative. They claimed that older adults with a high risk of falling considered privacy as less important than low-risk fall groups, and older adults in the former group were willing to accept visual sensors. Jo *et al.* (2021) reported that older adult participants positively perceived long-term data accumulation for other entities to achieve improved analysis of their health. Additionally, the older adult participants perceived the installation of devices within bathrooms as acceptable because of the noncollection of visual information (Reeder *et al.*, 2016); they also perceived that accidents mostly occur in bathrooms (Mihailidis *et al.*, 2008; Jo *et al.*, 2021). The older adult participants explicitly mentioned data regarding their location information. They preferred sharing personal information to potentially aid them in living a safe and independent life, instead of receiving no support or emergency assistance from not sharing their information (Jo *et al.*, 2021). In contrast, some studies indicated otherwise. For instance, participants had concerns about devices detecting their specific activity through analysis of body postures (Chung *et al.*, 2017; Reeder *et al.*, 2020). Thus, they hesitated to install devices inside their bathrooms, as they perceived them as a significant intrusion to their personal privacy (Chung *et al.*, 2017).

4.2 Environmental monitoring devices

4.2.1. Perceived usefulness

In many studies, the participants perceived environmental monitoring devices to be useful (Barnicoat & Danson, 2015; Dimitrokali *et al.*, 2015; Parag & Butbul, 2018; Brown & Markusson, 2019). They perceived that environmental monitoring devices reduce financial expenses for household energy consumption (Hargreaves *et al.*, 2010; Paetz *et al.*, 2012; Balta-Ozkan *et al.*, 2014), improve the personal behavior patterns to effectively manage the energy consumption of household appliances (Hargreaves *et al.*, 2013), and effectively manage iAQ (Kim *et al.*, 2019; Ghorayeb *et al.*, 2021). Studies (Paetz *et al.*, 2012; Wania, 2019) have indicated that participants positively perceive the cost factor of devices because they considered the potential saving of energy consumption expenses. Dimitrokali *et al.* (2015) also reported that a smart home-heating controller successfully changed more than 70% of the home heating behavior of participants. However, this useful perception was strengthened after the participants were provided with sufficient knowledge and increased awareness of the potential benefits of environmental monitoring device applications (Dimitrokali *et al.*, 2015; Kim *et al.*, 2019; Kim & Li, 2020). In a study, approximately two-thirds of the participants perceived environmental monitoring devices to be useful for managing various appliances, and women were more interested in adopting environmental monitoring devices than men (Parag & Butbul, 2018). In addition, older Israelis (45 and over) were more willing to change their energy consumption habits by adopting environmental monitoring devices than younger Israelis (under 45). Wong-Parodi *et al.* (2018) observed that iAQ sensors aided in increasing the knowledge of the participants and caused them to actively reduce indoor air pollution. In another study, participants admitted that environmental monitoring devices after installation compelled them to be more conscious of their energy consumption (Hargreaves *et al.*, 2010). However, after a year, the participants were no longer conscious about energy consumption as much as at the initial installation, and it became embedded in their daily life (Hargreaves *et al.*, 2013). Nevertheless, the participants did not simply overlook and stop using the environmental monitoring devices; in fact, they learned their domestic energy consumption pattern well and increased their energy awareness while using these devices (Hargreaves *et al.*, 2013).

Negative emotional responses were also presented by participants, which were primarily skeptical attitudes toward the disappointment resulting from insignificant financial savings, e.g. “saving pennies,” instead of “saving tens of pounds” (Hargreaves *et al.*, 2013). In another study, three-quarters of the participants expected less than 20% energy saving with a smart home heating controller (Barnicoat & Danson, 2015). The burden of the financial cost of an environmental monitoring device application was observed to be another factor influencing the negative users’ perceptions on usefulness. For instance, despite the potential benefits of effectively improving their QoL, in some studies (Wong-Parodi *et al.*, 2018; Ghorayeb *et al.*, 2021), the participants showed perceived concerns of the cost of environmental monitoring device applications. Participants also considered the installation and maintenance costs as barriers, and they were uncertain of the amount of potential cost savings to consider the usefulness of environmental monitoring (Balta-Ozkan *et al.*, 2013). Thus, some participants suggested their government to establish a system to provide the cost of device applications (Balta-Ozkan *et al.*, 2014), particularly for the older population.

Certain studies found that younger participants were more content in changing their normal behavior patterns to reduce their energy consumption through the monitoring of the devices than older participants (Balta-Ozkan *et al.*, 2014; Brown & Markusson, 2019). The former developed a positive habit of regularly monitoring the energy consumption of their household appliances, which significantly increased their self-awareness and sense of control. This, in turn, empowered them to pursue a cost-efficient living environment, such as turning off unnecessary appliances to reduce electricity expenses, without experiencing discomfort or inconvenience in their daily activity pattern and household appliance usage. In contrast, Brown and Markusson (2019) observed that older adults were already aware of their energy consumption behavior and practiced energy-saving habits in their everyday lives; thus, smart meters were not as useful as expected. Owing to the lack of technological barriers, confidence, comfort, and convenience, older adults were not highly engaged with environmental monitoring devices. However, although younger adults positively responded to the usefulness of environmental monitoring devices, which aided in increasing their awareness of energy use, it did not eventually change their behavior. Hargreaves *et al.* (2018) also claimed that the use of environmental sensors failed to change the energy use behaviors of participants.

4.2.2. Perceived ease of use

The findings on the ease of use of environmental monitoring devices were divergent. In a study, more than three-quarters of the participants considered that a smart home heating controller was easy to use (Dimitrokali *et al.*, 2015). Hu *et al.* (2016) claimed that with well-described installation instructions, even self-installment of environmental monitoring devices is easy for older adults, and they can install a device intuitively with a low failure rate. Furthermore, some participants indicated a positive perception of the comfort in using environmental monitoring devices owing to their remote control feature, which significantly caused a successful and positive change in their heating habits (Dimitrokali *et al.*, 2015).

In contrast, some participants experienced discomfort in the use of environmental monitoring devices. In a study, less than half of college students answered that smart thermostats would provide comfort (Wania, 2019). The discomfort experienced from the inconveniences caused by the requirement of changing personal behavioral habits to reduce energy expenses was perceived as a significant reduction in both comfort and QoL (Balta-Ozkan *et al.*, 2013; Hargreaves *et al.*, 2013, 2018; Brown & Markusson, 2019; Shirani *et al.*, 2020). The discomfort experience caused by the display of environmental monitoring devices has also been demonstrated (Hargreaves *et al.*, 2010). In some studies, older adult participants particularly expressed difficulty in understanding information from a display (Brown & Markusson, 2019). Children and their caregivers also experienced difficulties in understanding the display of iAQ sensor information (Kim *et al.*, 2019). These findings suggest that the application of an environmental monitoring device without an integrated visual sensor display monitor would be more effective in reducing the psychological discomfort caused in the energy-consumption monitoring of household appliances than that with a display. Moreover, people experienced difficulty and exhibited safety concerns with electrical works in installing smart meters (Patel *et al.*, 2010; Brown & Markusson, 2019). Even after the installation of environmental monitoring devices, several participants did not use them for several months, either because of their nonrequirement or the technical barriers hindering the use of automated functions (Hargreaves *et al.*, 2018). Participants also emphasized that a large amount of learning was required to fully understand and use environmental monitoring devices (Hargreaves *et al.*, 2018).

Environmental monitoring devices were negatively perceived, particularly by older adults, because their potential benefits did not outweigh the negatively perceived factors, such as the discomfort of significantly adjusting to a new daily routine (Hargreaves *et al.*, 2010; Paetz *et al.*, 2012; Brown & Markusson, 2019). Older adult participants experienced feelings of guilt and depression owing to their lack of control in using the household appliances whose energy expenses were very high, such as heating appliances to stay warm (Hargreaves *et al.*, 2010). Older adults expressed negative emotions toward smart energy monitors, which reduced their usage of these devices (Brown & Markusson, 2019). Consequently, a large number of participants in the studies reported that they ignored the application of the devices over time (Paetz *et al.*, 2012; Barnicoat & Danson, 2015; Shirani *et al.*, 2020). Thus, this particular age group demonstrated that the potential benefits of such devices were insignificant in sacrificing their comfort by changing their regular behavior patterns.

4.2.3. Perceived privacy

Perceived privacy concerns in environmental monitoring were relatively less focused on than health monitoring. There were some negative implications of the application of continuous real-time environmental monitoring devices in regard to their data collection methods (Hargreaves *et al.*, 2010; Balta-Ozkan *et al.*, 2014; Parag & Butbul, 2018). This was also for other nonwearable devices, specifically devices integrated with audio recording features (Choe *et al.*, 2012), because of privacy invasion into the personal lives of the participants. As our inherent tendency of being concerned when monitored by other people, most participants were averse to the placement of visual and audio sensors in their homes (Choe *et al.*, 2012). There was also a strong mistrust in energy companies, serving as a barrier to overcoming privacy concerns in environmental monitoring devices (Balta-Ozkan *et al.*, 2013, 2014). In a study, approximately 60% of college students were concerned about privacy and considered the service provider when selecting a smart thermostat (Wania, 2019). Participants were concerned about others monitoring their daily routines and occupancy data and feared their data being provided to those without permission to access and of being hacked (Balta-Ozkan *et al.*, 2013). However, participants were willing to share their information to third party providers when there was financial profit or incentive (Choe *et al.*, 2012).

The perceived privacy and related concerns about environmental monitoring devices differed based on the characteristics of the participants. Different age groups perceived the privacy invasion of environmental monitoring device applications differently (Kim *et al.*, 2019). Older adult participants perceived invasion of their privacy with low significance (Singh *et al.*, 2018), whereas younger participants did not perceive data sharing positively. Studies (Parag & Butbul, 2018; Ghorayeb *et al.*, 2021) suggested that most older adult participants perceived invasion of their privacy as a much lesser significant influencing factor than other factors such as ease of use and benefits of environmental monitoring. In addition, older adults with no experience with environmental monitoring devices had concerns about privacy; however, after they lived in smart homes with environmental monitoring devices, this concern was reduced as they became familiar with these devices (Ghorayeb *et al.*, 2021). In addition, the privacy concerns of the participants differed by nationality; for Asian nationalities, they were generally of lesser significance than for European nationalities (Singh *et al.*, 2018).

5. Discussion

We reviewed and classified smart home technology into two categories, namely, health and environmental monitoring, and focused on the corresponding devices. Of the two categories, health monitoring devices were further classified into two types: wearable and nonwearable devices. Because the adoption and use of both device types by users are related to and frequently hindered by the negative perceptions of smart home technology (Paetz *et al.*, 2012; Marikyan *et al.*, 2019), studies have examined the user perception of each device type. Users perceive wearable devices to be uncomfortable because they must be attached directly to their bodies and worn during their daily activities (Maher *et al.*, 2017; Ehn *et al.*, 2018; Kekade *et al.*, 2018; Farina *et al.*, 2019; Mackintosh *et al.*, 2019; Petrovic *et al.*, 2019). Users also perceive wearable devices to be inconvenient because they need to be worn daily (Gövercin *et al.*, 2010; Puri *et al.*, 2017; Reeder *et al.*, 2020; Jo *et al.*, 2021). In contrast, users perceive that nonwearable devices have lesser accuracy in measuring human health-related data if not directly attached to the human body (Lim *et al.*, 2011; Zakrzewski *et al.*, 2012). Moreover, they perceive the requirement of using multiple sensors as each sensor operates in limited boundaries, thus less mobile and more expensive (Crandall & Cook, 2013; Englert *et al.*, 2013; Kim *et al.*, 2014; De *et al.*, 2015; Jiménez & Seco, 2018). Nonwearable devices also intrude privacy, particularly when using video and audio sensors, which record private spaces and communications (Crandall & Cook, 2013; Claes *et al.*, 2015; Nosrati & Tavassolian, 2018; Petrovic *et al.*, 2019; Casalino *et al.*, 2020).

Owing to the above-mentioned negative user perceptions of both wearable and nonwearable devices, current studies and technological developments are focusing on reducing such perceptions to increase the application and adoption of both device types. To reduce the negative perceptions of the discomfort and inconvenience of wearable devices, studies used small wearable devices, such as RFID sensors, for fall detection (Wickramasinghe *et al.*, 2017; Toda & Shinomiya, 2018) and noncontact wearable devices such as smartphone accelerometers (Shahzad & Kim, 2019; Mrozek *et al.*, 2020). In contrast, electroencephalogram was used in studies in IoT-based telemedicine for monitoring and detecting epileptic seizures (Albahri *et al.*, 2021), but to a smaller extent in smart homes owing to the inconvenience of wearing it at home all day. If the device becomes smaller and more comfortable to wear, it may become a valuable addition to smart home monitoring systems. Similarly, in ADL monitoring, studies used wearable Wi-Fi sensors (Belmonte-Fernández *et al.*, 2017) and BLE beacons (Tegou *et al.*, 2018; Zambrano-Montenegro *et al.*, 2018) for reducing the physical contact. However, among the current sensor technology, these sensors cannot accurately distinguish fall accidents and identify indoor locations and activities (Dai *et al.*, 2010; Santoso & Redmond, 2015; Feng *et al.*, 2016).

In addition to the negative perceptions of these sensors, regarding their uncomfortable and inconvenient nature, studies employed various nonwearable devices to alleviate these problems, such as camera sensors (Ni *et al.*, 2011; Giakoumis *et al.*, 2015), acoustic sensors (Alsina-Pagès *et al.*, 2017; Vafeiadis *et al.*, 2020), and floor sensors (Braun *et al.*, 2012; Contigiani *et al.*, 2014). These devices monitor indoor locations and recognize the daily activities of users in smart homes with minimal direct physical contact with users. Similarly, studies on health monitoring (Kortelainen *et al.*, 2010; Lim *et al.*, 2011; Baek *et al.*, 2012; Hesse *et al.*, 2017; Su *et al.*, 2019) employed sensorized furniture with biomedical sensors, cameras (Bernacchia *et al.*, 2014; Kranjec *et al.*, 2014; Tarassenko *et al.*, 2014), and Doppler radars (Nosrati & Tavassolian, 2018; Petrovic *et al.*, 2019). These can identify biometric data for monitoring human health without wearing the devices. Nevertheless, nonwearable devices are less accurate and expensive as they are still at the early stage of the development phase (Braun *et al.*, 2012; Contigiani *et al.*, 2014; Kranjec *et al.*, 2014; Alsina-Pagès *et al.*, 2017; Su *et al.*, 2019).

Unlike wearable devices, nonwearable devices are used in both health and environmental monitoring devices. For example, recent studies could detect a fall (Mauldin *et al.*, 2018; Yoo & Oh, 2018; Santos *et al.*, 2019; Yacchirema *et al.*, 2019) and determine energy consumption (Filho *et al.*, 2014; Pandya & Ghayvat, 2021) using integrated sensor technology incorporating machine-learning-based classification models. In iAQ monitoring, portable multipurpose devices have been developed to maintain accuracy while reducing the number of sensors (Jiang *et al.*, 2013; Kim *et al.*, 2014; Tiele *et al.*, 2018; Gillooly *et al.*, 2019). Finally, various nonwearable devices have been developed as alternatives to camera sensors for eliminating the intrusion of privacy concerns. For example, acoustic (Zhuang *et al.*, 2009), floor (Minvielle *et al.*, 2017), PIR (Popescu *et al.*, 2012), RFID (Ruan *et al.*, 2015), and depth camera (Kong *et al.*, 2018; Zhao *et al.*, 2019) sensors have been applied for fall detection. Moreover, PIR sensors incorporating low privacy-invasive technologies have been developed for ADL monitoring (Crandall & Cook, 2013; Fanti *et al.*, 2016; Kim *et al.*, 2017; Luo *et al.*, 2017).

As stated earlier, both wearable and nonwearable devices have limitations. Although studies have used alternative device types to overcome these limitations (Belmonte-Fernández *et al.*, 2017; Gillooly *et al.*, 2019; Shahzad & Kim, 2019; Zhao *et al.*, 2019), using other type of devices results in alternative constraints. To overcome the perceived limitations of wearable and nonwearable devices, studies (Yuan & Herbert, 2014; Jaouhari *et al.*, 2019) explored various methods of integrating both devices. Studies used multiple sensors, e.g. wearable devices, such as BLE beacons and wrist-worn accelerometers, and nonwearable devices, such as magnetometers, floor sensors, PIR sensors, and door sensors, to monitor ADL with high accuracy and identify the locations of residents in smart homes (De *et al.*, 2015; Jiménez & Seco, 2018; Sridharan *et al.*, 2020).

Integration of wearable (i.e. BLE beacons, accelerometers, and smart bands) and nonwearable devices (i.e. floor sensors, door sensors, PIR sensors, power meters, and acoustic sensors) would increase accuracy while reducing installation and maintenance cost. This integration can be used for fall detection, ADL monitoring, and identifying the location of users. For example, when we use either wearable or nonwearable devices alone, the accurate recognition of the exact location and detailed user activities for ADL monitoring is challenging. Therefore, in some studies (De *et al.*, 2015; Jiménez & Seco, 2018), multiple sensors were used with both wearable and nonwearable devices for higher accuracy of ADL monitoring. Moreover, acoustic sensors were also integrated with wearable devices to increase the accuracy of ADL monitoring (Alsina-Pagès *et al.*, 2017; Vafeiadis *et al.*, 2020). In addition, integrating the use of biometric sensors (i.e. ECG, BCG, and GSR) and video sensors (i.e. cameras and Doppler radars) would increase accuracy while reducing physical and psychological discomfort and risk of injury during the monitoring of both physiological and respiratory variables. In some studies (Al-Naji *et al.*, 2017; Casalino *et al.*, 2019), cameras were used to monitor skin RGB color and brightness to measure the HR, RR, and SpO_2 of users, to use wearable devices for a lesser duration to alleviate their intrusive nature. However, these cameras cannot monitor all the physiological and respiratory variables; consequently, they cannot completely replace biometric sensors. Moreover, the cameras are less mobile and are effective only in certain conditions, such as when a user spends most of the time in bed.

In contrast, wearable and nonwearable devices have not yet been integrated for environmental monitoring. Various nonwearable devices have been used for improving monitoring. Paredes-Valverde *et al.* (2020) and Matsui *et al.* (2019) developed an energy-consumption monitoring device using multiple sensors, such as power meters, PIR sensors, and indoor temperature sensors, and (Zhou *et al.*, 2020) used PM, humidity, and indoor temperature sensors in iAQ monitoring. On the other hand, nonwearable environmental monitoring devices are beginning to be adopted in health monitoring with the integration of wearable health monitoring devices. The combination of power meters and acoustic sensors, which are used in energy consumption monitoring (Englert *et al.*, 2013; Pathak *et al.*, 2015; Paredes-Valverde *et al.*, 2020) to increase the accuracy and reduce the installation and maintenance costs, is employed for accurate ADL monitoring by combining with wearable accelerometers (Alsina-Pagès *et al.*, 2017; Vafeiadis *et al.*, 2020). The integration of nonwearable environmental monitoring devices and wearable health monitoring devices needs to be further developed for use in various purposes, including ADL monitoring and fall detection. Recent studies (Jaschinski & Ben Allouch, 2019; Wania, 2019; Reeder *et al.*, 2020; Ghorayeb *et al.*, 2021; Jo *et al.*, 2021) have attempted to incorporate health and environmental monitoring by integrating wearable and nonwearable devices owing to the recent trends in smart home technology, such as providing all-in-one solutions. The idea behind this integration is that one sensor can monitor and serve various purposes, and integrating such multipurpose sensors would expand research and development opportunities.

In addition to the strengths and limitations of wearable and nonwearable devices, some user perceptions are applied to both wearable and nonwearable devices. Our review identified negative perceptions of complexity in terms of ease of use and privacy. Perceived ease of use is one of the significant barriers to the acceptance of both wearable and nonwearable monitoring devices (Holzinger *et al.*, 2010; Claes *et al.*, 2015; Maher *et al.*, 2017; Pal *et al.*, 2018b). Because the adoption of monitoring devices by older adults is strongly influenced by their perceptions (Hickman *et al.*, 2007; de Boer *et al.*, 2019; Kowalski *et al.*, 2019), lowering the complexity of the ease of use is critical (Kekade *et al.*, 2018; Pal *et al.*, 2018b; Brown & Markusson, 2019). Although smart homes can enable older adults to live independently at their home for a long time, reduce their reliance on caregivers, and enhance their QoL (Chan *et al.*, 2008; Demiris *et al.*, 2008; Alam *et al.*, 2012; Sanchez *et al.*, 2017), majority of older adults do not have much experience with smart technology. Thus, they feel burdened with technology and consider such devices as extremely complex for use (Demiris *et al.*, 2008; Kekade *et al.*, 2018; Pal *et al.*, 2018b; Brown & Markusson, 2019; Lee & Kim, 2020).

The use of health and environmental monitoring devices is associated with the technical skills of the user (de Boer *et al.*, 2019). Many older adults need technical assistance and training for more adoption of monitoring devices, whereas older adults with higher technical skills are more willing to adopt them (Kowalski *et al.*, 2019). There are three types of learning for adopting monitoring devices – practical learning (understanding how to use the monitoring devices), cognitive learning (acknowledging what services the monitoring devices may offer), and symbolic learning (incorporating the monitoring devices into the daily routine); thus, learning to adopt monitoring devices is complicated and requires effort (Hargreaves & Wilson, 2017; Sovacool *et al.*, 2020). Therefore, adequate guidance, such as instruction manuals and support in the form of images or videos, would increase the technical skills of the users and the adoption of monitoring devices (Chen & Chan, 2014; Ehrenhard *et al.*, 2014; Tsuchiya *et al.*, 2021). Studies (Selwyn, 2004; Friemel, 2016) have also found that support from family members and friends is key to the adoption of technologies, which in turn may apply to the adoption of monitoring devices in a similar sense. Moreover, regular workshops and home-based support services provided by the government would enhance accessibility to monitoring devices. Governments also have a potential role in generating standards and guidelines for the intuitive use of these devices (Hargreaves *et al.*, 2018).

Although guidance and training can lower the barriers to technology adaptation, the degree of learning varies with the age and physical and mental health of older adults as well as the learning process and method (Werner *et al.*, 2011; Lin *et al.*, 2012; Chen & Chan, 2014). Moreover, the effectiveness of learning is not limited to older adults. It can be extended to all subjects, including young users. Therefore, further research is required to measure the practical learning effects and provide effective learning environments, particularly to older adults. Because there is no overall verification of the effectiveness of learning, its long-term effect cannot be explained, and further study is required.

Another negative perception related to both health and environmental monitoring devices is privacy concerns. Although monitoring devices are becoming increasingly well known, privacy concerns negatively affect the attitudes of residents toward accepting monitoring devices (Balta-Ozkan *et al.*, 2013; Yang *et al.*, 2017). However, operation of monitoring devices requires the collection and analysis of user data, making these tasks particularly important (Cannizzaro *et al.*, 2020; Schomakers *et al.*, 2021). Thus, securing data and maintaining privacy are critical for users and key to the implementation of monitoring devices (Albahri *et al.*, 2018; Talal *et al.*, 2019). Additionally, the collection and storage of data should be translucent and shared with users (Pal *et al.*, 2019). In some scenarios, people, particularly older adults, may not have sufficient understanding of protecting their privacy (Lorenzen-Huber *et al.*, 2011); thus, providing an abundant explanation of potential privacy problems in the use of monitoring devices is required (Pol *et al.*, 2016). Therefore, it is the responsibility of the government to inform and provide suggestions to people to increase their awareness of privacy concerns (Li *et al.*, 2021). Monitoring devices are capable of protecting users in emergency scenarios but it can also intrude their privacy (Milligan *et al.*, 2011). Most users are aware of this double sidedness of monitoring devices. Studies (Pol *et al.*, 2016; Singh *et al.*, 2018; Matt *et al.*, 2019; Reeder *et al.*, 2020) showed that residents are willing to share their personal information with medical professionals, caregivers, and family members to receive appropriate health management and emergency assistance. In addition, some studies (Kong *et al.*, 2018; Can & Ersoy, 2021) have attempted to minimize privacy infringement by introducing machine-learning-based classification, which could minimize unnecessary monitoring from service providers and reduce privacy intrusion. However, machine learning techniques do not solve the problem of protecting stored personal information.

Protecting the personal information of residents has been considered a significant legal and ethical obstacle (Arabo *et al.*, 2012), and having trust in devices and service providers is a crucial factor in adopting health and environmental monitoring devices (Wilson *et al.*, 2017; Schomakers *et al.*, 2021). To create trust, some governments, such as the European Union and the state of California, established privacy regulations to protect user privacy (Zheng *et al.*, 2018). However, these regulations are insufficient and cannot fully protect the privacy of users (Goulden *et al.*, 2018; Zheng *et al.*, 2018); thus, more legislative action is required to build trust among users by providing a safety net. Enforcing the use of public-key cryptography (Albahri *et al.*, 2018) and encrypted cloud-based systems (Talal *et al.*, 2019) may improve data security. Furthermore, the use of personally identifiable information should be avoided or they should be replaced with generated pseudonyms (Neisse *et al.*, 2015; Talal *et al.*, 2019), to enhance users' privacy.

Furthermore, people have a trust issue in the industry. The users of health and environmental monitoring devices are uncomfortable with sharing their personal information with third parties (Boise *et al.*, 2013; Balta-Ozkan *et al.*, 2014). They do not trust third parties, such as insurance companies (Kim & Choi, 2019), energy companies (Balta-Ozkan *et al.*, 2013, 2014), and those who do not have the right to access their information (Dhukaram *et al.*, 2011; Boise *et al.*, 2013). Therefore, they do not want to share their information with such entities. Hence, although challenging, it is necessary to standardize the definition of the level of privacy regarding the acceptable extent of privacy infringement. However, participants are willing to trade their information and compromise privacy if the technology is perceived as beneficial (Peek *et al.*, 2014) and when they earn appropriate incentives (Choe *et al.*, 2012; Birchley *et al.*, 2017). Thus, it is important for governments and industries to establish methods to build trust using regulations and technological enforcement to secure personal information from third parties, and provide sufficient benefits when third parties seek to use the information. Finally, users must actively protest to protect their own privacy and raise their privacy standards when selecting monitoring devices to compel the industry to develop more secure devices (Williams *et al.*, 2016).

6. Conclusions

Smart home technology improves users' well-being and QoL by offering support for individual requirements. Although there has been an effort to increase the adoption of this technology, the adoption, particularly in health and environmental monitoring devices, has been delayed owing to various existing barriers from users' perceptions. Therefore, understanding user perception of health and environmental monitoring devices is crucial to lower the barriers and increase the adoption. To fully understand user perception, 159 articles were reviewed in this study. We explored the application of sensors in health and environmental monitoring devices for different objectives. In sequence, we identified user perception in accordance with the application of the monitoring devices. Moreover, we reviewed and classified health and environmental monitoring devices into wearable and nonwearable devices, as the users perceive the adoption of these devices differently depending on the device type. Finally, we analysed users' perception of monitoring devices by focusing on usefulness, ease of use, and privacy.

The studies reviewed indicated that participants perceived health monitoring devices as useful in remote real-time monitoring (i.e. ADLs, mental health, cognition, and heart conditions), efficient emergency assistance, and the improvement of the overall QoL of the users. Participants perceived the usefulness of health monitoring devices more positively when their awareness increased with sufficient knowledge on the devices. In addition, they perceived wearable devices as more useful compared with nonwearable devices for health monitoring. On the contrary, some older adult participants did not agree with the usefulness of health monitoring devices because they did not want to acknowledge their frailty. For environmental monitoring devices, participants perceived the devices to be useful while presenting some negative emotional responses due to insignificant financial savings and behavioral changes to reduce the energy consumption as a result of the use of these devices.

The studies we reviewed also showed that participants perceived the ease of use of health monitoring devices negatively, owing to maintenance concerns, discomfort, and complexity. Maintenance concerns, such as charging, wearing, repairing when damaged, and cost, influence the ease of use of both wearable and nonwearable health monitoring devices. By contrast, discomfort is more critical in wearable than in nonwearable health monitoring devices, which was predominantly due to physical factors, such as the discomfort from wearing, inconvenient installation points, and inconvenience in daily activities. Finally, complexity was critical to older adult participants owing to their cognitive decline, sensory capabilities, and chronic physical health conditions. The ease of use of environmental monitoring devices was divergent. Some studies found that participants positively perceived the ease of use of environmental monitoring devices. However, other studies showed that participants felt discomfort due to implicit pressure to change individual behavioral habits to reduce energy costs, and they had difficulties reading and understanding the information on the display.

The studies reviewed showed conflicting results in the perceived privacy of health monitoring devices. Participants agreed that there was a necessity to share their personal information with other entities, such as medical professionals, caregivers, and family members. However, they were not keen to share personal information with researchers, government agencies, and private corporations, such as insurance companies, and were concerned about how the security of their shared personal information was managed. Participants were also concerned with video and audio sensors in terms of privacy. Perceived privacy concerns in environmental monitoring were relatively less than those in health monitoring, but they were similar.

To overcome the barriers and increase the adoption, we provide three suggestions based on the articles reviewed. First, we recommend incorporating a multisensor approach by integrating wearable and nonwearable devices. This would enhance the accuracy of user activity recognition, such as location, ADL monitoring, and fall detection, while lowering physical and psychological discomfort by reducing direct contact with the human body, reducing unwanted attention from wearing the devices, and overcoming the limited boundaries of nonwearable devices. The integration would also minimize the number of devices required, their cost, and their maintenance compared with using either wearable or nonwearable devices alone. Second, we recommend adequate support, such as manuals and guidance in the form of images or videos, help from family members and friends, and government-led training, to lower the complexity of health and environmental monitoring devices, as each user, including older adults, has a different ability and technical skills. Finally, we recommend the government to regulate the industry to inform users on the precise scope of the personal information collected and used and the use of encryption and pseudonyms to ensure privacy.

Based on the articles reviewed, we identified some gaps in the literature and opportunities for further research; thus, we propose the following agenda for future research. First, unique vernacular factors, such as culture, beliefs, demographics, and geography, would influence the adoption of health and monitoring devices. Our review included studies conducted across all regions; however, as the number of studies from each region is limited, we could not differentiate the results and analyse them separately. Second, people with special conditions or impairments (i.e. dementia, chronic disease, and heart condition) may experience different user perceptions from people without such difficulties. However, most studies we reviewed focused on healthy participants; thus, we could not fully represent the participants' demographic characteristics.

This study presents practical implications that would aid researchers and designers for enhanced applications and user perceptions of health and environmental monitoring devices. The identified barriers and the recommendations for better user perceptions presented in this study would help key stakeholders to develop better health and environmental monitoring devices. In addition, policymakers and practitioners can refer to this study when establishing new policies and incentive programs.

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None declared.

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