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Systematic Review

Smart Home Technology Solutions for Cardiovascular Diseases: A Systematic Review

Jeban Chandir Moses [1], Sasan Adibi [1], Maia Angelova [1] and Sheikh Mohammed Shariful Islam [2,*]

[1] School of Information Technology, Deakin University, Burwood, VIC 3125, Australia; jcmoses@deakin.edu.au (J.C.M.); sasan.adibi@deakin.edu.au (S.A.); maia.a@deakin.edu.au (M.A.)
[2] Institute for Physical Activity and Nutrition (IPAN), Deakin University, Burwood, VIC 3125, Australia
* Correspondence: shariful.islam@deakin.edu.au; Tel.: +61-3-924-68393

Abstract: Cardiovascular diseases (CVD) are the leading cause of mortality globally. Despite improvement in therapies, people with CVD lack support for monitoring and managing their condition at home and out of hospital settings. Smart Home Technologies have potential to monitor health status and support people with CVD in their homes. We explored the Smart Home Technologies available for CVD monitoring and management in people with CVD and acceptance of the available technologies to end-users. We systematically searched four databases, namely Medline, Web of Science, Embase, and IEEE, from 1990 to 2020 (search date 18 March 2020). "Smart-Home" was defined as a system using integrated sensor technologies. We included studies using sensors, such as wearable and non-wearable devices, to capture vital signs relevant to CVD at home settings and to transfer the data using communication systems, including the gateway. We categorised the articles for parameters monitored, communication systems and data sharing, end-user applications, regulations, and user acceptance. The initial search yielded 2462 articles, and the elimination of duplicates resulted in 1760 articles. Of the 36 articles eligible for full-text screening, we selected five Smart Home Technology studies for CVD management with sensor devices connected to a gateway and having a web-based user interface. We observed that the participants of all the studies were people with heart failure. A total of three main categories—Smart Home Technology for CVD management, user acceptance, and the role of regulatory agencies—were developed and discussed. There is an imperative need to monitor CVD patients' vital parameters regularly. However, limited Smart Home Technology is available to address CVD patients' needs and monitor health risks. Our review suggests the need to develop and test Smart Home Technology for people with CVD. Our findings provide insights and guidelines into critical issues, including Smart Home Technology for CVD management, user acceptance, and regulatory agency's role to be followed when designing, developing, and deploying Smart Home Technology for CVD.

Keywords: cardiovascular disease; chronic disease; sensor; smart home; information technology; user acceptance; regulatory agency; COVID-19

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1. Introduction

Cardiovascular diseases (CVDs), including coronary heart disease (CHD), cerebrovascular disease, rheumatic heart disease and stroke, are the leading cause of global mortality [1,2]. The risk of CVD is higher amongst older people aged over 70 years [1]. Lifestyle choices significantly reduce CVD risk, especially regular physical activity (PA), sound nutrition, weight management, and quitting smoking [3]. Additionally, PA was associated with a larger magnitude of decreased odds of 10-year CVD risk when compared with an individual's weight status [4]. In addition, amongst the elderly, a significant inverse relationship between PA and CVD risk was observed [5]. Reducing modifiable risk factors, including high blood pressure (BP), smoking, high cholesterol, obesity, and PA, could significantly decrease CVD morbidity and premature deaths [6,7]. In contrast, CVD patients are at an increased risk of fatal outcomes if infected by COVID-19 [8]. Recent home quarantine and lockdowns measures due to COVID-19 have forced social isolation and a drastic decline in PA [9], further increasing the global risk of CVD burden [10].

The advancements in communication and sensing technologies and availability of remotely accessible medical devices have instigated a rapid development in Smart Home Technology (SHT) [11–13]. 'Smart homes' are residences equipped with hardware and software components, including sensors and home appliances capable of providing users demanded services such as energy management, remote monitoring and control, and support and assistance in living [11–13]. Additionally, a health smart home has various integrated technologies to monitor and evaluate the inhabitant's health and well-being to provide timely context-aware e-health services [14]. A recent study evaluated diabetes patients' activity, diet, and exercise compliance in SHT settings and observed that SHT settings are essential in providing accessible, low-cost health assistance in an individual's home and providing the best possible quality of life [15]. In contrast, an SHT developed and tested in laboratory settings to monitor the well-being of elderly residents with dementia in care homes was unable to be deployed in real time due to infrastructure deficiencies [16]. On the other hand, designing SHT in consultation with dementia patients, their caregivers, clinicians, and health and social care service providers to satisfy the functional, psychosocial, and environmental needs results in the development of SHT that provide patient-centric interventions and assist in seamlessly transitioning to clinical practice and public health strategy [17]. Finally, with the advances in sensor technology, big data, and artificial intelligence (AI), unobtrusive SHT systems would facilitate real-time monitoring of people's health.

Most CVD deaths occur while the individuals are at home and care homes [18]. However, healthcare systems to support CVD patients at home are lacking [7]. The associated healthcare expenses, human lives lost, and declining productivity due to CVD [19] increase the burden on hospitals in minimising healthcare costs and challenges to improve individuals' quality of life [20]. With the development of wearable sensors, the monitoring of CVD related physiological signs such as the electrocardiogram (ECG), electromyogram (EMG), heart rate (HR), body temperature, electrodermal activity (EDA), arterial oxygen saturation (SpO2), BP, respiration rate (RR), and activity-related signals can be easily monitored remotely from home [21]. Additionally, digital health technologies, including smartphone applications (apps) integrated with physiological sensors, can improve individuals' health outcomes at home [22–24].

With an increasing proportion of the older population and increased time spent at home, there is a need to monitor and maintain the health and well-being of CVD patients in home settings. Moreover, restricting individuals within their homes as a preventive measure against COVID-19 increases CVD risks [10], and individuals spending longer durations at home and working from home could be the new normal in the future [25,26]. Recent studies have evaluated home-based chronic disease monitoring and CVD management [27–29]. For example, a study evaluated home-based information and communications technologies (ICT) interventions in chronic disease management [27]. A review described various ICT intervention platforms to deliver alternative models of cardiac rehabilitation (CR) homecare programs [29]. Furthermore, a systematic review assessed the evidence around mHealth interventions for CR and heart failure (HF) management for service and patient outcomes, cost-effectiveness, and implementation scope for rural and remote cardiac patients [28]. However, there is no available recent literature evaluating SHT for CVD management to our knowledge. Hence, we have undertaken this systematic review to explore the different technologies available for CVD management in an SHT for adults and identify commercially available technologies acceptable to end-users.

The paper is organised as follows: Section 2 describes the materials and methods, the results are given in Section 3 and discussion in Section 4, followed by the conclusions in Section 5. The following are the significant contribution of our study to the body of knowledge:

- A systematic review of technological solutions for CVD in smart home settings.
- Highlight the paucity in SHT for CVD management.
- Underline the imperative need for remote health monitoring systems integrated with SHT for CVD management.
- Future directions for developing a real-time CVD monitoring system in smart home settings integrating the Internet of Things (IoT), cloud computing, and big data analytics.

2. Materials and Methods

We followed Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to organise the review [30]. Since this review is based on peer-reviewed studies for which primary investigators obtained informed consent, ethics approval was not required [31].

2.1. Protocol

This review is undertaken due to the unprecedented situation which has arisen due to COVID-19, and hence, it was not pre-registered in PROSPERO.

2.2. Data Sources and Search Strategy

The studies were identified through a systematic literature search using four online database, including Medline, Web of Science, Embase, and IEEE. The initial literature search focused on home-based technologies for CVD monitoring and management using a combination of key search terms, which include ("home based" OR "in house" OR home OR in-house OR house OR housing OR dwelling OR residence) AND ("cardiovascular disease" OR CVD OR heart OR cardiac OR "coronary heart disease" OR myocardial OR "heart failure") AND (technology OR computer OR tablet OR "mobile phone" OR smartphone OR internet OR "information technology" OR IT). We included studies published in English in peer-reviewed journals and conference proceedings. Table S1 represents the search strategy adapted in the web of science database and adapted as appropriate to the specifications of other databases.

2.3. Study Selection Criteria

Technological innovations progressively support the use of commercial smart wearable devices to monitor cardiovascular health remotely in real time; however, to date, challenges such as device accuracy, clinical validity, a lack of standardised regulatory policies and patient privacy concerns hinder the widespread adoption in clinical practice [32]. In addition, poor quality medical devices negatively affect CVD monitoring and management [33]. Hence, we have excluded studies undertaken using wearable devices for CVD monitoring and management in home settings and have considered studies using medical-grade CVD monitoring devices. On the other hand, cloud computing and machine learning (ML) could assist in monitoring the health status of heart patients [34]. The adoption of cloud computing in healthcare could improve healthcare delivery quality and reduce the economic burden, enabling governments to address healthcare challenges quickly [35]. A healthcare cloud architecture comprises ambient and wearable sensors capturing physiological data that are compressed and transferred to the cloud for further analytics, triggering alerts to healthcare and care providers according to the anomalies in the recordings [36]. However, since the cloud adoption rate is slow, governments could consider converting client–server models to web-based applications, quickening the cloud computing adoption rate [35] to reap the technical benefits of cloud computing. Hence, we have considered studies using clinically accepted devices integrated to function as client-server, web-based or cloud applications. Among CVD patients, reviews have been undertaken to evaluate the effectiveness of telemedicine [37,38] and telemonitoring [39–42]. Hence, we have not considered such studies. Additionally, we used a set of selection criteria as mentioned in Table 1 to narrow down the selection of articles that would fulfil the main objectives of the systematic review. Accordingly, Figure 1 illustrates an SHT for CVD management and vital signs monitoring.

Vital recordings such as HR, BP, ECG, steps walked, sleep, body temperature, and body weight are captured from the individual and transferred to the server for processing. After processing the information in the server, the data are transferred to healthcare providers for analysis and to initiate necessary care and intervention. Once the healthcare providers initiate alerts and interventions, the patients receive necessary notifications, including alerts and interventions to upkeep their health and well-being. Based on the selection criteria and the defined architecture of SHT, we have conducted this review to be unique and add knowledge by providing relevant future directions for CVD monitoring.

Table 1. Selection criteria for review articles (adapted from reference [43]).

Inclusion Criteria:
• CVD patients. • English language. • Year of publication: January 1990—March 2020. • Participants aged >18 years. • Studies describing SHT for CVD management with sensor devices (wearable and non-wearable sensors) connected to a gateway and has a web-based user interface. • SHT prototype/architecture deployed and evaluated in real-time with ≥5 patients.
Exclusion Criteria:
• Publications on incomplete or part of research (e.g., editorials, abstracts, workshop/conference summaries, research proposals, descriptive survey, clinical protocols, research methods, literature reviews, conceptual papers). • Studies evaluated healthy adults and non-CVD patients. • Non-human focused (e.g., animals, building, physical structures, bridges, health economic, evaluation of study ethics). • Non-SHT used amongst CVD patients (e.g., questionnaire, apps to monitor health and well-being, cardio signal processing, the influence of day-to-day activity on cardio health, home-based rehabilitation programme). • Hardware such as heart pump, pacemaker, microcontrollers used to measure a particular physiological parameter, oximeter, accelerometers, hardware assisting in the functioning of heart, and ECG device including portable ECG and ECG monitor. • Evaluation and development of research tools (e.g., hardware and algorithm improvement studies, signal processing, and clinical measurement technology to access and analyse secondary data). • Stand-alone devices (smartwatch, tablet, and smartphones). • Lack of sensors.

SHT: Smart Home Technologies, CVD: Cardiovascular diseases, ECG: Electrocardiography.

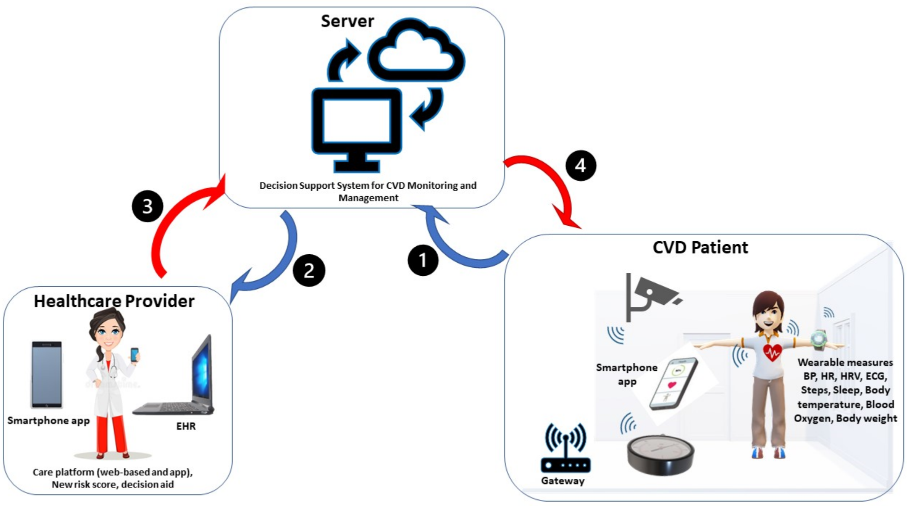

Figure 1. A smart home system for CVD and vital signs monitoring. (The arrows indicate the direction of the communication/transfer. Arrow 1: Transfer of recordings from patient to server for processing, Arrow 2: Processed information transfer to healthcare providers for analysis and initiate necessary care and intervention, Arrow 3: Alerts and intervention initiated by the health care provider, and Arrow 4: Patient receiving necessary notification, including alerts and intervention to upkeep their health and well-being).

2.4. Study Selection Process

We followed a step-by-step selection process to identify the relevant articles, as illustrated in Figure 2. We imported the obtained citations into the reference management software EndNote and removed duplicates, and then, we applied the selection criteria to screen the articles and select studies relevant to the review's objective.

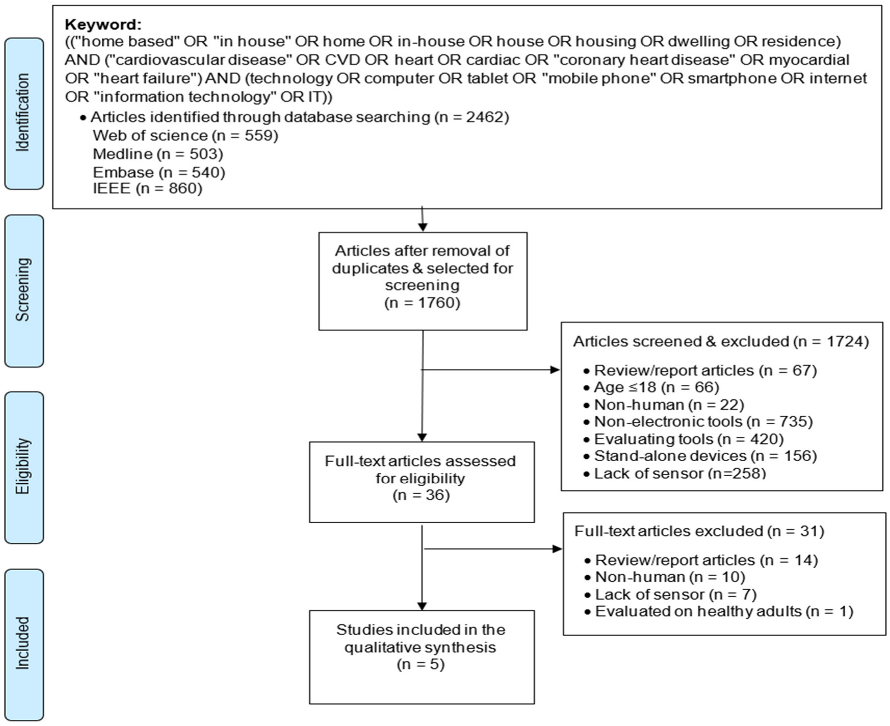

Figure 2. Flow diagram for selection of articles (adapted from reference [30]).

2.5. Data Extraction

One reviewer independently evaluated the titles and abstracts of all records identified in the initial database search; then, they reviewed the full text for eligibility according to the study's inclusion criteria [44]. We extracted data regarding study characteristics, including study type, duration, and participant characteristics, and the SHT used, including system configuration, parameters monitored, and the data analysis and interpretation methodology.

3. Results

We retrieved 2462 articles for the applied search key from the database. Upon removing duplicates, 1760 articles were there for full-text review. Furthermore, we screened the electronically obtained titles and abstracts for the relevance of selection criteria. The selected 36 articles were further accessed, assessed, and matched with the study's objectives. At each level of article screening, we excluded review articles such as systematic review and meta-analysis [45], literature reviews [46,47], perception survey [48], protocols [49] and similar articles. We further screened for non-human subjects [50] and other irrelevant articles to the objective, such as home telecare service consumption [51], HF treatment [52], database analysis [53], training coronary patients [54], and cardiac rehabilitation program [55]. Likewise, we eliminated studies undertaken on economic impact [56], among children [57], prototypes not evaluated on human subjects [58], and providing information and advice but lacking sensors to capture vital recordings in real time [59,60]. In addition, we excluded interviews to evaluate patient perspectives [61], improving knowledge [62], and multiple articles on a single study, e.g., My Heart [63,64], studies in healthy adults [65] and those lacking analytical results [66]. Finally, we included five studies comprising various integrated SHTs to monitor and assist CVD patients in home settings in this review, and Table 2 represents the characteristics of the included studies.

Table 2. Study Characteristics.

Articles Reviewed	Study Type	Study Duration	Country	Participants	Age (Years)	Male (%)	Female (%)
(Sciacqua, 2009) [67]	CO	Spot reading/day	Italy	10 elderly CHF	NS	90	10
(Katra, 2011) [68]	CO	90 days	Asia	180 HF	61 ± 13	70	30
(Fanucci, 2013) [69]	CO	1 month	Italy	30 CHF	µ: 62	NS	NS
(Alnosayan, 2017) [70]	CO	6 months	USA	8 HF	61.5 ± 9.3	63	37
(Kotooka, 2018) [71]	RCT	0–31 months	Japan	181 HF	Tel: 67.1 ± 12.8 Usual: 65.4 ± 15.6	59	41

CO: Cohort; RCT: Randomised Control Trial; CHF: Chronic Heart Failure; HF: Heart Failure; USA: United States of America; NS: Not Specified; Tel: Telephone.

The five included studies comprised 409 CVD patients, with a mean age of ≈63 years and ≈62% male participants [67–71]. The participant's medical conditions differed between the studies; for example, three studies included patients with HF [66,68,69], whereas two other studies had congestive HF (CHF) patients [67,69]. The studies with CHF participants had ten [67] and thirty elderly participants [69]. Likewise, studies with HF patients had one hundred and eighty participants [68], one hundred and eighty-one participants [71], and eight participants [70]. Moreover, a study did not mention the proportion of males and females [69], whereas other studies had predominant male participants [65,66,68,69]. The duration of the studies varied, i.e., from one day to 31 months. Three studies monitored the participants continuously for over a month [66,67,69], and one study monitored for six months [70]. In contrast, a study monitored participants for a short time in a day [67]. The studies were undertaken in different international settings, including two studies in Italy [67,69], one study each in Japan [71] and the United States of America [70], and a study in eight locations in Asia [68].

The objectives of the SHT differed between the studies; however, the developed systems effectively delivered the intended functionalities with acceptable accuracies. For example, a system developed to monitor CHF patients' HR, RR, and other parameters was generally well accepted irrespective of the sensors and protocols used, although they encountered minor difficulties [67]. In contrast, a study demonstrated that chronotropic incompetence (CI), typical in HF patients and associated with worsening outcomes, could be detected and tracked by capturing and analysing participants' HR, RR, PA, and body fluid at regular intervals [68]. Likewise, for early detection and minimised hospitalisation among CHF patients, their vital parameters, including ECG, SpO2, BP, and weight, were non-invasively captured and analysed in the permissible range and sent to hospitals regularly [69]. Moreover, a study undertaken to provide a personalised mHealth system to support HF patients effectively concluded that understanding users' requirements combined with physician and nurse requirements can yield a feasible telehealth system that effectively supports HF self-care [70]. Finally, a study concluded that home telemonitoring for HF patients was feasible but could be enhanced to make it more efficient [71].

3.1. Available Smart Home Technologies for CVD Management

Smart homes are integrated systems comprising sensing systems, including environmental and personal sensors responsible for data acquisition, communication systems to transfer the sensor captured data, and processing systems receiving the sensor captured data to analyse and provide the required services [14,72]. Table 3 details the technology and parameters monitored in the SHT for CVD management from the reviewed articles, and we discuss them in the following section.

Table 3. Smart Home Technology and monitored parameters.

Articles Reviewed	Parameters Monitored			System					
	Manual	Device		Communication System		Gateway	Interactive User Interface	Report Viewed by	Alarm Situation
		Wearable	Non-Wearable						
(Sciacqua, 2009) [65]	HR, BP, BW, SpO2, Temperature.	RR, ECG, Chest movement.	HR, BP, BW, SpO2.	Device to Gateway: BT, Wi-Fi.	Gateway to App: Internet.	Computer	User: questionnaire, guides in vital measurement.	Health Practitioner	Doctor contacted patients.
(Katra, 2011) [66]	-	HR, RR, Body Movement, Posture.	NA	Device to Gateway: BT.	Gateway to App: Internet.	Device	NA	Researcher	NA
(Fanucci, 2013) [67]	-	-	RR, ECG, Chest movement, BP, BW, Posture, SpO2.	Device to Gateway: BT.	Gateway to App: Internet.	Computer	User: assist in therapy. Clinician: interact with the system	Health Practitioner	Caregivers or relatives are contacted via SMS.
(Alnosayan, 2017) [68]	Symptoms	-	BW, BP, BG	Device to Gateway: BT.	GW to App: Internet.	Device	User: personal health tracking system. Clinician: view patient recordings.	Heart failure nurses	Nurse contacted the patients.
(Kotooka, 2018) [69]	-	-	BW, PR, BP.	Device to Gateway W: BT.	Gateway to App: Internet.	Device	NA	Health Practitioner	Nurse notified the patient's physician.

HR: Heart Rate, BP: Blood Pressure, BW: Body Weight, RR: Respiration Rate, ECG: Electrocardiogram, SpO2: Oxygen saturation, BT: Bluetooth, NA: Not Available.

3.1.1. Sensor and Monitored Parameters

The vital signs generally monitored to evaluate CVD patients' health are HR, BP, RR, SpO2, and body temperature [73]. Sensors recorded the participant's vital signs, and the readings were acquired either manually or automatically at normal home settings [67–71]. The sensors were vests [67] and attached to the body at different positions such as at the torso [68], arm, wrist, finger, and chest [69,70]. The vital signs recorded by the sensors include HR [65,66,69], BP [67,69–71], respiratory rate [67–69], blood glucose [70], and SpO2 [67,69]. Furthermore, HR computation as a function of cardiac vibration extracted from the obtained ECG signals was performed [69]. Additionally, an SHTs system had non-wearable sensors such as weighing scales [67,69–71].

3.1.2. Communication Systems

The communication system comprises an internal network connecting the sensors, the gateway functioning as an interface between the internal and external networks, and an external network transferring the captured data from the gateway to applications [14]. The internal network consists of interconnected sensors using popular short-range wireless protocol communication technologies such as Zigbee, Wi-Fi, and Bluetooth [14]. The internal communication systems used in the studies differed. For example, studies had used devices interconnect through short-range wireless protocol communication technologies such as Wi-Fi [67,70] and Bluetooth [67–71].

A gateway is a significant component in an SHT, performing functionalities including network interconnection, network management, and application management; however, the gateway could be a dedicated device or a mobile device such as a smartphone, a tablet, or a local smart sensor node placed in the environment or mounted on a computer server [14]. The studies have used computers [67,69] and dedicated devices [66,68,69] as the gateway to receive the sensor data through the internal communication system, perform the necessary management functions, and forward the information to the end-user application over the external network.

The gateway relays data using different external network systems such as fixed telephony networks, Wi-Fi, cellular networks, satellite networks, and other technologies to healthcare applications [14]. The healthcare applications were installed at a computer running in external networks as a web application [67–71] and app [70], and internet communication (telephony networks, cellular networks) was established to transfer information from the gateway to healthcare applications running in an external network [67–69,71].

3.1.3. End-User Applications

The SHT had an interactive user interface enabling the users to complete the questionnaire followed by guiding in vital physiological measurements [67], assisting in therapy [69], and assisting them to track their health [70]. Likewise, clinicians had the provision to interact with the system [69] and view patients' recordings [70]. Additionally, the end-user applications displayed the processed information to the relevant stakeholders, including health practitioners [65,67,69], HF nurses [70], and researchers [68] for caregiving. In a study, the health practitioner viewing the report was able to identify the dangerous increase in BP and necessary measures to avoid health risk and hospitalisation [67]. Likewise, caregivers or relatives were contacted via SMS [69], and nurses notified the patient's physician [71] for detected irregular readings. In addition, a system had provision for the patients to contact nurses through the app to discuss their health, and the nurses had the option to continuously monitor their patients using the web application [70]. On the contrary, a study stored data during the study period but was not analysed and could not be used to guide or alter patient treatment [71].

3.2. User Acceptance

Performing usability testing in the deployed environment is essential to evaluate the system's ease of use, usefulness, and user acceptability [74]. On evaluating the satisfaction and usefulness of the system, 89% of the patients responded that the system was satisfactory, and 70% responded that it was useful [69]. On the other hand, on a scale of ten, physicians positively rated greater than nine, highlighting the effectiveness and usefulness of the system [69]. Likewise, patients expressed that the system was helpful and helped them, since it facilitated recording and tracking readings, reassuring nurses, resolving system issues, providing insights, and assisting them in communicating with their healthcare professionals easily [70]. In contrast, a few studies have not used standard or customised methodologies to evaluate the user and healthcare perception of the developed system [65,66,69].

3.3. Role of Regulatory Agency

The revolution in smartphone technologies, direct-to-consumer genetic testing, crowd-sourced information, big data, and many other technologies have enabled researchers, including independent researchers, citizen scientists, patient-directed researchers, do-it-yourself researchers, and self-experimenters, to innovate and develop health monitoring systems that are easily accessible [75]. On the other hand, easy access to health monitoring systems increases the potential of unregulated health research [75], which could be beneficial but could pose risks such as compromised accuracy, privacy invasion, and minimised safety to the users [75–77]. Hence, there is an imperative need for the governments to regulate the development and deployment of health monitoring systems through competent regulatory agencies [75–77]. However, although the studies have fabricated hardware and used available commercial products, they have not obtained any regulatory approvals [67–71].

4. Discussion

In this study, we aimed to explore the different Smart Home technologies available for CVD monitoring and management in home setting. Five studies were identified using SHT amongst HF patients and included sensor and physiological monitoring, communication systems, and end-user applications. We found that stakeholders well-accepted SHTs for CVD management. However, none of the studies had obtained relevant regulatory approval. Although there is a surge in smart home studies, very minimal studies have been evaluated experimentally in research settings [11]. Given the limited number of smart home experimental studies, it is evident from our study that there is a lack of experimental studies focused on SHT for CVD management.

A systematic review evaluated various ICT intervention platforms to deliver alternative models of CR homecare programs [29]; in contrast, another systematic review assessed the evidence around mHealth interventions for CR and HF management for service and patient outcomes, cost-effectiveness, and implementation scope for rural and remote cardiac patients [28]. This systematic review aimed to evaluate SHT available for CVD management and highlights the paucity in SHT for CVD management, necessitating the importance of real-time remote health monitoring systems integrated with SHT for CVD management.

IoT connects the physical world, including the human body, with the internet, and IoT application to healthcare could improve the individuals' quality of life, assist in chronic disease management, danger warning and life-saving interventions remotely [78] and could assist in death prevention and cost reduction due to CVD [79]. The real-time monitoring of CVD patients through the IoT, which is a system of wireless, interrelated, and connected digital devices that could non-invasively collect physiological and environmental data, send, and store data over a network without requiring human-to-human or human-to-computer interaction, could be realised [80,81]. In conjunction with other novel technologies such as big data and cloud computing, IoT could be used to develop a remote monitoring system for CVD patients [82]. However, apart from barriers, such as internet access, user-friendliness, organisational support, workflow efficiency, and data integration in deploying digital health technology in CVD care [83], most systems are in prototype stages and have not been exhaustively evaluated clinically.

Globally, HF is rising in prevalence; however, there are several unmet severe social and healthcare needs for both patients and caregivers, necessitating research to develop and evaluate disease management toolkits [84]. A smart healthcare framework using IoT, and cloud technologies could monitor HF patients based on real-time data and provides timely, effective, and quality healthcare services [85]. However, although several prototypes have been developed to monitor HF patients, there is a need to carry out future clinical trials, including those targeting a reduction in HF hospitalisations [20]. On the other hand, CHF patients are at a high risk of suffering from morbidity and mortality and poor quality of life [86]. A remote CVD management system could assist in the early identification of decompensation and promote better adherence to lifestyle changes and medication and interventions resulting in reduced hospitalisation need [86]. Moreover, mobile health-driven interventions integrated with other parameter monitoring such as activity trackers and weighing scale capabilities could benefit HF patients [87].

Studies are developing a system to monitor stroke, which happens due to brain-cell death in the absence of blood flow to brain cells [88–91]. An IoT-based real-time EEG brain–computer interface medical monitoring device significantly reduce the complexity of real-time monitoring and data acquisition among stroke patients providing better healthcare management [92]. Furthermore, wearable sensors and ML could play a vital role in post-stroke rehabilitation through activity recognition, movement classification, and clinical assessment emulation [93].

High BP is directly associated with a high risk for CVD [94]. With the advancements in technology, BP could be monitored at fixed intervals during sleep and at different intervals during the day and could determine BP in response to a specific trigger, such as increased heart rate [95]. BP monitoring at home could assist in predicting the onset of CVD events, enabling proactive interventions to avert adverse outcomes [95].

Sleep disturbance could be a common factor that might increase CVD risk; participants with short sleep duration had significantly higher CVD and hypertension; on the contrary, participants with long sleep durations had no increase in CVD, CHD, myocardial infarction, or hypertension prevalence [96]. Furthermore, sleep onset timing could initiate CVD risk; hence, collecting sleep parameters via accelerometry-capable wearable devices may serve as novel CVD risk indicators [97]. In addition, a study identified three sleep–cardiovascular health phenogroups, such as resilient (non-adequate sleep and ideal cardiovascular health), uncoupled (adequate sleep and non-ideal cardiovascular health), and concordant (sleep and cardiovascular health metrics were aligned), highlighting the advantage of incorporating sleep assessments into studies of cardiovascular health [98]. Finally, with sleep disturbances and disorders implicated in CVD morbidity and mortality, there is an imminent need for a transdisciplinary research framework integrating knowledge, methods, and measures of psychology and sleep research to advance CVD prevention and treatment [99].

Monitoring patients using technologies, including telemedicine, creates a void in evaluating vital parameter recordings and could result in misdiagnosis [100]. Moreover, with many forced to stay at home for a prolonged period [101], and with the associated risk surrounding CVD patients and the restrictions in healthcare services due to COVID, there is a greater need for remote monitoring of CVD patients in real time, especially while they are at their homes [100,102]. In addition, we observed that the SHT functionalities and components, including sensors, communication systems, and end-user applications, differed; however, all the systems lacked real-time data processing, analysis, and reporting capabilities [67–71]. With 53.6% of global households and 84% of households in developed countries having internet access [103], there are research prospects to develop SHT to monitor CVD patients in real time.

Wearable devices are finding widespread applications in healthcare in health and safety monitoring, chronic disease management, disease diagnosis and treatment, and rehabilitation [104]. A study observed that activity data from wearables could monitor CVD patients remotely, enabling safer and higher resolution monitoring of patients [105]. However, on the downside, although current studies highlight the wearables' potential to monitor cardiovascular events, the lack of a real data set and proper systematic and prospective evaluation hampers their deployment as a diagnostic or prognostic cardiovascular clinical tool [106]. Additionally, to date, wearable devices possess challenges in cardiovascular care, such as device accuracy, clinical validity, a lack of standardised regulatory policies and concerns for patient privacy hindering the widespread adoption of smart wearable technologies in clinical practice [32].

With an imperative need to develop affordable and reliable real-time SHT CVD monitoring systems, IoT-based healthcare systems could be an effective solution. For example, IoT systems developed using Raspberry Pi, which is an affordable small-sized computer that finds widespread healthcare applications due to its technical capabilities to connect with a wide range of sensors and process and transfer the data in real time to a cloud environment for further processing [107,108], could be an effective solution. Our study examined the available SHT used amongst HF patients among the various CVD. On the contrary, studies are developing a system to monitor other CVD, such as stroke, which happens due to brain-cell death in the absence of blood flow to brain cells [88–91]. Hence, there is a need to consider end-user needs and develop a system accordingly to be used effectively amongst the target audience [109].

The healthcare systems developed based on theory-guided user-centred design approaches could effectively address the healthcare needs of the target group [110]. Conversely, using standard user acceptance models such as the technology acceptance model could inform end-user acceptance of the system [110]. However, the studies had not used any models to gauge the user acceptance of the system [65,66,69], although there is a need to obtain medical approval to comply with standards and guidelines to be used globally seamlessly [111]. Moreover, the COVID-19 pandemic has highlighted the need for a comprehensive real-time health monitoring system. Nevertheless, since healthcare needs depend on physicians, patients, and external users, it is worth designing and developing the system based on user requirements [112] complying with regulatory standards [111].

4.1. Limitations of this Study

This study had several limitations. Although smart home development is at various developmental stages globally, since we have not considered articles published in the non-English language, we could have missed relevant studies published in other languages. Secondly, we excluded ML and deep learning (DL) model studies if they omitted SHT as well as studies only evaluating telemedicine or telemonitoring, which are not part of SHT using IoT. Thirdly, we have exclusively considered articles published in peer-reviewed research journals and conference proceedings to select studies undertaken in research settings that could have excluded grey literature and incurred publication bias. Fourthly, given the time sensitivity, an experienced reviewer performed the article selection, screening, and data extraction outlined in the methods section, which could have caused selection bias. Finally, the heterogeneity of the data and the lack of standard models to evaluate the user perception of the SHTs have restricted us from conducting meta-analysis. However, our study's findings could be beneficial in addressing the needs of CVD patients.

4.2. Future Directions

With limited SHTs to monitor CVD patients in real time evaluated in research settings and accessible to patients, there is an urgent need to design, develop, and deploy effective solutions. Moreover, the disruption in healthcare due to COVID-19 and the severity of COVID-19 is an impetus for the innovation of IoT-based SHTs to address residents' day-to-day healthcare needs [80,113]. An IoT-based SHT architecture comprises the perception layer that includes sensors such as radio frequency identification sensors, infrared sensors, cameras, global positioning systems, medical sensors, and smart device sensors, the network layer comprises wired and wireless technologies which communicate and store the perception layer captured information, and finally, the application layer interprets data and delivers application-specific services to the user [80]. Figure 3 illustrates an overview of an IoT-based SHT for CVD monitoring [88–91]. The system comprises four layers: the perception layer, connectivity layer, processing layer, and application layer. The perception layer consists of all sensors in an SHT setting to capture vital recordings, such as BP, HR, heart rate variability (HRV), ECG, blood oxygen and other signals, such as sleep, step count, body temperature and weight. The connectivity layer comprises gateway and telecommunication networks that facilitate the transfer of the sensor data from the internal network to the processing layer over an external network. The processing layer stores the data and performs the specified analysis. Finally, the application layer displays the processed data to healthcare providers, who initiate necessary intervention through caregivers or patients.

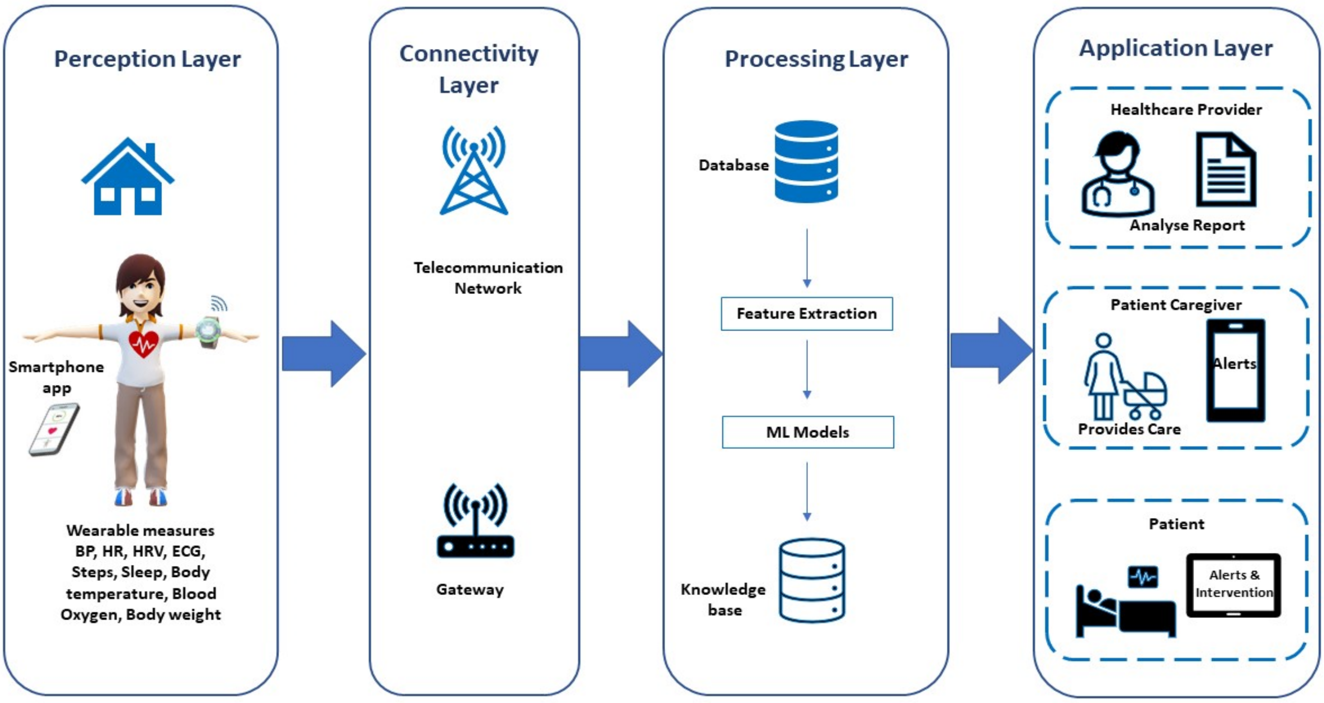

Figure 3. An IoT-based SHT for CVD monitoring. (The layers have specific functionalities. Perception layer: Consist of all sensors in an SHT setting to capture vital recordings, such as blood pressure, heart rate, heart rate variability, electrocardiogram, blood oxygen and other signals, such as sleep, step count, body temperature and weight. Connectivity layer: Transfer the sensor data from the internal network to the processing layer over an external network. Processing layer: Stores the data and performs the specified analysis. Application layer: Displays the processed data to healthcare providers, who initiate necessary intervention through caregivers or patients.)

An IoT health monitoring system could leverage the features of AI, wherein developed algorithms emulate human cognitive function, encompassing but not limited to ML, DL, natural language processing, and computer vision, to deliver enhanced personalised healthcare services [34,112,113]. Moreover, the capabilities of ML algorithms facilitate the prediction of CVD [114,115]. Furthermore, the application of DL could accurately estimate the CVD risk [116]. Constructively, COVID-19 has fuelled the development and utilisation of real-time patient monitoring systems, which are enabled by automated alert systems explicitly tailored to the patient's needs, which could be the cornerstone of a more continuous, patient-centric healthcare model subsequently [117]. Moreover, integrating adjunct technologies, including big data, cloud computing, smart sensors, AI, and virtual reality/augmented reality, with IoT could maximise the potential benefits [118]. Hence, developing SHT for CVD monitoring integrating IoT with adjunct technologies could facilitate real-time monitoring, facilitating the upkeep of the health and well-being of CVD patients [88–91].

HRV could be used as a marker for cardiac status and for predicting cardiovascular outcomes quickly with wearable devices capable of measuring HR in real time; HRV is a measurable reflection of the balance between sympathetic and parasympathetic tone [119]. A meta-analysis of studies amongst CVD patients observed that lower HRV is associated with a higher risk of cardiovascular events and mortality, although the extent of the association is uncertain [120]. In addition, current research suggests that HRV parameters may have utility as a biomarker for stroke and post-stroke complications and functionality [121]. Likewise, HRV could classify CHF patients from healthy adults [122]. Finally, a study observed an association between HRV and BP [123]. ML models are applied to computed HRV parameters to classify cancer patients [124] and predict the risk of suspected sepsis patients in the emergency department [125]. Hence, research prospects are to capture HR in real time from wearable devices and apply ML to classify healthy and CVD patients.

5. Conclusions

With elderly adults spending most of their time at home and the pandemic restricting healthy lifestyles such as outdoor PA further confining adults at home, there is an increased risk of CVD, instigating an imperative need to monitor vital parameters regularly. However, the limited SHTs available to address the needs of CVD patients and monitor healthy adults for risks, although CVD is a leading cause of death globally, highlights the urgent need to develop such solutions. Hence, our findings could provide insights and guidelines into critical issues, including SHTs for CVD management, user acceptance, and regulatory agency's role to be followed when designing, developing, and deploying integrated solutions for CVD monitoring at home. Our findings also contribute to the development of patient-centred care for managing CVD related chronic conditions in ambient assisted living.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/asi5030051/s1, Table S1: Web of Science search strategy.

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