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Driving Healthcare Monitoring with IoT and Wearable Devices: A Systematic Review

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Wearable technologies have become a significant part of the healthcare industry, collecting personal health data and extracting valuable information for real-time assistance. This review article analyzes 35 scientific publications on driving healthcare monitoring with IoT and wearable device applications. These articles were considered in a quantitative and qualitative analysis using the Natural Language Processing framework and the PRISMA methodology to filter the search results. The selected articles were published between January 2010 and May 2024 in one of the following scientific databases: IEEE Xplore, Springer, ScienceDirect (i.e., Elsevier), Association for Computing Machinery (ACM), Multidisciplinary Digital Publishing Institute (MDPI), or PubMed Central. The analysis considers population, methods, hardware, features, and communications. The research highlights that data collected from one or numerous sensors is processed and accessible in a database server for various uses, such as informing professional careers or assisting users. The review suggests that robust and efficient driving healthcare monitoring with IoT and wearable devices applications can be designed considering the valuable principles presented in this review.

This work is funded by FCT/MECI through national funds and when applicable co-funded EU funds under UID/50008: Instituto de Telecomunicações. This work was also funded by FCT/MEC through national funds and co-funded by the FEDER-PT2020 partnership agreement under the project UIDB/00308/2020 (DOI 10.54499/UIDB/00308/2020).
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ACM 0360-0300/2025/06-ART294
https://doi.org/10.1145/3731595

CCS Concepts: • **Hardware** → **Emerging tools and methodologies;** • **Human-centered computing** → **HCI design and evaluation methods**; **Interaction devices;** • **Applied computing** → **Health informatics**; **Electronics**; **Computer-aided design**;

Additional Key Words and Phrases: Healthcare monitoring, sensors, wearable devices, systematic review, driver, Internet-of-Things

ACM Reference Format:
João Baiense, Eftim Zdravevski, Paulo Coelho, Ivan Miguel Pires, and Fernando J. Velez. 2025. Driving Healthcare Monitoring with IoT and Wearable Devices: A Systematic Review. *ACM Comput. Surv.* 57, 11, Article 294 (June 2025), 38 pages. https://doi.org/10.1145/3731595

1 Introduction

Nowadays, we frequently rely on various types of appliances or gadgets, such as computers, copy machines, mobile phones, microwave ovens, refrigerators, air conditioning and television remotes, smoke detectors, **infrared** (**IR**) thermometers, turning on and off lamps, and fans, which help us interact with the physical environment. Many of these applications perform their task with the help of sensors [9]. For example, driving healthcare monitoring with IoT and wearable devices is an application that uses medical sensors to measure the driver's data during driving. The application calculates the data in real-time and performs different tasks to assist the driver's well-being, such as providing and displaying data to a health professional and performing decision-making employing artificial intelligence. **Internet-of-Things** (**IoT**)-assisted wearable sensor systems are becoming pivotal in healthcare applications, as they can connect information from different sectors into one application through innovative technologies [7].

The basic layout of a **Healthcare Monitoring System** (**HMS**) is a sensor (or sensors) that, most of the time, is wearable [30]. A sensor is defined as a device or module that aids in detecting changes in physical quantities, such as pressure, heat, humidity, movement, force, and an electrical quantity, like current, and thereby converts these to signals that can be detected and analyzed [9, 37]. The sensor is the heart of the measurement system. The sensor's data are sent to the cloud via a communication protocol like Zigbee, Bluetooth, Wi-Fi, or others [4]. These data are then sent via a communication layer to the data center for further processing. For emergency awareness, the same data is visible in real time to the doctor, patient, and the patient's caretakers.

IoT wearable devices have increased drastically over the years, not only in the healthcare field but in many other verticals. The combined use of hardware, electronics, and software programs makes improving and achieving many results for a patient's healthcare possible. Undoubtedly, these devices are already part of people's lives, such as fitness trackers that monitor a person's pulse, movements, sleep schedule, etc. When the person adds valuable information to the device, such as its weight, height, and age, it is possible to calculate metrics such as the number of calories they have burnt, the altitude of the highest points they have been to, or the number of stairs they have climbed or descend. Some of the most common IoT applications in healthcare are activity recognition, stroke rehabilitation, blood glucose monitoring, cardiac monitoring, respiration monitoring, sleep monitoring, **blood pressure** (BP) monitoring, stress monitoring, Alzheimer's Disease monitoring, cancer patient monitoring, and medical adherence.

The technology used in **Internet of Medical Things** (**IoMT**) applications differs significantly from one application to another, depending on what the application requires. Over the years, several IoMT projects have been tested and built with various tools. For hardware, there are many components available in different categories. On the other hand, the panorama is like software and revolves around functionalities related to saving and charting data. Sensors such as the **Passive Infrared** (**PIR**) sensor, **Electrocardiogram** (**ECG**), **Radio-Frequency Identification** (**RFID**), and

BP sensor are some of the many used in several prototypes [22, 23]. Moreover, microcontrollers are an essential part of these projects. Some examples are the Raspberry Pi, Arduino, STM32 Microcontroller, ARM7, Intel Galileo, and others [17, 26, 27, 42, 49, 52]. A heartbeat monitoring application uses An ECG sensor to measure and graphically represent the heart's electrical activity. It is used in most healthcare systems to detect heart conditions and helps identify chest pain and other common symptoms. The research in [44] deals with anomaly detection in the ECG readings taken, using filters, and calculating the energy variances.

In terms of comfort and safety of the user, a wearable device should be comfortable enough so that the person wearing it can use it throughout the day. Hence, the device should be lightweight, ergonomic, water-resistant, skin-friendly, and durable. Safety should also be a priority in wearable sensor development. Together with the devices, sensors should be safe to be worn. Wearing them should neither have any side effects nor be harmful to the body in the long term.

This systematic review sought scientific works related to driving healthcare monitoring with IoT and wearable devices applications, published between January 2010 and May 2024 in the following scientific databases: PubMed Central, **Multidisciplinary Digital Publishing Institute** (**MDPI**), IEEE Xplore, **Association for Computing Machinery** (**ACM**), ScienceDirect (i.e., Elsevier) and Springer. It was possible to find a wide range of technologies through the studies found. However, the focus of this systematic review was the presence of technologies for measuring the driver's vital signs during a driving situation. As an outcome, it was possible to verify the correlation between the most used methods and the most used features and the potentialities and limitations of the studies. It is worth mentioning that the found results will be used to improve the application and minimize the identified limitations by integrating efficient and accurate wearable technologies.

Despite substantial research in this field, existing literature reviews, such as those by [14, 54, 57], and [5], predominantly emphasize general healthcare applications, digitalization, and IoT integration without addressing the unique challenges and specific applications pertinent to driving environments. While these reviews acknowledge the potential of IoT and wearable technologies, they frequently overlook their crucial role in monitoring driver health, where real-time health data can significantly enhance safety and well-being. This systematic review seeks to address this gap by conducting a targeted analysis of healthcare monitoring in driving contexts using IoT and wearable devices, thereby providing novel insights into the effective utilization and implementation of these technologies to improve driver safety and health outcomes.

2 Methodology

2.1 Research Questions

The main questions of this systematic review were as follows: (RQ1) Which methods are used to detect the individuals' vital signs? (RQ2) Which sensors are used for the measurements? (RQ3) How do such measures impact individuals' performance in a driving situation? (RQ4) Which technologies could potentially improve the drivers' security?

2.2 Inclusion Criteria

Driving healthcare monitoring with IoT and wearable devices is being studied for implementation with different sensors available. Therefore, the selection of the various studies for this systematic review was performed with the following eligibility criteria: studies that (1) consist of healthcare monitoring; (2) make use of wearable devices in an IoT environment; (3) benefit from one or more embedded sensors; (4) present the purpose of the study; (5) characterize the population of the study; (6) present precise results about a healthcare monitoring application; (7) present original research; (8) were published between 2010 and 2024; (9) were written in English.

2.3 Search Strategy

The search approach used the PRISMA technique [43] to discover and analyze the driving healthcare monitoring with IoT and wearable devices-related material published between January 2010 and May 2024. Some of the electronic databases used to search for articles using the **Natural Language Processing** (**NLP**) toolset automatically were PubMed Central, MDPI, IEEE Xplore, ACM, ScienceDirect (i.e., Elsevier), and Springer.

The input parameters for the NLP framework were a collection of keywords to potentially find relevant articles and a list of criteria the identified articles must meet. "Driving healthcare monitoring with IoT devices" OR "Driving healthcare monitoring with wearable devices" OR "Healthcare monitoring for drivers" were used as search keywords. The program was able to remove any duplicates by considering the DOI numbers. The pertinent publications were also found based on the inclusion criteria and the first keyword search. The reader is referred to the work of Zdravevski et al. [58] for further in-depth information regarding the elements of the NLP toolbox.

The authors of this systematic review independently evaluated the retrieved articles to check if they were following the search's eligibility requirements. The multidisciplinary research involves experts in computer, electronics, and health sciences. To extract the relevant information about the analyzed articles and connect them to the automobile security industry, the studies have been analyzed, their hardware components have been verified, and their information has been mapped. The search was conducted on November 8, 2022, and updated on September 10, 2024.

2.4 Extraction of Study Characteristics

Table 1 summarizes key parameters extracted from the identified studies, including the publication year, study location, target population, research objectives, integrated hardware components, methods employed, specific methodologies used, features analyzed, and the communication technologies utilized for data transmission and reception. Regrettably, the source code and datasets utilized in the examined research are unavailable to the public.

3 Results

The NLP toolkit automatically selected 18343 research studies from the various databases, as presented in Figure 1. The framework could discard 13947 articles by removing 4396 duplicate data found via the **Digital Object Identifier** (**DOI**). By performing an analysis based on the paper's title, it was possible to exclude 243 publications. After eliminating 13540 articles based on an automatic investigation by the NLP toolkit, the remaining 164 articles underwent an abstract examination. Additionally, after a deeper and more focused analysis of the studies not excluded by the framework, it was possible to eliminate 99 research studies that were not associated with driving healthcare monitoring with IoT and wearable devices, nor employ devices, nor are literature reviews. Finally, the quantitative synthesis and meta-analysis incorporated the final 35 studies.

The 35 selected studies were examined to extract the relevant data, presented in Table 1. The query performed in this study retrieved papers published between January 2010 and May 2024. As reported in Table 1, two studies (5.714%) were published in 2023, four studies (11.43%) in 2022, four studies (11.43%) in 2021, three studies (8.572%) in 2020, nine studies (25.71%) in 2019, four studies (11.43%) in 2018, one study (2.857%) in 2017, two studies (5.714%) in 2016, three studies (8.571%) in 2015, two studies (5.714%) in 2014 and the remaining study was published (2.857%) in 2013. Regarding the location of the different studies, six studies (17.14%) were performed in the USA, four studies (11.43%) in the United Kingdom, three studies (8.572%) in Egypt, three studies (8.572%) in Italy, three studies (8.572%) in India, two studies (5.714%) in Australia, two studies (5.714%) in South Korea, two studies (5.714%) in China, and the remaining twelve studies were each one (2.857%) in

Table 1. Study Analysis

Paper	Year	Location	Population	Purpose of Study	Integrated Hardware	Type of Methods	Methods	Features	Type of Communication
Mulhall et al. [36]	2019	Victoria, Australia	20 healthcare workers	Effectiveness of a pre-drive ocular examination for detecting sleep-related impairment when driving naturally in shift employees	MobilEye; Camera; Steering wheel angle sensor	Statistical methods; Predictive methods	Pre-drive ocular assessments	Ocular parameters	N/A
Mohsen et al. [47]	2020	Cairo, Egypt	Individuals	Discussion about a wearable medical sensor system for long-term healthcare applications	Temperature sensor; Pulse oximeter sensor; Accelerometer sensor; **Bluetooth Low Energy (BLE)** Module	Statistical methods	Wake-up and sleep; Hybrid energy harvester	Body Temperature; Heart rate; SpO_2; Body acceleration	BLE
Kajor et al. [29]	2020	Kraków, Poland	2 healthy volunteers	Investigation of a system architecture for monitoring vital indicators in a residential environment	Digital thermometer ADT7410; Nordic Development Kits based on RF52832 chip	Descriptive analysis	Measurements of stationary conditions or during movement	Body temperature; Respiration rate	BLE
Yue et al. [57]	2020	Moscow, Russia	Dataset with 70,000 records [60]	Creation of a hardware-software system for keeping track of a driver's health	Huawei Smart Bracelet	Statistical methods; Predictive methods	Cloud server; Saves data in a database for data analysis; User's data display and notification.	BP; Heart rate; SpO_2	Bluetooth; 3G/4G Network
Digiglio et al. [39]	2014	California, USA	Healthy volunteers	Creation of the so-called microflotronic device using cutting-edge microfluidics and electronics for arterial BP monitoring.	Microfluidic sensing layer of ethylene glycol	Statistical methods	High sensitivity and fast response time; Arterial tonometry	Arterial BP	**Universal Serial Bus** (**USB**)-6210
Croatti et al. [3]	2017	Cesena, Italy	Trauma patients	Presentation of the Trauma Tracker, a project that explores agent technologies to create **Personal Medical Digital Assistant Agents** (**PMDA**), assisting a Trauma Team in trauma management operations	Tablet; Smart-glasses	Descriptive analysis	Architecture based on agent and service; Trauma Assistant Agent; Web-based services; Set of pervasive services; Set of Web-apps	Vital signs	Bluetooth
Kang et al. [18]	2018	Preston, Australia	Drivers	Implementation of a methodology for integrating mHealth and vehicle information systems to forecast and alert alarms when a driver encountered unforeseen circumstances	Distance sensor; Ultrasonic sensor; Pulse oximeter sensor; BP monitor; Accelerometer sensor	Predictive methods	Data processing and transferring to a cloud server; Integrated vehicular alarm system	Vital signs	N/A
Pandiyan et al. [32]	2016	Bangalore, India	Dataset with 63 data of patients	Presentation of an integrated **Fuzzy Decision Making** (**FDM**) chip in an ultra-low power ECG on a chip for **Wireless Body Sensor Networks** (**WBSN**) applications.	ECG sensor; **Fuzzy Decision Maker** (**FDM**) chip	Statistical methods; Predictive methods	Heart Rate Calculation and QRS Detection; FDM chip takes the decisions for alerting the patients	ECG data	ZigBee

(Continued)

Table 1. Continued

Paper	Year	Location	Population	Purpose of Study	Integrated Hardware	Type of Methods	Methods	Features	Type of Communication
Zito et al. [8]	2013	Cork, Ireland	Adult and infant volunteers	Research and development of a **System-on-a-Chip** (**SoC**) UWB pulse radar for respiratory rate monitoring in nano-scale CMOS technology and related practical testing in operational situations	Ultra wideband radar sensor; Planar **antennas** (ANT); QFN32	Descriptive analysis	Sub centimeter chest movements detection; Continuous-time monitoring of respiratory rate associated with the normal activity	Respiration rate	**Ultra-Wideband** (**UWB**)
Dorairaj et al. [41]	2015	Blekinge, Sweden	Drivers	Design of a location-aware remote system for safety, emergency, and health situations that utilize Google's Android mobile platform and discusses the Android application created for this function	Amarino; Arduino; GPS; Smartphone's camera; Accelerometer	Predictive methods	Fabric sensor to detect data; The speed and distance displayed on the device; Extreme body motion tolerance; Heart rate monitoring	Heart rate	Bluetooth
NITA et al. [46]	2019	Biskra, Algeria	17 participating drivers; MIT-BIH PhysioNet Database [12]	Discussion about a monitoring system that uses an improved random forest classification method to detect driver stress	ECG sensor	Predictive methods	ECG data monitoring; Stress state level classification	ECG data; **Electromyogram** (**EMG**); Foot **galvanic skin response** (**GSR**); hand GSR; **Intermittent Heart Rate** (**IHR**); Respiration rate	N/A
K. Hassan et al. [21]	2018	Mansoura, Egypt	MIMIC-II dataset with 40000 patients [34]	Presentation of the hybrid ambient assisted living framework with a naive **Bayes-firefly algorithm** (**HAAL-NBFA**) to monitor elderly patients with chronic disorders	**Systolic Blood Pressure** (**SBP**) sensor; **Diastolic Blood Pressure** (**DBP**); HR; RR; Body Temperature sensor; SpO_2 sensor; ECG sensor	Statistical methods; Predictive methods.	**Edge of Things** (**EoT**); **Naïve Bayes** (**NB**); **Firefly algorithm** (**FA**); Cloud, fog, and edge computing	SBP; DBP; Heart Rate; Respiration Rate; Body Temperature; SpO_2; ECG data	Bluetooth; **Near-Field Communications** (**NFC**); ANT; Zigbee
Latif et al. [11]	2019	Kota Samarahan, Malaysia	Healthy individuals	Design of an integrated prototype that includes a smart medicine dispensing system, wearable extendable health monitoring device, cloud-based big data analytical diagnosis tool, and AI-based reporting tool	Arduino; ECG sensor; Pulse Rate sensor; BP sensor; Body Temperature sensor; Stress Level sensor; Sweating monitor; SpO_2 sensor; GPS sensor; GSR sensor	Predictive methods; Descriptive analysis	Cloud computing and big data analysis (Amazon Web Services GovCloud); ROC curve (RIMARC) algorithm; Data security	ECG data; Pulse Rate; BP; Body Temperature; Stress Level; SpO_2	Wi-Fi

(Continued)

Table 1. Continued

Paper	Year	Location	Population	Purpose of Study	Integrated Hardware	Type of Methods	Methods	Features	Type of Communication
Mohsen et al. [48]	2021	Cairo, Egypt	Patients	Method for gathering solar energy to serve as a primary power source for a patient monitoring node's autonomous, continuous functioning in sunny conditions	NodeMCU board; ESP8266 MCU; MAX30100 Pulse Oximeter sensor; LEDs; MAX30205 Body Temperature sensor; Flexible PV Panels; Charging Controller chip	Descriptive analysis	Patient's vital acquired parameters; Data sent to a cloud computing service; Solar energy harvester	Heart Rate; SpO_2; Body Temperature	Wi-Fi
Haque et al. [24]	2021	Michigan, USA	A set of 322 chest Xray images	Discussion of several IoT applications that support healthcare systems in identifying and keeping track of Coronavirus patients. Two further IoT-based models are created for automated heat monitoring and real-time heart rate monitoring using wearable IoT devices.	ESP8266; AMG8833 IR thermal camera; TFT LCD display; Raspberry Pi; Raspberry Pi camera; Arduino Pro Mini; MAX30102 Pulse Oximeter sensor	Predictive methods	Real-time thermal temperature monitoring; Data transfer to the cloud; **Convolutional Neural Network** (**CNN**)	Body Temperature; Heart Rate; SpO_2	Wi-Fi
Currie et al. [19]	2019	United Kingdom	3 females and 11 males	Examination of three methods for obtaining metrics for wearable technologies, such as eye tracking and psychophysiological measures (such as **electrodermal activity** (**EDA**)), and (3) accelerometry to measure hand- and arm-movement	Eye tracking glasses; E4 wristband	Statistical methods	Eye gaze and psychophysiology metrics measurement	Eye tracking; EDA	N/A
Bichindaritz et al. [16]	2018	Oswego, USA	MIT-BIH PhysioNet Database [12]	Discussion of **electrocardiography** (**ECG**) monitoring to provide a reliable and effective technique for correctly identifying stress	EEG sensors	Statistical methods; Predictive methods	Individual stress analysis including three stress levels; Data accuracy using Machine Learning	ECG data	N/A
Sahu et al. [50]	2021	Nebraska, USA	MIT-BIH Database [12, 33]; BIDMC Database [12, 45]	Presentation of a system that extracts the patient's health status while a preliminary diagnostic algorithm is running in real-time on a local embedded computing platform	ECG sensors	Statistical methods; Predictive methods	Measured health information processing by DL algorithms; Complex **Deep Neural Networks** (**DNNs**)	ECG data	BLE; Wi-Fi
Zhang et al. [59]	2019	Hangzhou, China	2 volunteers	Proposal of a wearable wireless respiration sensor based on a lateral sliding mode **triboelectric nano-generator** (**TENG**) to track respiration rates by detecting changes in abdomen circumference.	Respiration sensor; Wireless Transmission chip	Descriptive analysis	High voltage output by TENG but relatively low current; High output impedance	Respiration rate; Apnea symptom detection; Real-Time Breathing	ANT

(Continued)

Table 1. Continued

Paper	Year	Location	Population	Purpose of Study	Integrated Hardware	Type of Methods	Methods	Features	Type of Communication
Perego et al. [38]	2014	Milan, Italy	30 newborns	Evaluation of the use of wearable technology for monitoring the first two hours of life following a clinical procedure	ECG 1-Lead; Bluetooth 2.1+EDR; Wi-Fi router	Statistical methods; Predictive methods	Smart garment and monitoring unit; All acquired data denoised by the electronics	ECG data	Bluetooth; Wi-Fi
Ha et al. [51]	2019	Incheon, South Korea	20 healthy male volunteers	Demonstration about the optimal placement position of biosensor-based wearable healthcare systems is affected by a combination of different biosensors	ECG sensor; **Thermocouple** (**TC**) sensor; **Photoplethysmogram** (**PPG**) sensor; Arduino Uno	Statistical methods	ECG-TC and PPG-TC arrays; **User accessibility** (**UA**); **skin extensibility** (**SE**); **Perspiration weight** (**PW**)	Heart Rate; Body Temperature	N/A
Duong et al. [20]	2015	Washington DC, USA	Heartbeat dataset	Discussion about optical sensors to measure the human body's heart rate using **photoplethysmography** (**PPG**)	TI AFE4400; Photodiode (PD); Dual LED (DLED)	Descriptive analysis	Reflection mode and transmission mode; Butterworth band pass filter; **Digital Signal Processing** (**DSP**)	Heart rate	**Serial Peripheral Interface** (**SPI**) communication
Adiono et al. [55]	2016	Bandung, Indonesia	Patients	Proposal of a **visible light communication** (**VLC**) system design that comprises two devices (the patient and coordinator devices) for wearable patient monitoring devices	AFE modules; STM32 NUCLEO-F446RE	Descriptive analysis	AFE modules for the patient device and the coordinator	Vital signs	**ON-OFF Keying** (**OOK**)
Moreira et al. [35]	2019	Enschede, Netherlands	Five use cases	Creation of an interoperable **Internet of Things** (**IoT**)-based **Early Warning System** (**EWS**) to identify the danger of accidents involving vehicles delivering cargo in the Valencia port region	Shimmer ECG sensor	Predictive methods	IoT EWS; TinyOS application; Data annotated with core ontology and stored in a NoSQL database	Vital signs	Bluetooth
Ali et al. [1]	2019	Egham, United Kingdom	Five subjects	Development of the use of a low-cost health monitoring sensor system that simultaneously measures body temperature, heart rate, and blood saturation levels (SpO_2)	Arduino MCU; Pulse Oximetry sensor; LCD; HC-05 Bluetooth module; Android mobile; ESP8266 Wi-Fi shield; DS18b20 digital thermometer	Statistical methods	AC and DC components calculation; Graph visualization on the Internet Server	SpO_2; Heart Rate; Body Temperature	Bluetooth; Wi-Fi

(Continued)

Table 1. Continued

Paper	Year	Location	Population	Purpose of Study	Integrated Hardware	Type of Methods	Methods	Features	Type of Communication
Balasubramanian et al. [10]	2021	Staffordshire, United Kingdom	Survey in person or telephone; 44 patients and 7 informal carers	Examination of the experience of using a small tablet with a screen, speaker, and voice control that transmits personal digital help and has several built-in talents with various uses	Tablet; Speaker	Statistical methods; Predictive methods.	Voice activated assistive device; Built-in Alexa skills	Voice	N/A
Bircher et al. [6]	2022	Norwich, England	429 patients	Deployment of a flexible **maternity virtual ward** (**MVW**) service utilizing the Current Health platform to provide treatment for expectant mothers throughout the pandemic	AM801 Pulse Oximeter sensor	Statistical methods	Health platform as a cloud-based analytics system; Web dashboard for monitoring patients' vital signs; Alarms via push notification	SpO_2; Respiratory Rate; Pulse Rate; Motion Rate; Skin Temperature; BP	3G Network
Singh et al. [31]	2015	Punjab, India	15 subjects	Presentation of a mobile monitoring terminal and an Android-based integrated wireless smart device that can track and analyze real-time health metrics, including heart rate, skin temperature, and the saturation percentage of oxygen (SpO_2)	ATmega128A MCU; Finger Clip Probe; DS1820 Temperature sensor; Bluetooth module	Statistical methods; Predictive methods	Measured body parameters sent to the mobile phone; Power consumption reduction by Bluetooth technology	SpO_2; Heart Rate; Skin Temperature	Bluetooth
Sodhro et al. [54]	2018	Sukkur, Pakistan	30 subjects	Creation of a wearable wireless ECG monitoring device using a single chip and the Texas Instruments ADS1292R **analog front end** (**AFE**) chip	ECG sensor; ADS1292R chip model	Statistical methods	ETPC transmission power control; Notch, low-pass, and high-pass filters	ECG data	Bluetooth
Ivanciu et al. [15]	2019	Cluj-Napoca, Romania	2 different individuals	Presentation of a novel approach to protecting the transfer of sensor data in a **Wireless Body Area Network** (WBAN) utilizing Named Data Networks and the ECG signal	ECG sensor; Smartwatch; Smartphone	Descriptive analysis	**Named Data Net** (**NDNs**) used for data transmission security	ECG data	NDN
Bolat et al. [13]	2022	California, USA	9 healthy volunteers	Presentation of a soft, stretchable, wearable sweat epidermal microfluidic device that can simultaneously stimulate, gather, and analyze sweat electrochemically	Depiction of fluidic device with an electrochemical sensor; Electronic board	Statistical methods	PDMS layer; Microfluidic features coupled with the PDMS pillar inlets for sweat capture; Screen-printed iontophoretic electrode	Electrochemical gas	N/A

(Continued)

Table 1. Continued

Paper	Year	Location	Population	Purpose of Study	Integrated Hardware	Type of Methods	Methods	Features	Type of Communication
Pazienza et al. [2]	2022	Molfetta, Italy	401 patients	Proposal of an on-edge system that can collect, analyze, and interpret real-time clinical data and deliver an EWS-like clinical risk evaluation when linked to one or more wearable medical devices	Android smartphones; Eight-core Snapdragon 835 CPU; Huawei Y7; Eight-core Snapdragon CPU; BLE module; Raspberry Pi 3 Model B MCU	Statistical methods; Predictive method	The patient's condition is evaluated using a **triage risk class (TC)** and an **emergency phase (EC)** prediction.	SBP; Heart Rate; Respiratory Rate; SpO_2	Bluetooth
Ponnan et al. [40]	2022	Chennai, India	15 willing participants	Creation of a wearable gadget for driver health in autonomous cars and a passenger interface system that manages the motor, accelerometers, and gyroscopes of the car	Smart gloves; Smart socks	Statistical methods	SQL database to collect real-time changes in driver behavior; Smart gloves and socks to monitor the driver's biological parameters; **Global System for Mobile Communication (GSM)** network to inform emergency situations.	Heart Rate; BP; Respiration Rate; SpO_2	Bluetooth
Kim et al. [25]	2023	Seoul, South Korea	2 subjects	Demonstration of a workable, fully continuous diabetic treatment system by integrating a self-powered glucose sensor, low-energy micropump, and an endless power source	Arduino MCU; **Thermoelectric Generator (TEG)**; Glucose sensor	Statistical methods	Self-Powered Glucose Sensor; CeaseLess Power Supply; Energy Harvest	Type 1 Diabetes	N/A
Luo et al. [28]	2023	Chongqing, China	10 subjects	Design of a green, stretchable **triboelectric sensor (TES)** to monitor dangerous driving behaviours, and development of an intelligent neck ring based on the sensor array to recognize different neck movements employing machine learning models	Pressure Sensor	Statistical methods; Predictive method	**K-Nearest Neighbor (KNN)**, **Support Vector Machine (SVM)**; CNN	Neck movement	N/A

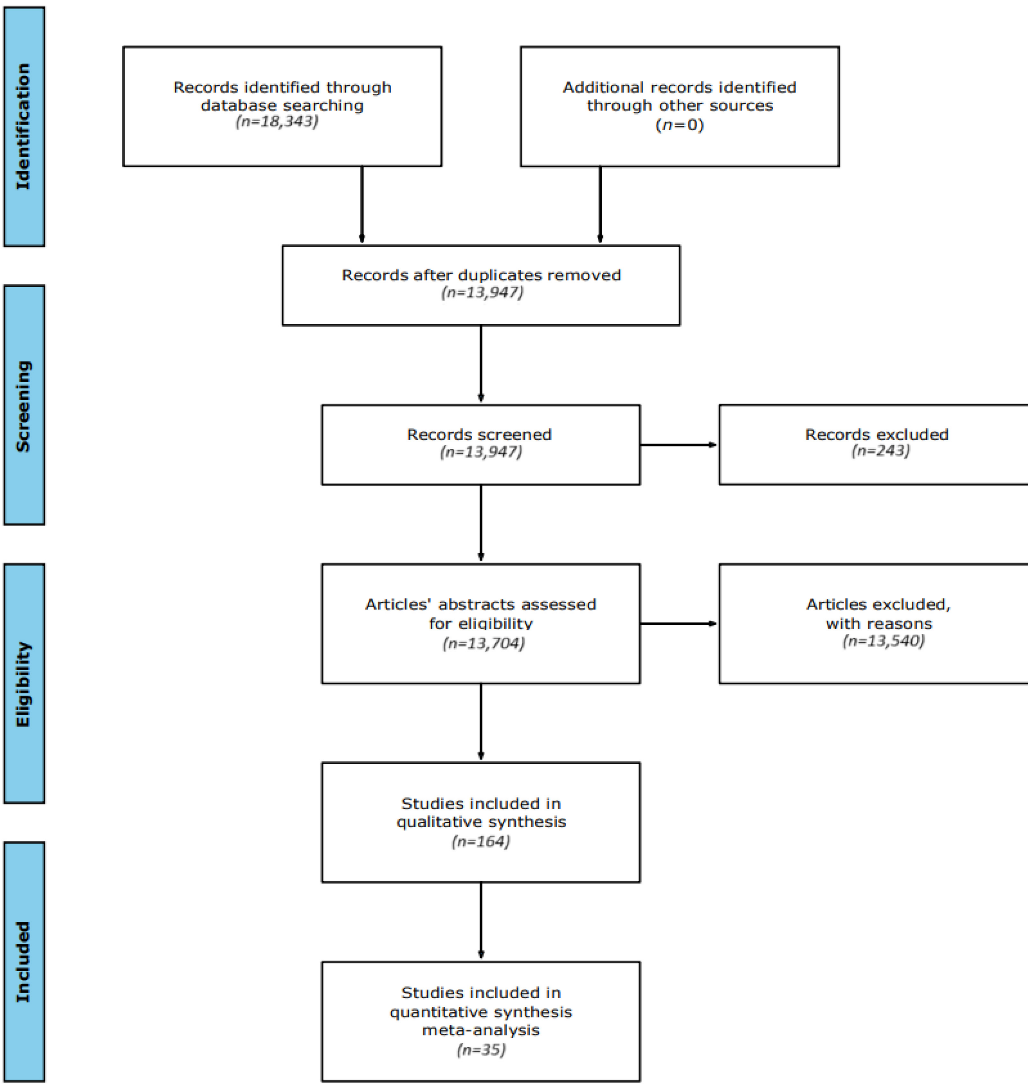

Fig. 1. Flow diagram of the selection of the relevant studies.

Algeria, Indonesia, Ireland, Malaysia, The Netherlands, Pakistan, Poland, Romania, Russia, and Sweden. In relation to the considered hardware, ten studies (28.57%) used a ECG sensor, six studies (17.14%) used a temperature sensor, six studies (17.14%) used an Arduino microcontroller, five studies (14.29%) used a pulse oximeter sensor, three studies (8.572%) used a camera, three studies (8.572%) used an accelerometer sensor, three studies (8.572%) used a smartwatch, three studies (8.572%) used a BP monitor, three studies (8.572%) used an ESP8266, two studies (5.714%) used a bracelet, two studies (5.714%) used a radar, two studies (5.714%) used a LCD display, two studies (5.714%) used LEDs, two studies (5.714%) used a GPS sensor, two studies (5.714%) used a Raspberry Pi microcontroller, two studies (5.714%) used an Android mobile and other hardware components are distributed by one study (2.857%) each, such as glucose, pressure, smart gloves, smart socks, thermoelectric generator, MobilEye, steering wheel angle sensor, Nordic Development Kits based on RF52832 chip, microfluidic sensing layer of glycol, tablet, smart-glasses, FDM chip, planar ANT, QFN32 chip, GSR sensor, PV panels, charging controller chip, eye tracking glasses, respiration sensor, PPG sensor, PD sensor, STM32 NUCLEO-F446RE microcontroller, speaker, finger clip probe, ADS129R chip model, depiction of fluidic device with electrochemical sensor, Snapdragon 835 and Snapdragon 430. Regarding the features analyzed, the studies showed different kinds of monitoring measurements, including thirteen studies (37.14%) related to the heart rate, eleven studies (31.43%) related to the SpO_2, nine studies (25.71%) related to the ECG data, eight studies (22.86%) related to the body temperature, eight studies (22.86%) related to the respiration rate, seven studies (20%) related to the BP, four studies (11.43%) associated with the vital signs, two studies (5.714%) related to the skin temperature, and the other remaining studies contained different measurements each one (2.857%), including ocular parameters, Type 1 Diabetes, Neck movement, body acceleration, EMG data, GSR, hand GSR, stress level, EDA data, apnea symptom detection, real-time breathing, and electrochemical gas. For a wearable device design demonstration purposes, the choice of the low-power communication technology that enable the detection of individuals' vital signs is of fundamental importance, and a comparison of the communication protocols is in order. Referring to the type of communication analyzed in the studies, it showed that nine studies (25.71%) used Bluetooth and BLE technologies (Section 3.1), three studies (8.572%) used Wi-Fi (Section 3.2), three studies (8.572%) used Bluetooth/BLE technologies and Wi-Fi together (Section 3.3), ten studies (28.57%) used different type of communication technologies (Section 3.4), such as 3G/4G network, USB-6210, ZigBee, NFC, ANT, SPI communication, OOK, UWB and NDN. Finally, ten studies (28.57%) did not specify the considered communication protocol (Section 3.5).

3.1 Bluetooth

The authors of [47] developed a healthcare application using temperature, pulse oximeter, accelerometer, microcontroller, BLE module, and batteries for continuous monitoring. The implementation of the BLE communication protocol enables low-power wireless data transmission between the wearable sensors and the mobile device, "My Health," which tracks sensor data. This efficient communication significantly reduces power usage to 2.13 mW and extends the system's lifetime by over 46 hours. Additionally, the system incorporates a hybrid energy harvester with two super-capacitors, a DC-DC boost converter, a thermoelectric generating module, and a flexible solar panel.

In [29], a wearable gadget was used to track the vital signs of two healthy volunteers at AGH University of Science and Technology. The device included an ADT7410 digital thermometer and a respiration rate sensor. The system consisted of two Nordic Development Kits, a data recorder and a host connected to a PC or tablet via USB. Subject 2 held the client module, while subject 1 wore the health monitoring system prototype. The experiment involved pairing the devices, sending sensor data samples, and measuring the BLE range. BLE enabled low-power, wireless data transmission between the wearable device and the host system. The results showed that the recorded temperature value was accurate, with a maximum distance of 65.7 meters for BLE data transmission with a group of 10 people and 77.8 meters for line-of-sight.

In [3], the Trauma Tracker project utilizes agent technologies to create PMDA agents to assist trauma teams in their operations. The Trauma Leader uses a tablet and wearable (smart glasses) to run the PMDA Agent, which communicates with the GT2 infrastructure and GT2 ubiquitous services through BLE. The GT2 infrastructure consists of web-based services installed in the hospital's local area network, serving as back-ends for web apps and the PMDA Agent. The primary function of the PMDA is to record relevant events during trauma management, automate report production, and enable offline data analysis. Tracking is necessary to utilize wearable technology effectively, and more involved assistance features are designed. The **Belief-Desire-Intention** (**BDI**) agent model/architecture is used to create a PMDA that possesses reactive abilities for the Tracking Level and is prepared for more proactive features for the Assisting Level. Smart glasses for taking pictures and videos and displaying vital signs have proven beneficial. However, the physical head mounting of smart glasses is a crucial issue that must be resolved. The current configuration is stable enough to handle rapid movements. Still, flexibility improvement is needed to enable dynamic and seamless movement of the glasses and minimize the effort and time needed to adjust the device.

The authors of [41] proposed an Android application and location-aware remote system for safety, emergency, and health scenarios. The system uses the Amarino tool kit microcontroller, which integrates with Arduino and allows Bluetooth connectivity between the microcontroller and an Android-enabled mobile smartphone. Bluetooth communication enables real-time, wireless data exchange between the Zephyr HR Bluetooth heart rate monitor and the Android application. Bluetooth allows seamless integration of wearable sensors and enhances the system's responsiveness in critical situations. The Zephyr HR Bluetooth heart rate monitor is suitable for this application due to its open-source nature and ease of development. The ETS application sends a signal to an Arduino microcontroller if the heart rate detects abnormalities. The application can transmit precise location information to a pre-stored number and email address if the user is in an emergency. The system counts down for 14 seconds before obtaining position data using a GPS API if the user does not respond. The converted city and country location data and an alert "This person is under emergency take necessary action" are delivered via SMS and email and posted on the registered user's Facebook page. The program is intended for use by individuals driving a car and with a mobile phone in a secure location. An embedded accelerometer on the mobile device detects unusual movement, and the ETS takes action to alert emergency services of the accident's occurrence and location. Using the ETS on Android smartphones, the study successfully managed various emergency scenarios, including heart rate, accidents, and personal safety.

Moreira et al. [35] developed an interoperable IoT-based EWS to identify potential accidents involving delivery vehicles at the Valencia port. The goal is to enhance semantic interoperability between EWSs and their constituent parts for efficient emergency response. The Shimmer ECG 3 gadget gathers ECG information from drivers and sends it to an Android mobile app through Bluetooth. The European Telecommunications Standards Institute's SAREF ontology, supplemented with HL7 Annotated ECG (aECG), sends data to the cloud and publishes it in a broker as RDF/XML messages. The MyDriving logistics mobile app sends truck information to the cloud infrastructure, and the Smart Applications REFerence ontology serializes it into JSON messages. The authors are developing an EWS prototype to verify the framework's support for interoperability through the INTER-IoT-EWS. Initial testing shows the solution is sufficient to address the problems, but this is a work in progress.

The authors of [31] developed a mobile monitoring terminal and Android-based integrated wireless smart device to track and evaluate real-time health metrics like skin temperature, heart rate, and oxygen saturation percentage. The system includes a finger clip probe, temperature sensor, Bluetooth module, and ATmega128A microcontroller-based circuit. Bluetooth communication plays a crucial role in facilitating the wireless transmission of sensor data to the "Heart Rate" app, which was tested on a Micromax Canvas II, A110 smartphone. This wireless communication protocol allows real-time, low-power data exchange between the wearable sensors and the smartphone, enhancing the device's portability and ease of use. The study involved 15 participants aged 6 to 64 years. The results showed a strong correlation between the prototype and standard equipment for measuring skin temperature, heart rate, and SpO_2. The system is clinically valuable and user-friendly due to its small size, low cost, wearability, and potential applications in hospitals, home healthcare, community healthcare, and athletic training.

Sodhro et al. [54] developed a single chip-based wearable wireless ECG monitoring device using Texas Instruments' ADS1292R chip type. The device includes real-time continuous ECG monitoring and respiration monitoring channels. The device uses BLE, a CC2540F256 wireless Micro Control Unit, and a 1 Mbps physical data rate. BLE ensures efficient data communication between the wearable device and other connected systems, making it highly suitable for prolonged usage without frequent battery replacements. A Right Leg Drive driver circuit with lead-off detection and a medically graded test signal was constructed using these channels and the AFE. Bilinear transformation was used to create notch, high-pass, and low-pass filters to eliminate noise from ECG data. The **energy-Efficient Transmission Power Control** (**ETPC**) algorithm was verified during ECG data transmission. Thirty people without a history of cardiovascular disease participated in the study. The experimental findings showed that the low-pass filter reduced power-line noise levels and artifacts better, while the high-pass filter outperformed the notch filter.

Pazienza et al. [2] proposed an on-edge system for analyzing and interpreting real-time clinical data to evaluate EWS-like clinical risk when linked to wearable medical devices. The system splits the learning problem into two simpler ones, allowing it to choose the most practical configuration while correctly differentiating between low-urgency and emergency cases. The system uses two Android smartphones as simulators and two terminal devices with BLE communication to communicate with a single edge node, the Raspberry Pi 3 Model B. The configuration file allows for parametrization of the maximum number of devices and time window for collecting vital signs. Real-world data from 401 patients was collected, and experiments were conducted with two alternative sets of vital signs. The AdaBoost classifier was the outperforming method for risk classification when dealing with 6 and 5 vital signs. At the same time, SVM, RF, MLP, XGB, and ADA were comparable in accuracy, precision, and recall for 4 vital signs.

The authors of [40] developed a wearable device for autonomous vehicle driver health and passenger interaction systems. The device is affixed to the vehicle driver and can control the vehicle's motor operation, accelerometers, and gyroscopes. Bluetooth technology links the wearable sensor to an integrated system, transmitting the data to cloud-based electronic healthcare services through the global network. The experiment involved around 15 participants and explored the benefits of **Intelligent Transport Systems** (**ITS**). Smart gloves and socks are wearable sensors to monitor the driver's biological parameters while driving. The device also measures driving style, fuel drop rate, and acceleration rate. The collected data is sent to cloud electronic healthcare services via the GSM network and is used to inform emergency healthcare centers of the accident's location. The system integrates an SQL database to collect real-time driver behavior and characteristics changes. The experiment involved drivers traveling 460 km in 6 hours, taking three distinct routes, and covering various aspects of driver behavior and vehicle functionality. The results showed that driving experts from the industrial sector are better able to withstand critical conditions, and their biological signals are more stable than cab drivers. The proposed model achieved a 72.54% match with the existing database's data for driver biological features, effectively identifying error profiles and updating a new SQL database with tested feature samples.

3.2 Wi-Fi

The proposed integrated prototype comprises a wearable health monitoring system, smart medicine dispensing system, cloud-based big data analytical diagnosis, and AI-based reporting tool [11]. The system uses a battery, GPS, GSR, Arduino microcontroller, ECG, pulse rate, BP, body temperature, stress level, sweating, peripheral capillary oxygen saturation, and body temperature sensors. The monitoring system is equipped with Wi-Fi to transmit the readings to the medicine dispenser, which then forwards the data to the cloud and handles emergency case notifications. The SMART automated drug distribution system and wearable health monitoring gadget interact through a personal area network and handshake protocol. A user interface is created to access and update physiological signal recording and medication dispensing information. Two analytical algorithms are developed to categorize, gather, and evaluate health data for individuals or all persons on the cloud. The captured data can be linked with the **Electrical Health Record** (**EHR**) to retain patient history. The system offers a user interface for obtaining generated reports and further decision-making analysis. The prototype was tested on a limited number of healthy people aged 20–29 to ensure its functionality. The system monitors body temperature, prescribes fever medicine, and measures ECG for emergency actions.

In [48], a solar energy harvesting approach is presented in (2021) to provide a main power source for an independent continuous operation of a patient monitoring node in sunny conditions. The device consists of an IoT wearable sensor node, a solar energy harvester, a MAX30100 pulse oximeter sensor, two LEDs for heart rate and SpO_2, and a MAX30205 body temperature sensor with a resolution range of 37–39 °C. The NodeMCU board, which integrates an ESP8266 microprocessor and Wi-Fi connection, is also included. The IoT wearable sensor node operations flowchart involves initializing the body temperature and pulse oximeter sensors, setting up the I2C connection protocol, initializing the Wi-Fi chip, and accepting the NodeMCU board. The NodeMCU reads critical sensor data and transmits it wirelessly to the Ubidots cloud service. The sensors are turned off, Wi-Fi is turned off, and the NodeMCU is put into sleep mode for 55 seconds. The patient's heart rate, blood oxygen saturation, and body temperature are continuously measured, resulting in a continuous operation of 28 hours using 20.23 mW of power.

The authors of [24] developed two IoT-based models for automatic temperature monitoring, measuring, and real-time heart rate monitoring using wearable IoT devices. The first version includes a temperature monitoring node with an ESP8266 processor, an AMG8833 IR thermal camera, and a TFT LCD. The data is sent to the cloud while connected to a Wi-Fi network. The Raspberry Pi serves as the processing unit, and the system uses the eigenface method to recognize subjects' faces and calculate their thermal profiles. The second model incorporates a device for continuously measuring SpO_2 and heart rate, using a combined ESP8266 and Arduino Pro Mini. The MAX30102 pulse oximeter and heart rate monitor sensor are integrated into the node, and the I2C bus links it to the Arduino Pro Mini board. A sequential CNN model is suggested for identifying X-ray pictures to prevent overfitting. Two more CNN models were created for the comparison study, with overall accuracy of 97.5%, 93.75%, and 95%, respectively. The suggested model (Model 1) outperforms the other models in terms of accuracy.

3.3 Bluetooth and Wi-Fi Together

The proposed **Diagnosis-Steganography-Transmission** (**DST**) architecture for health monitoring and diagnosis uses a distributed wireless network of wireless sensing equipment to monitor a patient's health status [50]. The quality-conditioned ECG signal is transmitted using Joint Steganography-Source-Channel Coding. The data is then sent to a **Base Station** (**BS**) using low-energy Bluetooth connections. Deep Learning models are used in smart devices to process the measured health data and transmit it via Wi-Fi to a medical cloud for long-term archival and access by caregivers and medical decision support. An algorithm to recognize ST-segment changes in the ECG is necessary to diagnose CAD patients. The proposed USE approach delivers minimal distortion and good security protection for patients' data. The system achieves large energy savings by only transmitting when there is an abnormality in the physiological signal identified by a CNN-based ECG classifier. The USE method secures patient information while maintaining low WWPRD (less than 0.44%).

The authors of [38] developed a wearable device for tracking a newborn's first 2 hours of life using a clinical procedure. The device utilizes Bluetooth 2.1+EDR to transmit signals to an access point via an **SPP** (**Serial Port Profile**) connection. The access point is a commercially available device that receives data from the Bluetooth SPP connection and forwards the packets to a designated TCP-IP port. For convenience, the TCP-IP connection is established through a router using a Wi-Fi connection. The clothing is hypoallergenic, soft, and pleasant, allowing skin-to-skin contact with the mother without restricting caregivers' activities. The monitoring unit, consisting of two automated snaps, was attached to the infant during bonding. The device continuously recorded one ECG lead and tri-axis accelerations for 17 hours at a 128 Hz sample rate. The study included 30 babies with gestational ages between 38 and 41 weeks. The study found 21 successful recordings and 1 unsuccessful try due to the monitoring device's low battery. The average percentage of high-quality signals was 75.8% and 18.9 SD (median 85.6%). The clinical experiment received high user compliance and acceptability marks, particularly from mothers and family members. These findings suggest that introducing such a system into hospital practice would be highly usable and anticipated.

In [1], the authors developed a cheap medical technology health monitoring sensor device to assess the body's temperature, heart rate, and blood oxygen saturation levels (SpO_2). The pulse oximetry sensor uses spectrophotometry to determine the proportion of oxygenated blood levels by calculating the ratio of oxygenated hemoglobin to deoxygenated hemoglobin. The integrated sensor system tracks body temperature, heart rate, and SpO_2 and displays the data on an LCD. The measured vitals are relayed to an Android mobile device through Bluetooth and the Internet via a Wi-Fi module, creating an Internet-of-Things platform. Light-emitting diodes with 640 and 940 nanometers wavelengths are used for the sensor portion and heart rate monitor. The system uses the Bluetooth module HC-05 and Arduino Bluetooth terminal application to transfer data to the Android phone. A doctor or staff member remotely monitors the system and updates vitals through the ESP8266 Wi-Fi module to the internet in a cloud-based system. The study involved five people and showed encouraging results, with a high error percentage of 3.25 percent compared to medical thermometers and a maximum variance of 2% compared to commercially available ChoiceMMed pulse oximeters.

3.4 Other Protocols

In [57], the authors developed a hardware-software system for tracking a driver's health using an IoT-based remote health monitoring system. The system comprises wearable tech, an Android smartphone terminal, and a cloud server. Personal health data, such as ECG, BP readings, and heart rates, is collected, processed, and transmitted via wearable technology. The Android mobile terminal receives and displays the data, while the cloud server stores it for further analysis or medical diagnoses. The Huawei Smart Bracelet's interaction with the SDK ensures data transmission to the Android mobile terminal. The health assessment module notifies users of arrhythmias or abnormal BP, while the user module handles registration, login, and personal information. The disease prediction module predicts cardiovascular disease based on physiological measurements and machine learning. The random forest algorithm has the best prediction accuracy (72.26%).

In [39], a microflotronic arterial BP monitoring system has been developed, featuring a small, flexible, wearable pressure sensor with sensitive microfluidic components. The sensor's top and bottom flexible polyethylene terephthalate membranes are patterned with orthogonally aligned **indium tin oxide** (**ITO**) transparent electrode arrays, forming the functional structure. The microfluidic sensing layer is ethylene glycol, and polymeric micropillars are a support structure. The microflotronic device has two essential characteristics previously considered obstacles in commercial arterial tonometry systems. First, its remarkable transparency (more than 80%) makes positioning over the pulse measurement point simple. Second, the redundant matrix of pressure sensors provides a wide buffer for horizontal and vertical misalignment errors. This design addresses the challenges in existing devices by providing transparency and ultra-flexibility and allowing for alignment error. The sensor operates at 1, 10, and 20 Hz pulsed mechanical loads, with a pass band of up to 20 Hz, enabling quick tracking of BP readings.

A **fuzzy decision-making** (**FDM**) chip and a wearable textile electrode are combined to create an ultra-low power ECG chip for WBSN applications [32]. The ECG System-on-Chip and FDM chips are developed, with the ECG on-chip containing a QRS detector, control circuitry, processing interfaces, and a 12-bit SAR ADC for signal conditioning. The proposed healthcare architecture consists of two components: the main unit, which includes wearable textile electrodes, an ECG front-end chip, an FDM chip, a controller, and a ZigBee transceiver, and the remote unit, which can be a smartphone or computer with a USB interface. The primary device wirelessly transmits ECG data to a remote unit, with the ECG data delayed by internal low-power microcontroller memory. The FDM module can forecast human health status using ECG data, and the system checks its condition and sends an alarm signal if it is abnormal. The accuracy of the fuzzy-based ECG classification has been proven reliable, with over 95% of effective early detections. The device has been tested against a reference high-quality measurement system, demonstrating sufficient accuracy and acceptable differences between key ECG parameters for clinical use.

The authors of [21] proposed a hybrid ambient assisted living framework using the naive HAAL-NBFA for monitoring older adults with chronic illnesses. This architecture uses biological and ambient sensors to gather data on elderly patients, utilizing theIoT. The HAAL-NBFA uses context states to predict patient health conditions, and the smart hospital manages patients remotely through various **Edge-of-Things** (**EoT**) layers. The **Patient Local Monitoring Module** (**PLMM**) collects and stores data from EoT layers, while the **Patient Cloud Monitoring Module** (**PCMM**) provides a knowledge repository for the patient's health state. The **Dual Classification Module** (**DCM**) combines local and cloud-based components, allowing for a classification model that forecasts the patient's health condition based on the context state. The HAAL-NBFA is reliable, quick, fault-tolerant, and appropriate for monitoring elderly patients with chronic illnesses like BP issues. The model accurately forecasts health status by considering surrounding circumstances and behaviors.

Another study proposes the use of a sensor that considers a fully integrated **analog front-end** (**AFE**) and an LED driver to measure human heart rate [20]. The sensor has two operational settings: transmission mode and reflection mode. The hardware consists of an AFE4400 chip, a photodiode, and a dual LED with wavelengths of 660 nm (RED) and 905 nm (IR). The data is analyzed to determine the heart rate, using a sixth-order Butterworth band pass filter in Matlab. The method will be implemented on an FPGA platform after testing for functionality. The PPG signal will undergo three phases of DSP, including pre-processing, processing, and post-processing. The pre-filter module produces the zero-mean signal needed for the filter to function, and the filtered signal is sent through a peak detector circuit to identify peaks. A series of manual heartbeat observations are used to test the design, and the heart rate recorded on the wrist agrees with the experimental findings.

The authors of [55] propose a wearable patient monitoring device using VLC. The system consists of coordinator devices and patient devices, with IR for uplink schemes and visible light for downlink schemes. The system uses OOK modulation, the most straightforward available. The device uses two Analog Front-Endmodules for the coordinator and the patient device, with the visible light receiver and IR LED driver modules. The visible light receiver has a trans-impedance amplifier, high-pass filter, band-notch filter, amplifier, and comparator circuits. The middleware layer's **Service Access Point** (**SAP**) function connects the application and optical layers. The middleware comprises the **medium access control layer** (**MAC**) and the **physical layer** (**PHY**). Changes in frequency and distance determine the system's signal characteristics. The optical frequency for IR light is 1500 Hz, while for visible light it is 25 kHz. The clock synchronization mechanism allows the receiver to receive data without being aware of the transmitter's frequency setting.

The Norfolk and Norwich University Hospitals Trust established a flexible MVW service to care for expectant mothers during the pandemic [6]. The MVW monitored patients using wearable devices or finger pulse oximetry. Between October 2021 and February 7, 2022, 429 patients were referred to the MVW. The wearable collected vital signs, including oxygen saturation, respiratory rate, pulse, mobility, and skin temperature. A 3G network sim card connected the equipment to the Current Health cloud. The MVW discovered pregnant patients who tested positive for COVID-19 through hospital discharge, direct contact with a patient in the neighborhood, and positive swabs. The MVW had 1,182 bed days and a mean stay of 6 days. One patient required escalation to critical care, while 15 needed hospital treatment. No deaths were reported. The MVW provided monitoring and reassurance for pregnant women and peace of mind for obstetricians.

The authors of [15] presented a novel approach for safeguarding data transfer in a WBAN using NDNs and ECG signals. The authors exploit the built-in capabilities of these networks to safely send private health information to the cloud, which is then made available to interested parties like doctors. The method encrypts the data and offers a quick and easy authentication mechanism between devices in the WBAN using characteristics of the ECG signal. The proposed body area network comprises sensors and actuators that can detect and decipher ECG signals. Health-related data is sent to a smartphone via a wristwatch, with mutual authentication required for all sensors. NDNs encrypt communication between the cloud, wristwatch, and smartphone. The ECG morphological analysis algorithm used for feature extraction is a two-step process, with the ECG signal processed using a mean filter, denoised before morphological analysis, and compared with a reference ECG signal. NDNs ensure safe transmission and easy modification of information dissemination techniques. The ECG signal is also used as the starting point for creating symmetric keys for content encryption, providing an extra security layer.

A wearable wireless respiration sensor based on lateral sliding mode **triboelectric nanogenerators** (**TENG**) has been developed to track breathing rates by detecting changes in belly circumference [59]. The system consists of a wireless communication system, a sliding mode TENG sensor integrated into a wearable bilayer belt, and the belt itself. The deformable belt components support the abdomen's expansion during respiration and restore force during abdomen contraction during inhalation. The device's straightforward design and use of common materials make it inexpensive and simple to manufacture, potentially aiding its marketability. A wireless transmission system for signal transfer is created using an ADC, a microprocessor, an ANT, and a battery, with real-time respiration information displayed on a mobile phone. A series of real-time monitoring experiments confirmed the device's viability as a respiratory sensor. Two volunteers, aged 22 and 24, were asked to evaluate the smart belt's sensitivity to various respiratory rates. The electrical signals produced by the TENG sensor were effectively detected for the two volunteers while breathing in distinct rhythms. **Fast Fourier transforms** (**FFT**) findings showed that the TENG sensor can detect respiratory rates and apnea symptoms, demonstrating its potential for marketable marketing.

Zito et al. [8] developed a SoC UWB pulse radar for monitoring respiratory rate on nano-scale CMOS technology. The radar uses a board with two planar ANT for transmitter and reception, and a 90 nm CMOS radar. The pulse generator emits electromagnetic pulses with a period of a few hundred picoseconds and a pulse repetition frequency through the transmitting ANT. The Low Noise Amplifier amplifies echoes picked up by the receiving ANT after a delay equal to the pulse's flight time. The radar uses 73.2 mW of power. The sensor's functionality was established through functional and field operating testing. The radar can follow reflecting objects for motions of up to 2 cm at 70 cm and 45 cm on adult and newborn volunteers. The findings demonstrated the radar's ability to detect sub-centimeter chest motions, enabling continuous real-time monitoring of respiratory rate associated with normal activities, including apneas.

3.5 Protocol Not Specified

In [36], the study aimed to use a vehicle's **Driver Monitoring System** (**DMS**) to monitor and extract various ocular metrics, including mean blink duration, averaged eye closures duration, percentage of time with closed eyes (PERCLOS), time spent with eyes closed for at least 80% of five minutes, average long eye closures, eye closures duration > 300 ms averaged over a minute, and behavioral microsleeps. Twenty healthcare professionals from Austin Health's Intensive Care Unit and Emergency Department in Melbourne, Australia, participated in the study. Participants recorded their drives, subjective tiredness, near-misses, and accidents. Participants also mentioned difficulties staying awake, resting their eyes, braking suddenly, fixating on objects, being distracted, hitting roadside rumble strips, drifting in the lane, pulling over for a nap, and swerving violently. The predictive factors for lengthy average closures were approximately 120 travels.

The authors of [18] developed a methodology to connect mHealth and the vehicle information system to anticipate and alert alarms when long-distance motorists encounter unforeseen circumstances while driving. The integrated system immobilizes a vehicle safely and provides real-time alarming notifications for current and anticipated emergencies to drivers and related parties. The model incorporates various sensors in mobile health and vehicular applications, such as BP monitors, distance, radar, ultrasonic, proximity, and speed sensors. Smartphones link mHealth networks with various sensors and monitoring equipment to vehicle networks. In an emergency, the system can trigger alarm notifications and actuation, forcing the vehicle to stop and turn off the engine while sending an alarm to the appropriate parties. This proposal allows for predicting sudden health conditions, such as heart attacks, by comparing current health data against pre-defined thresholds. Alarms can be sent to medical professionals and other parties without interfering with traffic flow.

The authors of [46] proposed a monitoring system for detecting driver stress using an improved random forest classification technique. The system analyzes and tracks a driver's ECG signal while operating a motor vehicle to determine their stress level. Seventeen drivers participated in the experiment, with phase one using ECG signals from the MIT-BIH PhysioNet Multi-parameter Database. Phase two involved reducing data sounds using sophisticated denoising methods. Phase three identified 17 significant points from the annotated ECG signals using interval characteristics and T-wave-related properties. Phase four marked the beginning of the classification process, allowing varied stress levels to be predicted using pooled ECG signals. The system applied standard Random Forest and SVM to an Enhanced Random Forest for comparisons. The results showed the effectiveness of the proposed classifier, with the best accuracy of 97.02% with a fixed number of trees of 914. The accuracy for the short dataset (with a 90% split) for Enhanced Random Forest with a fixed number of trees at 932 is 96.33%.

The authors of [19] explored three methods for obtaining metrics from wearable technology: eye tracking, psychophysiological measures like EDA, and arm and hand movement accelerometry. The E4 wristband provided real-time measurements of participants' heart rate, inter-beat intervals, EDA (4 Hz), and skin temperature. Eye-tracking glasses allowed participants to move freely while performing procedures, capturing temporal and spatial metrics. The study also included playing cards on an LCD screen for visual stimulation. The cards accurately recognized were compared to all stimulus cards presented using lab cameras and eye-tracking film. The results showed that novices had 2.8 years of experience, while specialists had 19.9 and 5.9 years of experience. Simulation-based training was more familiar to experts, with 86% and 43% of participants having never used the VIST-Lab simulator. The study suggests that eye tracking may be helpful in the automated evaluation of interventional cardiology trainees using a high-fidelity surgical simulator.

Bichindaritz et al. [16] developed a system for accurately identifying stress in drivers of cars using ECG monitoring. They used the MIT-BIH PhysioNet Multi-parameter Database and extracted 14 fiducial point interval features from the annotated ECG signals. The system used multiscale entropy to examine the signal's entropy, which gauges its degree of chaos and complexity. The algorithm moves forward in two stages, averaging samples in length windows and computing the entropy for each coarse-grained time series. The study found that J48 (decision tree) on LOOC (68.66%) and Random Forest and J48 on 10-fold cross-validation (62.69%) achieved the maximum accuracy. The K-Star algorithm approaches 100% accuracy with a 90% split, which is adequate for a small data set. Random Forest achieved 1 with a 90% split and.832 in 10-fold cross-validation. MLP surpassed Random Forest following feature selection, with the greatest performance on 74 features due to its ability to distinguish between features.

The authors of [51] emphasized the importance of optimizing biosensor positioning for high-accuracy measurement and robustness in wearable healthcare systems. They adjusted the placement locations of two biosensor arrays: the ECG-TC array and the PPG-TC array. The PPG-TC array consists of PPG and TC sensors. In contrast, the ECG-TC array includes an ECG sensor for heart rate and a TC sensor for body temperature. The biosensor signals were converted to digital form using an Arduino Uno Rev3 microcontroller and collected using a Python real-time data-gathering application. Twenty healthy male volunteers were used to assess heart rate and body temperature at 34 important locations on the human body. The study found that biosensor placement location significantly impacts monitoring precision, indicating that healthcare systems utilizing wearable devices must be situated on the ideal body region. This technique enables high accuracy and reliable functioning of wearable device-mediated healthcare systems rather than relying on advanced biosensor technology.

After developing a wearable sweat epidermal microfluidic device, The authors of [13] have developed a device that can stimulate, collect, and analyze sweat electrochemically. The device comprises three primary layers: a thin PDMS layer, microfluidic elements combined with pillar inlets for sweat collection, and an iontophoretic electrode and gel. The device was tested on nine healthy volunteers before and after ingestion of carbohydrate-rich meals. Blood glucose levels were tested before and after meals using commercial fingerstick glucose strips. The integrated device successfully measured glucose levels, and the connection between the results and the associated blood glucose levels was strong. Control studies were conducted during fasting to evaluate the sensor performance further. The device's selectivity in the presence of potential sweat-interfering electroactive analytes (ascorbic acid, lactic acid, acetaminophen, and uric acid) was proven in vitro. The device's performance was evaluated using a 12-hour fasting condition and blood glucose testing.

The work from [25] aimed to develop a continuous healthcare system for type 1 diabetes that can operate for a long time without running out of energy. They combined a low-energy micropump, self-powered glucose sensor, and continuous power supply to achieve this. The micropump is connected to a water reservoir and a flowmeter, while the glucose sensor is connected to an Arduino board. The system demonstrated that glucose concentrations can be continuously monitored and voltage values responding to the same concentration are consistently similar. They also used glutaraldehyde to ensure the stability and durability of enzymes coated on microneedle surfaces. The results indicate that a true continuous healthcare system can be realized with low-energy actuation and monitoring supported by long-lasting energy feed from the patients.

The authors from [28] proposed a stretchable and eco-friendly sensor called NH-TES, made from a NaCl/PVA hydrogel. They also designed a smart neck ring using NH-TES to monitor neck movements with the help of machine learning. Adding a sodium chloride solution to the PVA

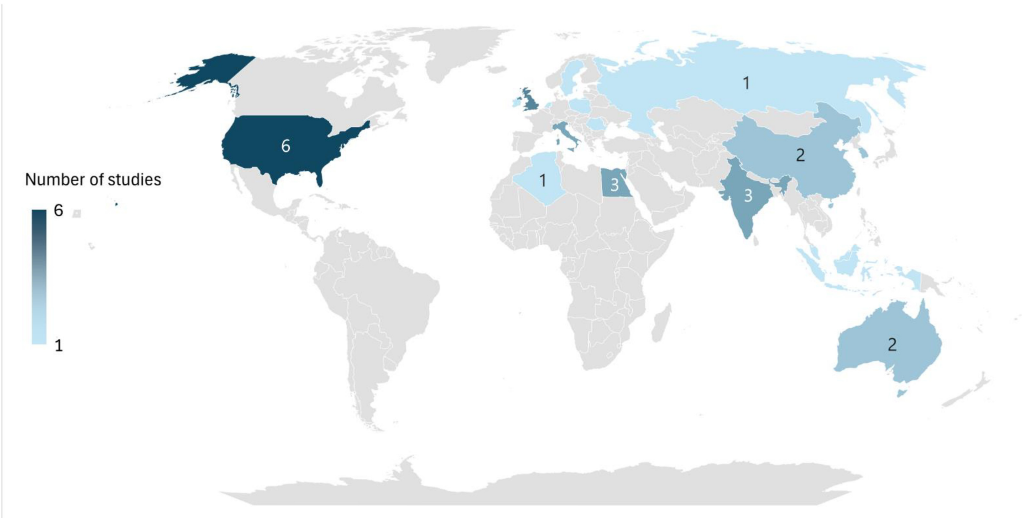

Fig. 2. Map representation of the number of studies and their locations.

hydrogel significantly increased the sensor's sensitivity, output voltage, and current. The neck ring, worn around the neck, detects muscle movements like head turning, coughing, and speaking. It sends these signals to a data acquisition card, which converts them into digital signals for computer processing. Three machine learning algorithms—KNN, SVM, and CNN—were used to classify these movements, achieving the highest accuracy of 96.10%. This system effectively minimizes external interference and has potential applications in monitoring driver status.

In [10], the authors examined the effects of a pilot service redesign using the Alexa Echo Show 8 voice-activated device to enhance health and wellness. The device is a small tablet with a screen, speaker, and voice control that transmits personal digital help with various uses. The study involved patients and unofficial caregivers from the Burton diabetic patient network, Home Instead Senior Care, and a GP office in Northern Staffordshire. The survey had an 88% response rate, and the assistive equipment was well-received by both patients and caregivers. The diabetic focus groups found that 34% of patients used the device for general assistance and 32% for help specific to their diabetes. The remaining patients had different illnesses. Nearly 91% of patients used the device daily. The study contributes to understanding the possibilities of assistive technology for empowering and assisting social and health care, particularly during the COVID-19 pandemic. By encouraging shared care between care providers and service recipients, assistive technology may play a crucial role in ensuring the sustainability of health and social care delivery.

4 Discussion

4.1 Interpretation of the Results

After comprehensively analyzing the 35 studies previously described, we synthesized results across the various parameters delineated in this review. Figure 2 depicts the geographical distribution of these studies, offering insights into global research trends and regional emphases in the application of IoT and wearable devices for healthcare monitoring. Notably, the majority of the studies (6) were conducted in the United States, underscoring the country's prominent role in integrating advanced technologies into healthcare systems. This predominance can be attributed to robust funding opportunities, a well-developed infrastructure for research and development, and the strong

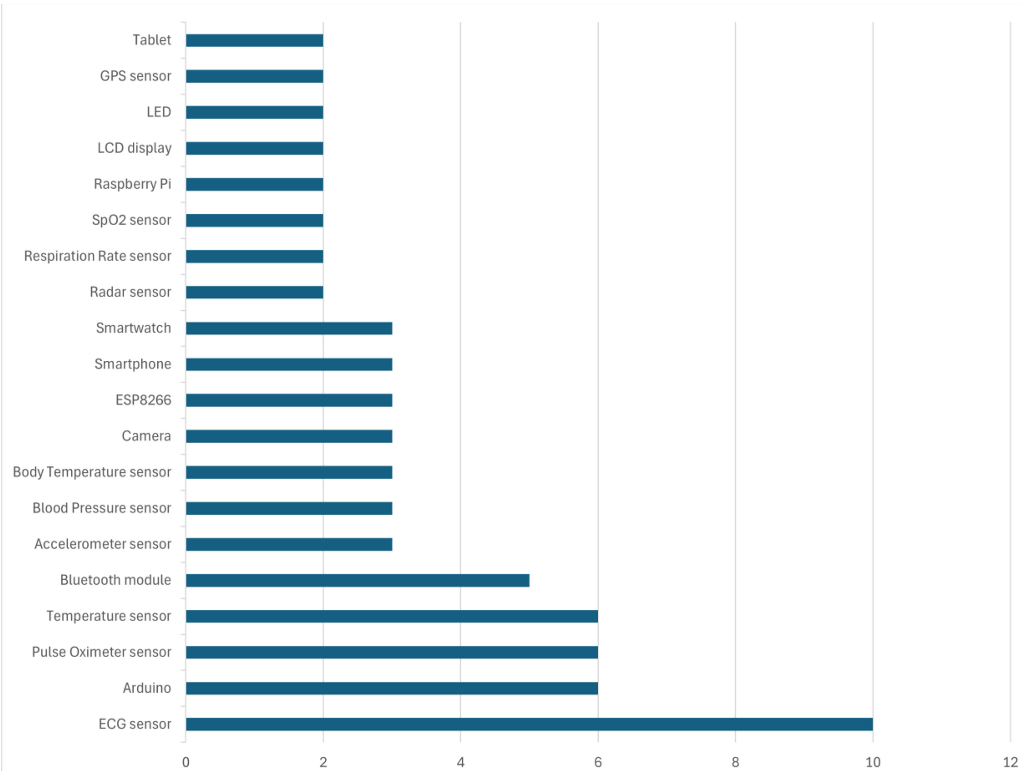

Fig. 3. Bar representation for the number of studies for each hardware component used.

presence of technology companies and healthcare institutions. Similarly, with four contributions, the United Kingdom demonstrates a significant commitment to this area, reflecting the nation's focus on digital health innovation and public healthcare initiatives. Additionally, three studies were conducted in Egypt, India, and Italy, suggesting a growing interest in wearable healthcare technologies within these regions. This trend is likely driven by the need to address specific healthcare challenges, such as improving access to and the quality of care for diverse and often underserved populations. Countries like Australia, China, and South Korea, each contributing two studies, also exhibit emerging engagement in this field. The remaining countries, each represented by a single study—including Algeria, Indonesia, Ireland, Malaysia, the Netherlands, Pakistan, Poland, Romania, Russia, and Sweden—highlight the global interest in leveraging IoT and wearable devices for healthcare monitoring. However, the limited number of studies from these regions may indicate challenges such as restricted research funding, lesser prioritization of IoT in healthcare, or other external factors that may impede research development in this area.

Figure 3 presents the distribution of hardware components employed across the analyzed studies. The most frequently used hardware is the ECG sensor, which has been featured in 10 studies, underscoring its role in monitoring cardiovascular health. This is followed by temperature sensors, pulse oximeters, and Arduino microcontrollers, each utilized in six studies, reflecting their application in collecting and processing physiological data. The Bluetooth module, appearing in five studies, enables wireless data transmission for real-time monitoring. Multiple hardware components were employed in three studies each, including accelerometers, cameras, smartwatches, body temperature sensors, ESP8266 microcontrollers, BP monitors, and

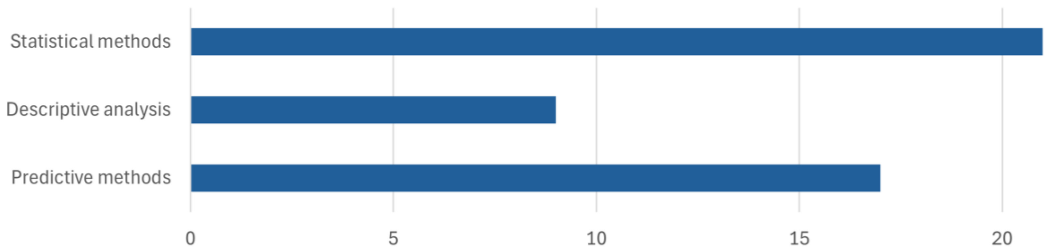

Fig. 4. Bar representation for the number of studies for each type of method used.

smartphones. These devices enhance the system functionality and expand the scope of health monitoring capabilities. Moreover, the specialized hardware was utilized in two studies: tablets, GPS sensors, radar sensors, respiration rate sensors, SpO_2 sensors, LEDs, LCD displays, and Raspberry Pi microcontrollers. Finally, several unique hardware components were featured in individual studies, including devices such as the Huawei Y7 smartphone, Snapdragon CPU, electrochemical sensors, ADS129R chip, finger clip probes, ATmega128A MCU, speakers, STM32 MCU, photodiodes, PPG, Wi-Fi routers, wireless transmission chips, EEG sensors, eye-tracking glasses, charging controller chip, flexible photovoltaic panels, NodeMCU board, GSR sensor, sweating monitor, stress level sensor, pulse rate sensor, heart rate sensor, Amarino, QFN32 chip, planar ANT, FDM chip, ultrasonic sensor, Microfluidic sensing layer of ethylene glycol, RF2832 chip, steering wheel angle sensor, thermoelectric generator, glucose sensor and, MobilEye, and various smart components such as gloves, socks, and glasses. These specialized components highlight the diverse approaches explored to address specific healthcare monitoring challenges.

Figure 4 presents a comprehensive synthesis of the type of methods employed in the reviewed studies, classifying them into three main categories: statistical methods, predictive methods, and descriptive analysis. Statistical methods are the most prevalent approach in 21 of the 35 studies. They are critical for validating the effectiveness and reliability of wearable devices and IoT applications in healthcare monitoring. By processing and interpreting extensive datasets from sensors, these methods enable the identification of patterns, correlations, and trends in physiological and behavioral data. Predictive methods, employed in 17 studies, reflect an increasing focus on using machine learning and artificial intelligence to foresee and mitigate potential health risks. These techniques involve developing models to predict future states or events based on current and historical data. Although less common, descriptive analysis, used in 9 studies, plays a foundational role in research by providing a detailed account of the collected data. This approach is often used to describe the characteristics of participants, the study context, and the functionalities of the devices tested, offering a crucial initial understanding that informs further analysis and interpretation.

Interestingly, it was found that none of the methods used in the studies analyzed in this article was present in multiple studies. To that end, every study examined implemented a unique kind of method explicitly designed for its application.

Figure 5 offers a detailed summary of the features analyzed across the selected studies. Heart rate and pulse rate, although classified separately, refer to the same physiological parameter, with a combined presence in 15 studies, emerges as the most analyzed feature, underscoring its significance as a key indicator of cardiovascular health and stress levels, both of which are crucial for ensuring driver safety. SpO_2, or blood oxygen saturation, is the second most frequently analyzed feature, appearing in 11 studies. Its inclusion reflects its importance in monitoring respiratory efficiency and detecting hypoxemia, which could impair driving performance. ECG data, utilized in 9 studies, provides valuable insights into cardiac activity, enabling the detection of arrhythmias or other cardiac abnormalities that may compromise the driver's ability to operate a vehicle safely.

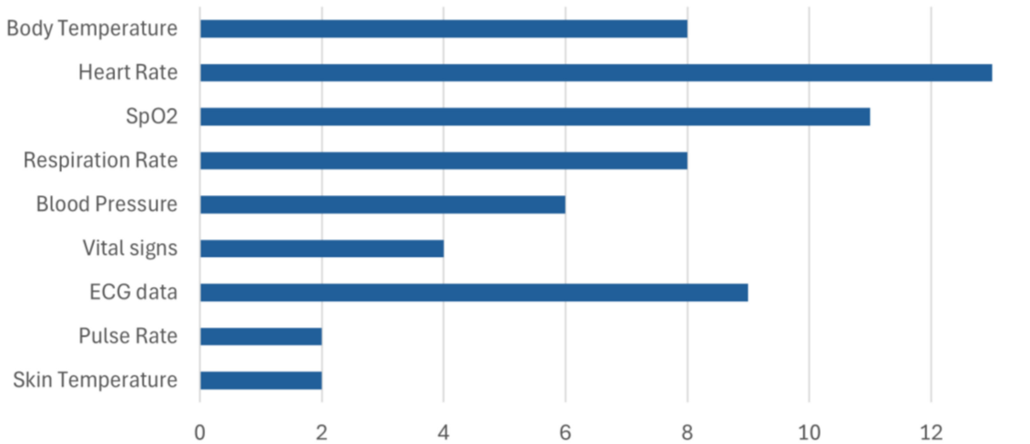

Fig. 5. Bar representation of the number of studies for each of the features used.

Each featured in 8 studies, body temperature, and respiration rate also play significant roles. Body temperature is a potential indicator of infection or other health issues, while respiration rate is a critical parameter for assessing respiratory health and identifying conditions such as apnea. BP, measured in 6 studies, offers insights into both chronic conditions like hypertension and acute stress responses. Additionally, vital signs, comprising body temperature, BP, pulse, and respiration rate, were specifically evaluated in 4 studies, highlighting their comprehensive utility in health monitoring. Lastly, the skin temperature feature was utilized in 2 studies. Various features are unique to only one study, such as an electrochemical gas, motion rate, voice, real-time breathing, apnea symptom detection, EDA, eye tracking, stress level, DBP, SBP, hand GSR, foot GSR, EMG, body acceleration, Type 1 Diabetes, neck movement, and the ocular parameters. The overlap among these features suggests that effective driver health monitoring does not necessitate the independent measurement of every parameter. Instead, a core set of features—heart rate, SpO_2, ECG data, and key vital signs such as BP and respiration rate—can provide a robust and reliable system for monitoring driver health. This subset offers a comprehensive cardiovascular and respiratory health assessment, which is critical for determining a driver's readiness and capability to drive safely. Although features like body acceleration, stress levels, and eye tracking are less frequently used, they can offer supplementary information in specific scenarios, such as monitoring driver fatigue or distraction.

Figure 6 provides an overview of the communication technologies employed in the analyzed studies. Bluetooth technology is the most frequently utilized, appearing in 11 studies. Its prevalence can be attributed to its availability, ease of integration, and suitability for short-range data transmission in wearable devices. Wi-Fi, featured in 6 studies, is the second most used technology, offering robust connectivity and higher data transmission rates. This makes it well-suited for complex health monitoring applications that require real-time data transfer to remote servers. BLE, employed in 3 studies, is a power-efficient alternative to traditional Bluetooth, making it advantageous for continuous monitoring scenarios where battery conservation is crucial. ZigBee, ANT, and 3G networks are each utilized in 2 studies. Other communication technologies, including NDN, OOK, SPI, UWB, NFC, and 4G networks, are represented in single studies, suggesting that while these technologies may offer specific advantages, their application in the context of healthcare monitoring in driving scenarios is less extensively explored in the existing literature.

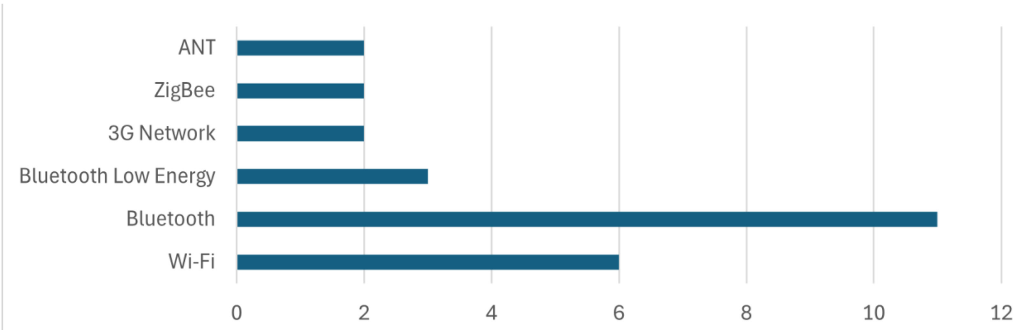

Fig. 6. Bar representation of the number of studies for each type of communication used.

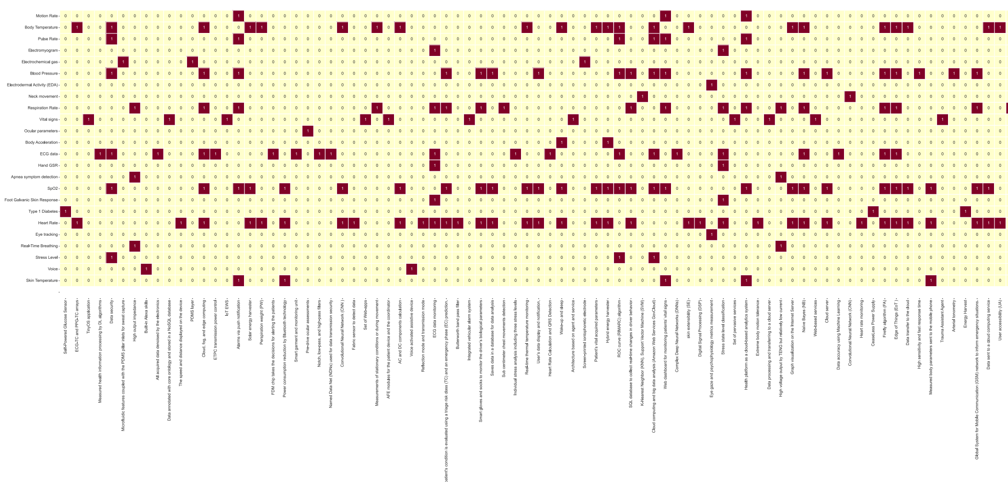

Fig. 7. Relation between the features and the methods extracted from the various studies.

4.2 Comparison of the Different Studies Analyzed

Figure 7 presents a comprehensive heat map visualization depicting the interrelationships between the various features and methodological approaches analyzed in the reviewed studies. This visual representation underscores the prominence of heart rate as the most frequently utilized feature, while simultaneously illustrating the diversity of methods employed across different investigations. These methods encompass database integration, advanced algorithmic frameworks, deep learning applications, and specialized analytical techniques, each playing a critical role in harnessing the multitude of features explored.

Figure 8 illustrates the relationship between the types of methods and the hardware components used across the reviewed studies. It reveals that predictive and statistical methods are predominantly employed compared to descriptive analysis, reflecting their importance in deriving actionable insights and data-driven predictions. The heat map also highlights the ECG sensor as the most frequently utilized, indicating its critical role in monitoring cardiovascular health. This prominence suggests that ECG data is pivotal for developing advanced predictive models and conducting detailed statistical analyses to drive healthcare monitoring.

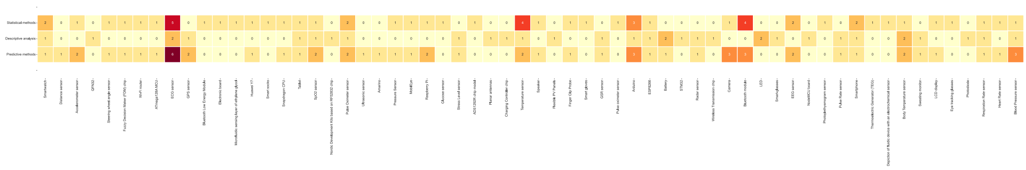

Fig. 8. Relation between the type of methods and the hardware extracted from the various studies.

Lastly, Figure 9 presents a heat map of the relationship between different types of methods and the specific methods employed in the reviewed studies. This visualization demonstrates the predominance of statistical and predictive methods in most applications. Statistical methods provide a robust framework for identifying trends and correlations within the data that are indispensable for data analysis and validation. Additionally, predictive methods are pivotal in the machine learning and deep learning applications integrated in the studies. The integration of these techniques contributes to the refinement and optimization of the presented methodologies, thereby improving their effectiveness for real-time health monitoring and intervention in driving scenarios.

As shown in Table 2, the studies presented in this review provided benefits and limitations related to their application. By analyzing these trade-offs, it can benefit from several possibilities to develop a new driving healthcare monitoring with IoT and wearable devices.

Based on the analysis of Table 2, a common advantage across the reviewed healthcare monitoring applications is evident: the use of wearable and mobile devices equipped with integrated sensors to collect user data continuously. This data is then automatically transmitted to a centralized database via wireless technology, enabling real-time management and analysis. Such systems are designed to provide actionable insights to healthcare professionals and users, facilitating timely interventions and informed decision-making.

An important aspect to consider from the limitations analyzed in Table 2 is the use of artificial intelligence technologies for the application, that is, an algorithm implemented to improve the data accuracy and assurance. The application can process raw data, eliminate noise, and generate precise and meaningful information, which is critical for health monitoring. Additionally, robust testing and validation of these systems are essential to ensure error tolerance and reliability in real-world applications, as the system must operate accurately under varying conditions. This highlights the importance of developing monitoring technologies and ensuring their dependability through rigorous testing.

4.3 Comparison with Previous Literature Reviews

It is vital to analyze previous literature reviews and discuss some aspects presented in them to the ones related to this review. Using the NLP framework, it was possible to filter the relevant articles from 11031 articles that were considered literature reviews and related to healthcare monitoring. To that end, the framework successfully found four literature reviews.

The analysis by [56] showed that the article relates mainly to digitalization and large-scale data analytics in healthcare. The initiatives toward personalized medicine and the political initiatives designed to shift care delivery processes are some of the topics presented in the article. As discussed in this review, the topics shown in [56] do not relate to Driving healthcare monitoring with IoT and wearable device applications. However, [56] addresses continuous monitoring of healthcare applications by wearables and stationary devices. Therefore, it is important to define how these applications could be used for personalized medicine, such as AI technology that assists the user with his medication.

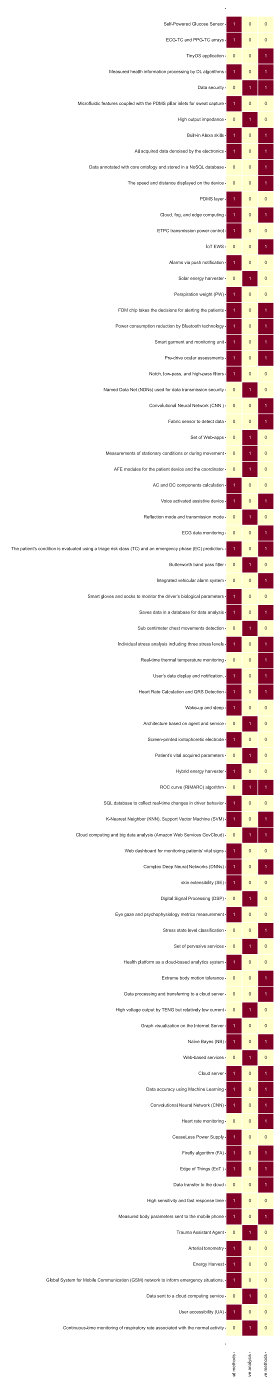

Fig. 9. Relation between the type of methods and the methods extracted from the various studies.

Table 2. Study Benefits and Limitations

Paper	Benefits	Limitations
Mulhall et al. [36]	For effectively predicting driving impairment and impaired alertness during the commute in night shift employees, a pre-drive ocular evaluation showed potential.	Most of the naturalistic driving in this study occurred in urban locations, where lane departures may be caused by everyday driving habits (such as avoiding barriers or strategically changing lanes) or distractions, which are not noticeable in controlled laboratory, track, and highway driving situations. This is corroborated by the observation that behavioral microsleeps were connected with all drowsiness measurements, but lane deviations were not correlated with subjective driving or alertness measures. This may suggest that lane deviations are not the most accurate indicator of sleep-related driving impairment in realistic driving situations in urban settings.
Mohsen et al. [47]	The sensor system offers a transportable option for continuously monitoring acceleration, heartbeat, SpO_2, and body temperature.	The suggested system might be implemented directly with IoT applications for a more integrated architecture. A flexible solar panel's power performance might also be tested at different bending angles, indicating the conditions under which the system would operate at maximum efficiency.
Kajor et al. [29]	The difficulty of delivering dependable wireless data transfer while meeting the low-power requirements for the wearable device was confronted by an AAL system based on the nRF52832 IC and biosensors.	The development boards and commercial modules utilized might not offer enough electrical characteristics based on the power consumption of sensor data collector nodes with BLE communication. As a result, a custom board with special electrical circuits would be required to boost the designed system's performance.
Yue et al. [57]	A health monitoring system based on the Internet-of-Things can monitor the user's physiological parameters in real-time. The outcomes might be incorporated into an intelligent system to guarantee driving security.	Although a few algorithm models were examined for this system, no official integrated one has yet been created. Therefore, further testing is required to determine which is best for real-time applications.
Digiglio et al. [39]	A low-cost, non-invasive hemodynamic monitoring system that can be worn comfortably for long periods and doesn't require a highly experienced operator is now possible thanks to the microflotronic sensor array. By monitoring a unique collection of hemodynamic parameters to test for CVD and give individualized health information, such a device might promote customized therapy.	A simple, low-cost technology that may be used at the point of care will considerably enhance access to hemodynamic analysis and help in the early detection and prevention of heart disease. Furthermore, by making human investigations more viable, a reliable and simple-to-implement system might enhance the study and standardization of hemodynamic parameters.
Croatti et al. [3]	This technology enhances the accuracy of trauma recording, automates report preparation (and maintenance), and allows offline data analysis, which helps assess performance and enhance the work of the trauma team. This is advantageous for the "augmented hospitals" concept, where software personal agents enable technologies such as augmented reality, wearable computing, and ubiquitous computing to build unique smart settings to assist healthcare professionals' individual and collaborative work.	This study needs to be improved, for example, by integrating more capability to provide real-time support to the trauma leader and team while fully utilizing the system's hands-free features. The automated production of alerts presented on the smart glasses regarding instances where the trauma leader may wish to be informed without necessarily interrupting her activity flow is another sophisticated feature currently being implemented.
Jin Kang et al. [18]	A system to foresee and alert alarms when a long-distance motorist encounters unexpected problems while traveling by fusing mHealth and vehicular information systems. By comparing the present health data to pre-defined thresholds of the user's health state, it is possible to even forecast a sudden health condition, such as a heart attack of the driver, using the continuous monitoring and inference system of mHealth wearable devices and vehicle sensors.	The system presents some limitations in terms of software development and, as such, it can be improved by developing and verifying an algorithm to define the thresholds of each personalized health data to determine the abnormality levels, and this would be in consultation with the health experts and physicians of the user (driver). Additionally, several restrictions must be overcome, including those relating to database administration, data collecting, analysis, and visualization, as well as mobile app development and support clearances.

(Continued)

Table 2. Continued

Paper	Benefits	Limitations
Pandiyan et al. [32]	The patient can benefit from a number of features of this gadget, including its portability, user-friendliness, extended battery life, and ability to wirelessly send continuous ECG data to a distant station for thorough diagnosis. The FDM chip is integrated with ECG on Chip to make decisions and alert patients when necessary.	N/A
Zito et al. [8]	This UWB sensor may be used in various biological settings, including observing infants in cot beds, hospital patients, and other people at risk of obstructive apnea. It may also identify abrupt driver sleepiness early on in automobiles. Other significant applications made possible by this contactless sensing technology include fitness tracking and individualized healthcare for independent and healthy living.	N/A
Dorairaj et al. [41]	Using Google's Android mobile platform, this emergency monitoring system demonstrated a notable presence in several emergency scenarios and the ability to take the appropriate steps. With regards to heart rate, accidents, and personal safety, the ETS on the Android mobile successfully handled emergencies.	This program is made to manage urgent circumstances and take appropriate action. As a result, having a reliable and secure system is essential for handling urgent circumstances. However, the system must be tested in a real car to ensure the vehicle can stop as intended. Signal loss is one of the problems with utilizing GPS, in these cases, a terrestrial navigation system or an aerial platform can be added to this system to enhance performance.
NITA et al. [46]	A strategy for stress detection has been discussed, investigated, and assessed in this article. To provide a fully automated and effective procedure, this technique proposes an Enhanced Random Forest method that combines conventional Random Forest with a Simulated Annealing algorithm to identify three degrees of stressed out automobile drivers using ECG data. According to the results, it was possible to accurately identify the driver's high levels of stress compared to the rest time (there are two degrees of stress: low and high).	Monitoring and identifying each person's unique stress levels is crucial for preventing numerous accidents and saving countless lives on the highways. Therefore, this system has to be improved to examine the accuracy of the delivered findings to prevent the erroneous detection of driver stress status.
K. Hassan et al. [21]	The HAAL-NBFA framework has demonstrated its capacity to properly forecast elderly patients' health condition in real time while monitoring them remotely at their residences. Instead of giving up their few beds, smart hospitals may utilize the HAAL-NBFA to monitor their patients remotely and in real time. The results of this study show that HAAL-NBFA is reliable, quick, fault-tolerant, and appropriate for monitoring elderly patients who live alone and have chronic illnesses like BP problems.	Cloud-based IoT healthcare solutions must overcome several obstacles to manage the large amounts of healthcare data that the IoT generates. Comparing the system reported in this study to other suggested models, it demonstrated greater speed and accuracy. However, changes must be made in order to optimize the system, such as the use of various algorithms for the selection of characteristics. The framework may also be used to monitor various illnesses and include more context states.
Latif et al. [11]	This research presents a fresh technique and develops an IoT-based prototype. The system offers ongoing health status monitoring and analysis and automatic, real-time emergency action that may ultimately save lives. It also gives information on pharmaceutical effects, side effects, and the patient's health state. The system can also provide reports and dates that include suggested choices for the doctor regarding medication doses, frequency, etc. In order to provide prompt care for the patient, the IoT-based cloud-application Rx expert system may also connect with close friends, nearby neighbors, and emergency contacts.	The integrated prototype was built and tested on a small number of people to ensure it is operating according to expectations. It comprises of a wearable expandable health monitoring system. However, a wider population of people in various circumstances must be tested to see the proposed system's full potential.
Mohsen et al. [48]	This device demonstrated how a patient monitoring node may operate independently and continuously in both bright and gloomy situations using solar energy collecting technology. The testing findings demonstrate that the wearable node can operate for more than 28 hours without a mains recharge, representing a significant improvement in power usage and battery life. The Ubidots IoT platform also keeps track of the sensor node's physiological data.	In healthcare applications, the remote monitoring of moving patients depends on wearable nodes that should be mobile. Additionally, the suggested approach works well for mobile applications that allow a battery independent from the mains. However, the system's environment must be expanded to include several wearable sensor nodes to assess the device's battery life. The suggested node can also be expanded to include more biomedical sensors.

(Continued)

Table 2. Continued

Paper	Benefits	Limitations
Haque et al. [24]	This study includes two distinct IoT model designs for thermal monitoring. These models do an initial screening for the COVID-19 virus and provide heart rate monitoring for patients who are at risk. The accuracy and precision of this model are rated at 97.5%. The comparison analyses reveal that the suggested model (Model 1) outperforms other models in terms of F1 score and overall performance.	The latest worldwide epidemic can be stopped in its tracks by mass testing and early COVID-19 diagnosis. Effective monitoring and treatment are also crucial in the battle against this. That said, this system produced excellent outcomes. It hasn't been tested in any way on patients, though. This model has to be further developed and put through clinical trials for use in clinical diagnosis. This model must become better as more data becomes available.
Currie et al. [19]	This research advances the creation of sensor-based smart theaters and the "quantified physician" for the assessment of operators and trainees, as well as maybe for the continuous automated analytical feedback to individuals and teams to enhance performance. This exploratory study successfully highlighted several novel factors that merit further investigation for determining proficiency, including dwell time on screens, fixation transition frequency between screens, SD of EDA signal, and card acknowledgment rates (when using an additional task to assess attentional capacity).	Despite the laboratory and virtual reality simulator being fairly precise, these results were not obtained with actual patients in a real clinical environment. Furthermore, because psychological realism is so challenging to reproduce, it could never be able to simulate a situation accurately. This becomes a limitation for this study since it is anticipated that measurements gained in simulation settings may be applied in real-world circumstances.
Bichindaritz et al. [16]	The study concentrated on monitoring ECG, which is now possible with minimally invasive wearable sensors and patches. The findings of this study open up the prospect of monitoring and diagnosing an individual's stress level and alerting users appropriately to avert mishaps brought on by excessive or extended stress.	The technology created is effective and offers a solid mechanism for precisely identifying stress, for instance, in car drivers. The proposed tailored signal classification analysis may also be used to other stressful scenarios, addressing issues like older people's failing health, weariness in factory employees, field athletes, and soldiers in combat zones.
Sahu et al. [50]	This work developed an original integrated DST paradigm to reduce transmission overhead and enable real-time diagnosis. One advantage of this study is an energy-efficient transmission of physiological signals in mobile wireless networks. Further energy savings come from diagnostic depth, which determines the amount of bits that must be broadcast based on the severity of the patient's condition.	It is suggested that diagnostic, steganography, and transmission activities be combined on a single platform, leveraging their natural connectedness that is based on **Unequal Error Protection** (**UEP**). But simulations were used to evaluate this system. Therefore, validating and testing the suggested system in a real-world setting is essential.
Zhang et al. [59]	A wireless respiration sensor that can be worn around the waist was created to track the real-time respiratory health of people going about their daily lives. A series of experiments were conducted with two volunteers to examine the device's viability, accuracy, and sensitivity to various people, varied breathing rhythms, and various active states to confirm its applicability in real life. The gadget was shown to be useful for both real-time breath monitoring and the diagnosis of apnea symptoms.	An established theoretical model was used in the study to confirm the device's viability as a respiration monitoring sensor, and a series of mechanical tests were used to examine the sensor's output performance. The findings show the wearable sensor's potential as a novel method of identifying real-time breathing rates. Although the system was tested and confirmed by volunteers, a larger portion of the population must be included in the application test to create an effective system and assess its performance under various conditions.
Perego et al. [38]	This study demonstrates how a clinical procedure may be applied to wearable technology for monitoring a newborn's first two hours. According to the system's results, wearable biomedical sensors deliver great results in terms of dependability, but problems in the wireless connection and control room software have been found and fixed. The clinical experiment showed highly strong user compliance and acceptance scores, especially from mothers and relatives, indicating great usability and high expectations from adopting such a system in hospital practice.	Based on the tests that were run, the system produced excellent results. However, a more robust system for battery power management and effective software is required due to a few failures during those tests, such as the device's low battery and software issues. Additionally, a strong and safe presentation of the system is crucial since users of this kind of program frequently express some degree of distrust if it is not demonstrated to be 100 percent secure.

(Continued)

Table 2. Continued

Paper	Benefits	Limitations
Ha et al. [51]	The study's technique enables biosensor arrays to operate with great precision and reliability while monitoring vital signs taken by wearable device-mediated healthcare systems. Instead of creating cutting-edge biosensor technology, this outcome was accomplished by improving the positioning of existing biosensors.	Even though the equipment operates with high precision and reliability in its current state. Working off the device's placement location also makes it fully dependent on it. Additionally, techniques for biosensor arrays must be developed to avoid this boundness due to their design and placement.
Duong et al. [20]	Wearable technology that continuously monitors heart rate has the potential to enhance fitness and healthcare while lowering the risk of cardiovascular illnesses. This study specifically focuses on realizing this advantage for society by creating an FPGA platform utilizing the **hardware description language** (**HDL**) to interface with optical sensors based on PPG.	In this study, a VHDL-based controller was designed and implemented that is suitable for the Texas Instruments AFE4400, a PPG-based optical cardiac monitoring system. However, a peak detection technique was used to identify heart rate for the processed data set, integrating the experimental findings. Therefore, efforts must be undertaken to evaluate the system in clinical settings and adapt it by adding an accelerometer for ambulatory heart-rate measurement.
Adiono et al. [55]	As it includes a VLC system design for a wearable patient monitoring device, the system created for this study has the capability to perhaps assist the doctor in monitoring the patient's condition.	Based on the testing done for this research, the VLC system provided showed remarkable and pertinent performance. However, the system must be tested and validated in a real-world setting before being evaluated and implemented in actual healthcare systems.
Moreira et al. [35]	The semantic integration of various data sources, processing in time-critical applications, and data analysis for optimal responses are only partially covered by current ideas for IoT-based EWS. To promote interoperability inside and amongst IoT EWS, the SEMIoTICS architecture suggested in this study employs a variety of modeling languages, ontologies, and technologies. An EWS prototype is now being constructed to test this framework and is being used to look for accidents in the Valencian port.	The SEMIoTICS framework has been created to be broad enough to be utilized in different emergencies. A method to deal with the **Quality of Information** (**QoI**) at the network level, including a Grubbs' test for outlier identification and a statistical algorithm that can categorize anomalous or false sensor results, are still missing from the framework.
Ali et al. [1]	A low-cost embedded IoT health monitoring system is built and developed using an Arduino Uno board. The technology accurately determines the body temperature and heart rate. The device will continuously monitor people's vital signs, particularly those of the elderly living at home.	Compared to a commercially available ChoiceMMed pulse oximeter, the pulse oximeter used in this study provided excellent findings; a maximum variance of 2% is seen, which is acceptable. Additionally, the device successfully determined the patient's body temperature and heart rate. Despite the positive outcomes demonstrated, this device does not yet come with a reliable and portable design that patients can use without worry.
Balasubramanian et al. [10]	Both patients and caregivers strongly accepted the technology since they were eager to use it. Reminders for hospital visits and prescription medicine led to increased adherence and treatment compliance, according to the results of the patient's answers. Most patients said that they improved their independence and productivity. The gadget also reduced loneliness and sadness for those living alone. It also made it easier for people to take charge of their health and welfare. Second, the caregivers felt the gadget enhanced the patients' physical and emotional welfare.	The study's small sample size was restricted to a single region of England, which may have reduced generalizability to other places. The convenience sampling approach was used to enlist the participants by selecting available respondents to the researchers. As a result, there could be some selection bias. Using probability sampling approaches in future studies with a bigger sample size might assist in combating this bias.
Bircher et al. [6]	Patients, medical staff, and the hospital system all benefited from the MVW. For expectant mothers who tested positive for COVID-19, it provided surveillance and confidence. It provides some continuity, which raises satisfaction and lowers intervention rates. In addition to providing a "third option" between primary care and admission, it was a safety net that reduced stress on hospital infrastructure and general practice.	Identifying clinical leaders, triage standards, technological choices, and flexible pathway establishment is necessary.

(Continued)

Table 2. Continued

Paper	Benefits	Limitations
Singh et al. [31]	To assess the saturation percentage of oxygen, heart rate, and skin temperature for ubiquitous healthcare applications, this article has detailed the design and implementation of a wireless vital sign monitoring system based on Android. It has shown that the prototype that was created produced trustworthy outcomes.	The method produces decent results, but it might be strengthened in several ways to get around its flaws. For instance, optimizing the hardware configuration can decrease the physiological measuring system constraint. Power consumption is another restriction that may be lessened by using the IEEE 802.15.6 protocol for wireless data transfer.
Sodhro et al. [54]	Experimental results demonstrate that the developed chip collects real-time ECG data more accurately and efficiently than conventional TPC (e.g., constant TPC and Gao's and Xiao's methods), and the proposed ETPC algorithm achieves a higher energy savings of 35.5% with little channel reliability (as indicated by packet loss ratio) compromise.	According to the results, the constructed system showed promise in the tests conducted. It was critical to confirm its consistency and dependability by testing it on a substantial sample of clients. To evaluate how well it functions in diverse circumstances, broadening the testing to a bigger population is essential.
Ivanciu et al. [15]	In this research, an innovative NDN-based approach is suggested for safeguarding the transfer of sensitive health-related data from a WBAN to the cloud. A wristwatch serves as a hub for communication with the cloud and a smartphone and receives data collected by the WBAN's sensors. A straightforward approach in the WBAN uses hash codes based on ECG data to achieve inter-device authentication.	In addition to securing the transmission, this system employs NDNs to provide readily adjustable mechanisms for dissemination. However, the suggested solution does not incorporate full NDN capabilities, which may be a significant upgrade. The solution might be expanded for sensors that are momentarily unable to measure the ECG or are not designed to do so.
Bolat et al. [13]	This study's invention allowed for the collection of stimulated sweat without dilution or contamination from the iontophoretic gels. Different volunteers can use the optimized iontophoretic and detection settings. Monitoring sweat glucose showed the device's detection capabilities and a strong connection with blood glucose readings.	By adopting enhanced inlet adhesion to the skin, epidermal iontophoretic microfluidic devices such as those described in the article can be further refined. This might prevent sweat leaking from the inlet collecting region, reduce filling time, and, as a result, reduce time lag. Pilocarpine can be swapped out with long-term sweat stimulation medications like carbachol to extend the device's useful life.
Pazienza et al. [2]	The article suggests an edge architecture in which an edge device uses the patient's current vital signs collected from wearable medical devices through IoMT and the top machine learning model to forecast a clinical risk level resembling EWS. As a result, the Ada Boost classifier acted as the outperforming approach for risk classification, and ADA's accuracy, precision, and recall performances were on par with those of ADA.	This research compares machine learning techniques under various sets of crucial parameter circumstances and selects the best one for the job. A more complex industrial on-edge solution that can collect, analyze, and interpret a greater number of real-time clinical parameters and evolve to ensure reliable predictions and understandable explanations needs to be developed. This is true even though the system has been tested using many populations.
Ponnan et al. [40]	The research discusses how driver behavioral changes impact the performance of intelligent vehicles through wearable sensors. The integration of wearable devices can swiftly access nearby medical facilities, providing timely assistance in case of a medical emergency. The system analyzes the impact on driving skills and determines which age group of drivers is best suited for handling multiple services simultaneously, contributing to more tailored driver training programs.	The research on ITS utilizing wearable devices to monitor driver health offers numerous advantages. However, it also faces limitations due to dynamic biological factors, which make it difficult to consolidate the necessary training features for future ITS development. The link between driver behavior and car performance quality presents a challenge in creating a standardized model that can be universally applied.
Kim et al. [25]	The study presents a new approach to a continuous healthcare system for type 1 diabetes. This approach ensures that the healthcare device can operate indefinitely without needing battery replacements, which is crucial for continuous health monitoring. The self-powered nature of the sensor eliminates the need for external power sources, reducing maintenance and improving reliability. As a result, the system reduces the risk of device failure due to power depletion, ensuring reliable long-term operation.	The study has some limitations that need to be addressed. These include the small sample size of subjects, which limits the generalizability of the findings, as the experiments were conducted on only two subjects. More extensive testing with a larger and more diverse population is necessary to validate the system's effectiveness across different user groups. Additionally, the performance of the TEG is highly dependent on temperature differentials. Variations in ambient temperature, such as those experienced during indoor and outdoor experiments, can affect power generation efficiency.

(Continued)

Table 2. Continued

Paper	Benefits	Limitations
Luo et al. [28]	The research article discusses developing and using green and TES to monitor dangerous driving behaviors. This sensor is beneficial for traffic safety as it can identify dangerous situations and prompt appropriate reminders to the driver. The system monitors various driver statuses, such as neck movements (turning, nodding, coughing), fatigue levels, concentration levels, and health conditions. This multidimensional monitoring provides a holistic view of the driver's status, which enhances the ability to prevent accidents and health-related incidents.	The system may face challenges when wearing the TES for long periods. Drivers might find the neck ring and other wearable components uncomfortable, which could lead to inconsistent use or hesitance in adopting the technology. Environmental factors such as temperature fluctuations, humidity, and vibrations may also affect the system. Lastly, it's crucial to securely store and transmit the collected data to protect drivers' privacy.

The literature review from the authors of [14] discusses the importance of IoT in the healthcare industry and how the healthcare business relies on digitalization via different technologies. The article also relates to the necessity of IoT technologies in the healthcare industry and how they are helpful in many ways. However, the review does not include any driving approach to these applications, which is something relevant to be added as the driving environment turns out to be a crucial aspect of the healthcare business.

The study in [53] provides a broad review of IoT applications in healthcare, including various technologies, datasets, and algorithms. It highlights key challenges such as security, privacy, scalability, cost, and energy efficiency, clearly understanding the limitations and areas needing improvement. The article proposes a novel architecture addressing IoT healthcare requirements and discusses various future applications and research opportunities. However, the review may be too broad and potentially lack an in-depth analysis of specific technologies or case studies. Additionally, the proposed solutions and frameworks might be more theoretical, with less emphasis on practical implementation and real-world validation.

The systematic and bibliometric review discussed in [5] provides a comprehensive checklist for reviewers to assess the quality of research articles. The review aims to help scholars understand illness prediction algorithms' current state, challenges, and potential future directions. It sheds light on modern algorithms, technological concepts, and how to conduct efficient research to advance the medical field. The study also aims to thoroughly review IoT-based embedded healthcare systems, highlighting their potential benefits and the obstacles that must be overcome for practical implementation. These obstacles include human factors, intelligence architecture, defense mechanisms, and social and ethical issues that still need to be fully addressed in the article. Finally, the article enhances the review process and contributes to scholarly research.

Therefore, the motivation for this study is to fill the identified gaps by providing a detailed review of the use of IoT and wearable devices for driving healthcare monitoring. This review aims to highlight this technology's practical applications, challenges, and future directions in a driving context, contributing to developing safer and more effective health monitoring systems for drivers.

4.4 Final Remarks

Our systematic review identified key findings about the characteristics extracted from 35 studies.

Concerning our first research question, "Which methods are used to detect individuals' vital signs?", our survey of the articles revealed a significant variation in methods depending on the specific application and target health metrics. Most studies utilized a combination of biosensors, such as ECG, SpO_2, and temperature sensors embedded in wearable devices like smartwatches, fitness trackers, and smart clothing for continuous data monitoring. Smartwatches, for instance, can track heart rate and SpO_2 levels, while smart glasses may include sensors to monitor eye movements and detect signs of fatigue. These devices capture real-time physiological data, which is then processed using algorithms for signal filtering and feature extraction to ensure accuracy and reduce noise. The data collected is typically transmitted through low-power communication protocols like Bluetooth or BLE to a central processing unit, often a smartphone or dedicated server, where advanced analytics are applied. This approach allows for continuous, non-invasive monitoring of vital signs.

As for our second research question, "Which sensors are used for the measurements?", we found that the analyzed studies employ a range of hardware components tailored to their specific applications. The functions of sensors vary from measuring vital signs to assisting individuals in different ways. Most studies utilized ECG sensors to collect individual data, while other commonly used medical sensors included pulse oximeters and temperature sensors. Furthermore, movement and location sensors were often employed to provide supplementary and valuable information, enhancing the overall monitoring system's effectiveness.

In relation to RQ3, "What impacts do such measurements have on individuals' performance in a driving situation?", the reviewed studies emphasize the importance of integrating a comprehensive monitoring system for individuals while driving. Implementing artificial intelligence capabilities offers significant advantages that can improve driver performance and safety. For instance, AI-powered applications that use GPS can offer real-time information about the driver's surroundings, enhancing situational awareness and decision-making. Moreover, systems that alert healthcare professionals about drivers' vital signs enable timely medical interventions, thereby preventing potential health emergencies. These technologies collectively contribute to better physical and mental health by providing accurate, actionable information and ensuring a safe driving environment.

In response to RQ4, "Which technologies could potentially improve drivers' security?" it is clear that modern healthcare technologies will play a crucial role in advancing driving systems. These applications have already become indispensable in people's daily lives, from fitness trackers to sleep monitoring devices. Similarly, applications designed to enhance driver security and well-being are undoubtedly essential in the driving environment. By gathering and analyzing data, these technologies can make informed decisions that assist the driver, creating a more intelligent and collaborative environment. This is achieved by efficiently managing travel and health information through various advanced features. For example, AI-driven applications can significantly enhance driver security through stress detection and management, as AI analyzes physiological data to identify stress levels and implement preventive measures. Fatigue detection systems utilize ocular metrics to monitor signs of drowsiness, alerting the driver or taking preventive actions to prevent accidents. Moreover, integrating AI with other technologies, such as GPS and vehicular sensors, enhances situational awareness and decision-making, ensuring a secure driving environment. Additionally, incorporating vehicle dynamics and cabin conditions, such as temperature and air quality, can provide a comprehensive view of the driver's health and environmental factors. This integrated approach is necessary to optimize system performance and deliver actionable insights. These innovations collectively contribute to a safer and healthier driving experience by providing accurate, real-time information and enabling timely interventions.

5 Conclusions

This comprehensive review analyzed numerous published articles to establish a framework for driving healthcare monitoring using IoT and wearable devices. Utilizing the NLP toolkit, 35 studies meeting specific inclusion criteria were included in this analysis. The review revealed a fundamental principle for healthcare monitoring through wearable device applications, wherein data collected from one or multiple sensors is processed and stored in a database server for various purposes, such as informing a professional caregiver or aiding the user. Additionally, the reviewed studies showcased the integration of diverse hardware and software technologies, illustrating different ways to implement and enhance this core monitoring principle.

The systematic review examined key parameters such as hardware types, methodologies, extracted features, and communication protocols, providing a foundation for developing effective driving healthcare monitoring systems. Future research should focus on several critical areas to advance this field. First, integrating advanced artificial intelligence algorithms to enhance the accuracy and predictive capabilities of these systems, thereby improving anomaly detection and personalized health insights. Second, developing multi-modal sensor fusion techniques by combining data from various sensors to offer a comprehensive understanding of the driver's health. Another essential aspect is improving real-time data processing and communication protocols to optimize low-latency communication, reducing reliance on constant cloud connectivity and enhancing system responsiveness. Additionally, incorporating human factors engineering and real-world usability testing is necessary to ensure that these systems do not distract or inconvenience drivers. Finally, addressing security and privacy concerns is crucial, as these devices collect sensitive health data. Research should prioritize robust encryption methods and secure communication channels to protect user data from unauthorized access. Future studies can contribute to developing robust and efficient driving healthcare monitoring systems by focusing on these areas, ultimately enhancing driver safety through innovative IoT and wearable device applications.

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Received 30 June 2023; revised 28 February 2025; accepted 22 March 2025